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Monsoon crop biomass estimation using terrestrial hyperspectral imaging

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Abstract

India's majority (60%) of the population depend on the agriculture sector for their livelihood. With the agriculture facing major challenges, remote sensing can be an effective tool in monitoring crop production and estimating the yield. It can lead to better planning and policies to ensure food security. This study was conducted with the main objective of predicting the fresh matter biomass (FMB) using the spectral reflectance extracted from hyperspectral images. Three monsoon crops (lablab, maize and finger millet) were grown simultaneously in each of these two experiments rainfed (R) and drip-irrigated (I) at University of Agricultural Sciences, Bengaluru, India. The images from full frame hyperspectral camera UHD-185 was used along with destructive biomass sampling to measure the FMB in t ha^{-1}. A total of 11 sampling dates in the monsoon season of 2016 to 2018 were sampled. The spectral data was used with random forest regression model to estimate the FMB in rainfed, irrigated experiments and generalised (data sets of R and I combined) condition. The prediction accuracies based on the relative error (rRMSEP) was found to be lower in generalised condition with 13.9% for lablab (R^2_{val} = 0.53), and 18% for finger millet (R^2_{val} = 0.46) and 18.7% for maize (R^2_{val} =0.53). Overall, the results show that the FMB prediction model is not specific to rainfed and irrigated experiments as it performed better in the generalised condition. In future, it must be tested to predict the FMB on a larger scale using the sensor on unmanned aerial vehicles.

Key words: hyperspectral imaging, biomass prediction, machine learning, multitemporal.

Introduction

India's majority (60 %) of the population depend on agriculture sector for their livelihood (Arjun 2013). Agriculture in India mainly depends on monsoon rainfall, surface water and ground water irrigation. Since the variability of monsoon rainfall is high, it forces the south Indian farmers to adapt to the local water availability (Ferrant et al. 2017). Therefore, timely water supply along with fertilisation can lead to a successful crop. With these conditions, remote sensing (RS) can be an effective tool in monitoring crop production (Aasen et al. 2015) and estimating yield (Wang et al. 2017). RS helps to collect the information about crop production using non-destructive methods on a large scale for many fields at the same time (Burkart et al. 2015). It can lead to better planning and policies to ensure the food security. Multi-temporal images provide more information on vegetation phenology than a single image (Knight et al. 2006). Many studies related to multi-temporal hyperspectral data are published for crops such as rice (Aasen et al. 2014), wheat (Yue et al. 2017) and maize (Wang et al. 2017). Apart from maize, although lablab and finger millet are the major crops grown in the state of Karnataka, accounting to 90 % (Lablab) (Byre Gowda n.d.) and 62 % (Finger millet) (Selected state-wise area , production and productivity of ragi in India (2016-17). 2019) production in India, there are no hyperspectral RS measurements done for these crops with varying N levels and water supply for estimation of biomass. The aim of the study was to assess the potential of terrestrial hyperspectral images to estimate the monsoon crop biomass of lablab, maize and finger millet based on dataset from three years 2016-2018.

Material and Methods

The study was conducted at GKVK campus, University of Agricultural Sciences, Bengaluru (UASB), Karnataka state, India (12°58′20.79″N, 77°34′50.31″E, 920 m.a.s.l). The two experiments R and I were maintained at three N levels low, medium and high for the three crops lablab, maize and finger millet. The crops were grown from June to November with 11 sampling dates in total for consecutive three years from 2016 to 2018.

Hyperspectral images using full-frame hyperspectral camera UHD 185-Firefly (Hyperspectral imaging - real snapshot technology - Cubert GmbH. 2017) were captured at 1.5 m above canopy using tripods. The fresh matter biomass (FMB) collected at the field were recorded. The machine learning algorithm Random Forest Regression was used for calibration (75 %) and validation (25 %) of the dataset in R software. The FMB model was run for 100 times and 100 prediction accuracies R^2 validation (R^2_{val}) and relative root mean square error prediction (rRMSEP) were obtained.

$$R^2_{val} = \left[1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}\right]$$

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

$$rel.RMSEP = \frac{RMSEP}{\max(y_i) - \min(y_i)}$$

where y_i is the measured fresh matter biomass, $\hat{y}_i$ is the predicted fresh matter biomass, $\bar{y}_i$ is the average measured fresh matter biomass, and n is the number of samples.

Results and Discussion

The FMB models developed for each water management levels R and I experiments showed the lowest median rRMSEP for lablab in I experiment with 17.9% (R^2_{val} = 0.34) and for maize and finger millet in R experiment with 18.5% (R^2_{val} = 0.60) and 19.8% (R^2_{val} = 0.46), respectively (Figure 1). With the combined dataset, i.e. the generalised condition, the rRMSEP for lablab was 13.9% (R^2_{val} = 0.53), for finger millet was 18% (R^2_{val} = 0.46) and for maize it was 18.7% (R^2_{val} = 0.53).

