COTTON CROP PHENOTYPING AND STRESS DETECTION USING HYPERSPECTRAL AND DRONE DERIVED VEGETATION INDICES

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Abstract

Crop monitoring at regular intervals using drones will be more helpful in taking appropriate measures. It also helps limit the risk of output loss due to any stress factor. The major goal in crop production is to lower the cost of cultivation, improve control, and increase resource use efficiency. It is extremely beneficial when analyzing various abiotic and biotic stresses in multiple crops and detecting and managing various agricultural concerns, even on small farm holdings. The field experiment was conducted at Tamil Nadu Agricultural University, Coimbatore, 2021-22 in cotton crop. The observations were taken on vegetative stage of the crop using spectroradiometer and Parrot drone (RGB sensor). For detecting the cotton stress five spectral vegetation indices *viz.,* Normalized Red-Green Difference Index (NGRDI), Modified Green Red Vegetation Index (MGRVI), Disease water stress index (DWSI), Normalized pigment chlorophyll ratio index (NPCI) and Triangular greenness index (TGI) were derived using hyperspectral data and drone data. Among the vegetation indices NPCI performed better for detecting the cotton reddening stress with higher correlation coefficient of R=0.928 and R^2=0.862 compared to other vegetation indices used in this study. This method of stress detection using vegetation indices will be very useful in correcting the crop stress at critical stages of crop growth to avoid any yield loss.

Keywords: Cotton, drone, hyperspectral reflectance, stress assessment, vegetation indices

Introduction

Vegetation Indices (VIs) obtained from remote sensing-based canopies are simple and effective algorithms for assessing the amount of vegetation, its robustness, and its growth dynamics on a quantitative and qualitative basis. They are computed without bias or assuming any assumptions about the kind of soil, the land cover class, or the weather because they are simple transformations of spectral bands (Huete *et al.*, 2002). Researchers can use VIs to monitor phenological and biophysical characteristics of vegetation cover, as well as seasonal, interannual, and long-term structural variations. To quantify plant biophysical and biochemical properties, hyperspectral vegetation indices (VIs) are frequently used in agriculture remote sensing and plant phenotyping (Koh *et al.*, 2022). VIs have also been frequently employed for crop monitoring studies, mapping, and identification. In addition, most crop yield estimation models that used remote sensing data also performed regression analysis using VIs as major input variables (Kern *et al.*, 2018; Meroni *et al.*, 2015). Vegetation indices (VI) are usually calculated as combining two or more spectral bands. Therefore, texture and spectral information may be used to create vegetation indices (Wang *et al.*, 2021). Texture information is paramount for detecting items or visual regions of interest. Numerous VIs are used to identify more spectral features to achieve high monitoring accuracy. In this study, the phenology of cotton crop and stress assessment was done using hyperspectral data and vegetation indices derived from drone imageries.

Materials and Methods

The field experiment was conducted at Tamil Nadu Agricultural University, Coimbatore, 2021-22 in cotton crop. The observations were collected using Parrot drone with RGB sensor and hand-held spectroradiometer. The Hyperspectral data were collected using GER 1500 portable spectroradiometer with 512 channels ranging from 350-1050nm with 1.5-3.2nm bandwidths. The following table lists several vegetation indices, their applications, and the method for estimating those using different spectral bands. For analyzing the cotton stress five vegetation indices *viz.*, Normalized Red-Green Difference Index (NGRDI), Modified Green Red Vegetation Index (MGRVI), Disease water stress index (DWSI), Normalized pigment chlorophyll ratio index (NPCI) and Triangular greenness index (TGI) were derived using hyperspectral and drone data.

Index	Equation	Applications (References)
NGRDI	$\frac{G - R}{G + R}$	Chlorophyll content, biomass and water content estimation (Hunt *et al.*, 2005)
MGRVI	$\frac{(G \times G) - (R \times R)}{(G \times G) + (R \times R)}$	Chlorophyll a-absorption, chlorophyll b-absorption and biomass estimation (Bendig *et al.*, 2015)
DWSI	G / R	Changes in leaf pigments, internal leaf structure and water (Kundu *et al.*, 2021)
NPCI	$\frac{R - B}{R + B}$	Changes in leaf pigments, Water stress (Klem *et al.*, 2018) and leafhopper infestation (Prabhakar *et al.*, 2011)
TGI	$G - (0.39 \times R) - (0.61 \times B)$	Chlorophyll content (Friedman *et al.*, 2016), yield, water content and nitrogen estimation (Reyes *et al.*, 2017)

Results and Discussion

The spectral reflectance curve of the cotton crop was derived using the hyperspectral data. The Fig.1 shows the cotton (healthy plant) reflectance and its reflectance under stressed condition. This will be more useful in varietal discrimination and for high throughput phenotyping (HTP) in breeding program for studying about different plant traits of particular interest. The healthy cotton shows the higher percentage reflectance than the cotton under stressed condition (reddening) which was having lesser percentage reflectance. This could be understood by the reason that plant under healthier condition reflects more of infrared than red wavelength. An increase in reflectance under red wavelength region depicts that the crop is under stressed condition.

