WCCLF 2021
II WORLD CONGRESS ON INTEGRATED CROP-LIVESTOCK-FORESTRY SYSTEMS
May 4th and 5th, 2021 - 100% Digital

CAN CANOPY HEIGHT OF MIXED PASTURES IN INTEGRATED CROP-LIVESTOCK SYSTEMS BE ESTIMATED USING PLANETSCOPE IMAGERY?

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ABSTRACT

Canopy height (CH) is one of the key parameters used to evaluate forage biomass production and support grazing management decisions in intensively managed fields. In this study, we demonstrate the potential of using textural information derived from PlanetScope (PS) imagery to estimate CH of intensively managed mixed pastures in an Integrated Crop–Livestock Systems (ICLS) in the western region of São Paulo State, Brazil. PS images and field data of CH were acquired during the forage growing season of 2019 (from May to November) to calibrate and validate the CH prediction models using the Random Forest (RF) regression algorithm. We used as predictor variables eight second-order texture measures derived from the green, red, near-infrared spectral bands of PS images using the grey level co-occurrence matrix (GLCM) statistical texture approach. Pasture CH varied from 0.12 to 1.20 m with a coefficient of variation equal to 63.34%. Our best RF model was able to predict the spatiotemporal changes in pasture CH with high accuracy ($R^2 = 0.88$) even with the high variability of the pasture CH through the forage growing season, mainly due to forage composition (different proportions of millet and ruzi grass) and grazing activities.

Key words: integrated systems; nano-satellites; texture measures

INTRODUCTION

Canopy height (CH) is one of the key parameters adopted to manage pasture fields since it is directly related to forage biomass production. Field measurements of pasture CH can be easily carried out using nondestructive sampling techniques (e.g., sward sticks and Robel poles) (BAXTER et al., 2017). However, these techniques are unlikely to give representative information of large pasture areas for being dependent on sampling design distribution and intensity.

Remotely sensed data derived from various sensors have been successfully used to predict pasture CH over the years (BATISTOTI et al., 2019; TISCORNIA et al., 2019) for providing wall-to-wall mapping of continuous measures of pastureland characteristics. The pasture canopy structure can be quantified using the spectral properties of remotely sensed imagery. Specifically, the spatial distribution and variation of spectral values across the pixels of a remotely sensed image result in this image's textural information (HARALICK; SHANMUGAM; DINSTEIN, 1973). Texture measures derived from high spatial resolution optical imagery hold particular potential for quantifying the variability in structurally complex canopies, such as in mixed pasture fields.

The high spatial and temporal resolutions offered by the recent constellations of nano-satellites such as Planet CubeSats are very promising for monitoring intensively managed pasture fields at a finer scale. To this date, only a few studies have explored the potential of using texture measures derived from PlanetScope (PS) images for monitoring mixed pasture fields. In this study, we assessed the performance of textural information derived from PS imagery to estimate canopy height (CH) of intensively managed mixed pastures in an Integrated Crop–Livestock Systems (ICLS) in the western region of São Paulo State, Brazil.

MATERIAL AND METHODS

The study area corresponds to four commercial fields of mixed pastures with approximately 50 ha each, located in the western region of São Paulo State, Brazil, between the geographic coordinates 21º37'30" S - 51°56'00" W and 21º38'30" S - 51°54'00" W. According to Köppen's climatic classification system, the study area has tropical climatic conditions (type Aw), with drier months during the winter (*i.e.,* June–August) (ALVARES et al., 2013). The mean annual rainfall varies between 1,200 mm to 1,400 mm, concentrated in December and January.

The four fields have trees for shade and are split into 13 paddocks on which grazing livestock (cattle) rotates between them throughout the forage growing season. The area has been intensively managed as an ICLS based on cultivated mixed pasture rotation during the dry season (usually between April and October) and soybean cultivation in the wet season (usually between November and March). The pasture under study comprises a mixture of ruzi grass (*Urochloa ruziziensis*) and millet (*Pennisetum glaucum*), sown at a proportion of 15 kg ha^{-1} of millet and 5 kg ha^{-1} of ruzi grass in a spacing of 17 cm between rows. Pasture sowing began after the soybean harvest on March 28th and lasted until April 6th, 2019.

Field data collection of pasture canopy height (CH) was carried out during the forage growing season of 2019 using a sampling grid with one hundred georeferenced points distributed within the study area with a sampling intensity of 25 points per field using a stratified systematic unaligned sampling design. Field data collection campaigns were conducted on six dates: May 17th, May 25th, June 18th, July 14th, August 12th, and November 02nd, 2019. The field campaign dates were defined to capture different phases of the forage growth cycle (millet and ruzi grass) and in the function of animals' entry and exit in the paddocks (defined by the farm manager). The numbers of sampling points measured in each field campaign varied according to paddock rotation, totalizing 346 field-sampled points.