Overall, it was found that the relative error was lower in generalised models compared to R and I experiments exclusively. The range of crop productivity from both R and I experiments became much broader which eventually might have increased the robustness of the generalised models. With the high number of samplings and covering the growth stages of the crops during the three consecutive monsoon seasons has increased the validity range of generalised models. Similar prediction errors were found by (Li et al. 2016) for maize biomass by RGB images (relative error 16.66%, R^2= 0.78). In contrast to our study they included canopy height parameter additional to RGB information. In generalised model, the relative error for lablab is less, followed by finger millet and then maize. As the height of the plant increases the relative error is also increasing, which shows that spectral reflectance from top canopy layer is less representing the lower parts of the plant. In general, the FMB model from generalised condition is not specific to R or I conditions, it is more applicable at varying N levels and water supply.

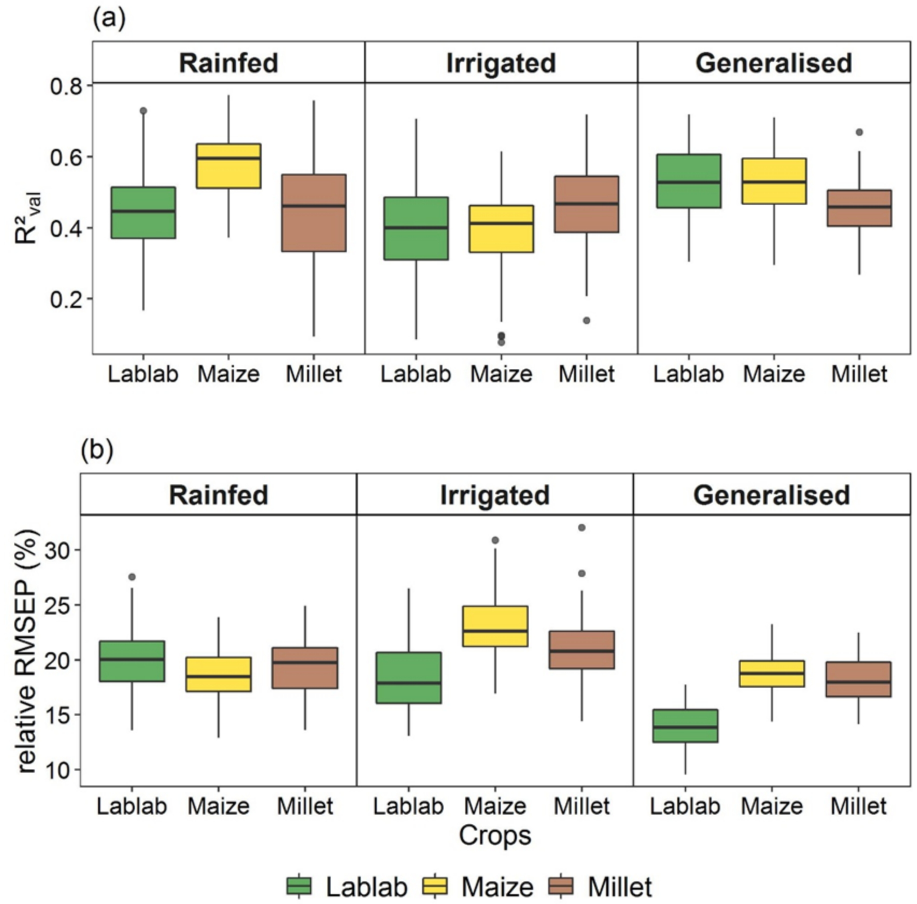

Figure 1. Prediction accuracies measured as R^2_{val} (a) and rRMSEP (b) values of the fresh matter biomass models (Rainfed, Irrigated and Generalised) for lablab, maize and finger millet. Models were built on data from three different years, three levels of N and two levels of water supply (i.e., rainfed and irrigated) at multi-factorial field experiments at University of Agricultural Sciences, GKVK Campus, Bangalore, India.

Conclusions and Outlook

The generalised model was found to be better compared to rainfed and irrigated experiments. In generalised model, the relative error was found to be lower for lablab, followed by finger millet and then maize. It shows the need of an additional sensor data which can complement the individual sensor data deficiencies to improve the prediction performance by sensor data fusion. In future, the hyperspectral camera fixed with Unmanned Aerial Vehicles need to be tested to cover larger areas for estimation of biomass.

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