The CH measurements were performed using a sward stick in 11 representative locations within a buffer of 5 m around the centroid of each sampling point. To obtain the mean CH, we calculated a weighted mean height based on the proportion of millet:ruzi grass in each sampling point. To determine that proportion at each sampling point, all millet and ruzi grass plants were collected in a 1 m^2 frame close to the ground. The fresh biomass of all plants was weighted in the field using a hanging scale, and then the ruzi grass and millet were separated and weighted again. Next, the samples of millet and ruzi grass plants were sent to the laboratory for drying, placed in an oven at 65 °C for 72 hours, and weighed to obtain the dry weight (dry mass in g m^{-2}). The proportion of millet at a specific sampling point was determined by dividing the weight of millet dry mass by the total plant weight in that sampling point. The same procedure was adopted to determine the proportion of ruzi grass in each sampling point.

Cloud-free PlanetScope (PS) CubeSat multispectral images covering the study area were acquired for this study on dates that most closely coincided with the field campaign dates (*i.e.*, May 20th, May 27th, June 17th, July 11th, August 10th, and November 02nd, 2019, respectively), and downloaded from the SCCON (Santiago & Cintra Consulting) platform. PlanetScope is a constellation of nano-satellites with more than 130 CubeSats 3U form factor (0.1 m by 0.1 m by 0.3 m) with the capability to image all of the Earth's land surface daily. The PS sensor has four spectral bands: blue (B: 455–515 nm), green (G: 500–590 nm), red (R: 590–670 nm), and near-infrared (NIR: 780–860 nm) with a spatial resolution of ∼3 m. The Planet Surface Reflectance (SR) Product was used in this study (PLANET LABS, 2020).

To explore the potential of using textural information from PS imagery to estimate CH in our study area, we used the grey level co-occurrence matrix (GLCM) statistical texture approach to derive texture images (HARALICK; SHANMUGAM; DINSTEIN, 1973). Texture measures quantify the heterogeneity in the greyscale values of pixels within a defined area of an image. Eight second-order GLCM texture measures, including mean (MEA), variance (VAR), homogeneity (HOM), contrast (CON), dissimilarity (DIS), entropy (ENT), second moment (2M), and correlation (COR), were calculated using the texture co-occurrence measures procedure available at ENVI/IDL software (Harris Geospatial Solutions, Inc., Broomfield, CO, USA). The eight texture measures were calculated for the G, R, and NIR bands of PlanetScope images using a window size of 5 × 5 pixels and the offset (θ) of 135°. All GLCMs were constructed using a 64 grey level quantization, and the B band was not used to derive GLCM textures for being strongly influenced by atmospheric scattering.

The Random Forest (RF) machine learning algorithm (BREIMAN, 2001) was used to estimate pasture CH, using as predictor variables the GLCM texture measures. From the coordinates of the sampling points, we extracted the textural information of the PS images and then associated it with the field-based measures of pasture CH for the model development. The 346 field-sampled points were randomly divided into 70% and 30% for training and validation of the RF models. The development of RF models involves a hyperparameter tuning process that maximizes the predictive accuracy of the models. Optimal values of the hyperparameters *ntree* (number of decision trees) and *mtry* (number of predictor variables randomly sampled at each split) were selected according to the accuracy estimation in the training dataset using the 5-fold cross-validation method. Next, we carried out the feature selection based on the built-in feature importance measures of the RF algorithm, enabling the most important variables in each model run to be identified. The importance of the predictor variables in the RF models was evaluated by calculating the mean square error increase (IncMSE) when a variable is randomly permuted (BREIMAN, 2001), reflecting the importance of each predictor in the prediction accuracy of pasture CH. The RF models' performance was assessed using the root mean square error (RMSE) in absolute and percentage terms and the coefficient of determination (R^2), calculated based on field-based pasture CH measurements in the testing dataset. All CH modeling analyses and evaluations were performed using the *mlr* package in R software (BISCHL et al., 2016).

RESULTS AND DISCUSSIONS

Pasture CH varied from 0.12 to 1.20 m with a coefficient of variation equal to 63.34%, highlighting the complexity and variability of mixed pastures throughout the forage growing season. The maximum values of CH (> 0.9 m) were measured in the fields in May, mainly due to the high proportion of millet (79%) in the pasture canopy structure. After the first grazing cycles, the proportion of millet in the pasture canopy structure was reduced (45% in June and 15% in July), and the growth of ruzi grass was favored. As a result, the measured values of CH were lower in June and July (< 0.68 m). In August, the proportion of millet in the pasture canopy structure was 3%. The entire ruzi grass establishment was observed in November, the month in which the lowest values of CH (< 0.38 m) were observed in the fields. Consequently, the high variability of pasture CH during the forage growing season was mainly due to the different proportions of millet and ruzi grass, grazing activities, and pasture coverage. Millet and ruzi grass are two plants with different structural properties and growth rates. Millet shows a rapid initial growth rate and is a tall, robust, and erect annual bunchgrass with long narrow leaves. On the other hand, ruzi grass is a creeping perennial with short rhizomes, which form a dense leafy cover over the ground.

The texture measures derived from the PS images were able to capture the variation in pasture CH throughout the forage growing season with high accuracy ($R^2 = 0.88$) and low prediction errors (RMSE = 0.10 m or 22.18%), based on the best RF model and the validation dataset (Figure 1 (a)). The predicted and measured values of CH showed a good agreement; however, we observed a slight trend of underestimation of CH higher than 1.0 m. The feature importance metric of the best RF model (Figure 1 (b)) shows that the MEA textures obtained from the G, R, and NIR spectral bands were the most important predictor variables in the estimation of CH. The ENT, CON, HOM, DIS, and 2M textures derived from the three PS spectral bands were the subsequent most important variables for CH predictions. On the other hand, the textures VAR and COR were not selected by the best RF model. The superior performance of the MEA texture in predicting vegetation structural parameters has been previously reported in the literature (WOOD et al., 2012; LI et al., 2019; ZHENG et al., 2019) and is mainly due to the MEA texture's ability in minimizing the interference of the background and smoothing the image. Texture measures are key spatial features derived from high spatial resolution remotely sensed imagery such as PS images and capture the canopy structure information needed for CH estimation in mixed pasture fields.

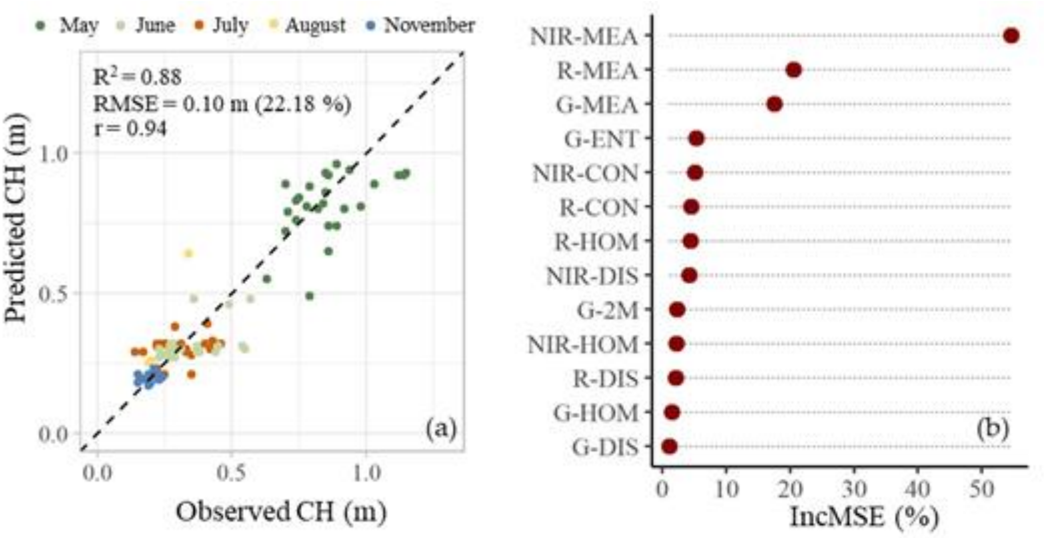
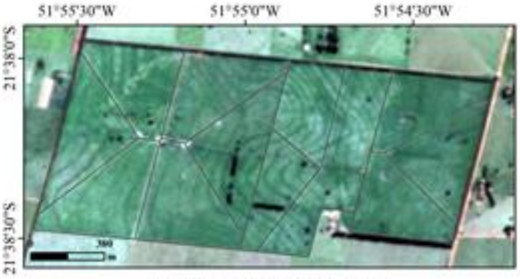


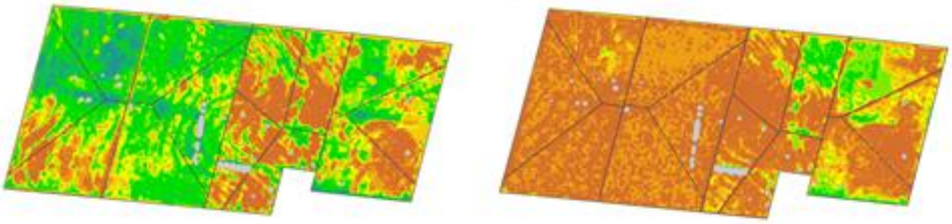
Figure 1. (a) Scatterplot of the predicted versus measured values of pasture canopy height (CH, m) obtained using the Random Forest (RF) model based on the testing dataset. A 1:1 line (black, dashed) is provided for reference. (b) Importance of the predictor variables as measured by the feature importance metric in the RF model.

The predicted values of pasture CH for the entire study area for different months of the forage growing season are shown in Figure 2. The spatiotemporal variations in pasture CH throughout the forage growing season agree with the field measurements of CH and the expected changes in pasture vegetation, mainly due to forage development (different proportions of millet and ruzi grass in the pasture vegetation) and grazing activities.

The unique combination of high temporal (daily) and high spatial (3 m) resolution imagery offered by the Planet's constellation of CubeSats is essential for pasture monitoring at a finer scale in intensively managed fields. The texture measures derived from PS imagery allow the incorporation of both spectral and spatial information in the CH prediction of pasture fields, resulting in enhanced estimation accuracy of CH models (DOS REIS et al., 2020). However, PS images obtained from different nano-satellites may present cross-sensor variations (HOUBORG; MCCABE, 2018), which affect the generalization of models produced based on the relationship between field-based CH measurements and variables derived from PS imagery. Despite possible limitations related to image calibration and data accessibility, PS imagery shows outstanding potential for estimating CH of pasture fields.

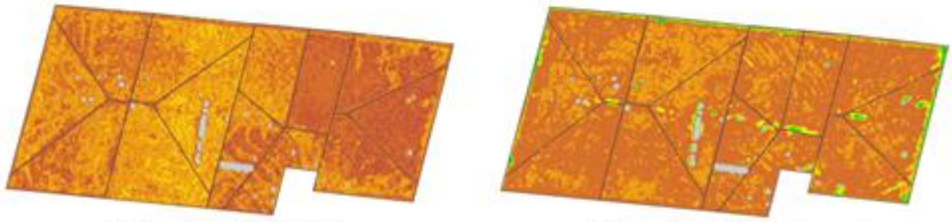


(a) PlanetScope image



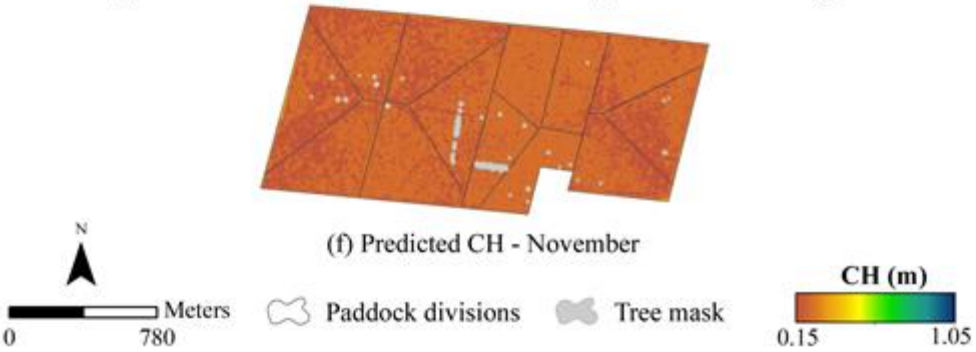
(b) Predicted CH - May

(c) Predicted CH - June



(d) Predicted CH - July

(e) Predicted CH - August



(f) Predicted CH - November

Figure 2. PlanetScope image (true color composite red-green-blue (RGB):321) of the study area on May 20th, 2019 (a), and the pasture canopy height (CH) spatial maps predicted by the RF model for the entire study area in May (a), June (b), July (c), August (d), and November (e).

CONCLUSIONS

We demonstrate in this study the potential of using textural information derived from PlanetScope (PS) imagery to estimate canopy height (CH) of intensively managed mixed pastures in an Integrated Crop–Livestock System (ICLS). Our best Random Forest (RF) model was able to predict the spatiotemporal changes in pasture CH with high accuracy ($R^2 = 0.88$) even with the high variability of the pasture CH through the forage growing season, mainly due to forage composition (different proportions of millet and ruzi grass) and grazing activities.

ACKNOWLEDGMENTS

The authors would like to thank FAPESP (Grants 2018/24985-0 and 2017/50205-9) for this study's financial support and the owner, manager, and staff of Campina Farm (CV Nelore Mocho) for their support and assistance.

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