In addition, vegetation indices were derived using the hyperspectral and drone data for detecting the cotton reddening stress. Statistical analysis was done to establish a relationship between drone-derived vegetation indices (predicted value) and ground truth hyperspectral data (observed value). Pearson correlation coefficient was done to identify the most sensitive vegetation index. The positive linear correlations between different vegetation indices and ground truth data are depicted in Fig 2.

Among the vegetation indices, the NPCI had recorded higher correlation coefficient with ground truth hyperspectral data with R value of 0.928 and R^2 of 0.862. MGRVI recorded a correlation coefficient value of R=0.827 and R^2 of 0.683. DWSI recorded a correlation coefficient value of R=0.819 and R^2 of 0.669. NGRDI recorded a correlation coefficient value of R=0.760 and R^2 of 0.578. TGI recorded the least correlation coefficient value of R=0.686 and R^2 of 0.470. This shows that the NPCI was the most suitable vegetation index for detecting the cotton reddening stress condition.

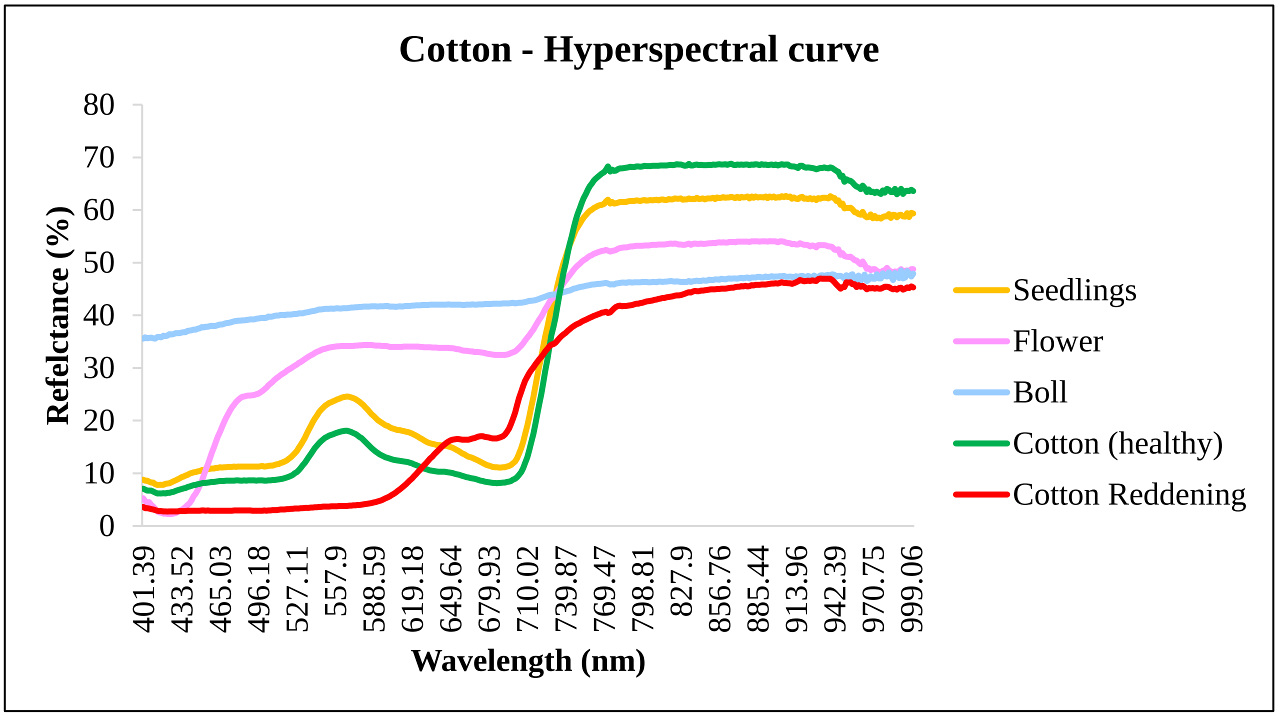
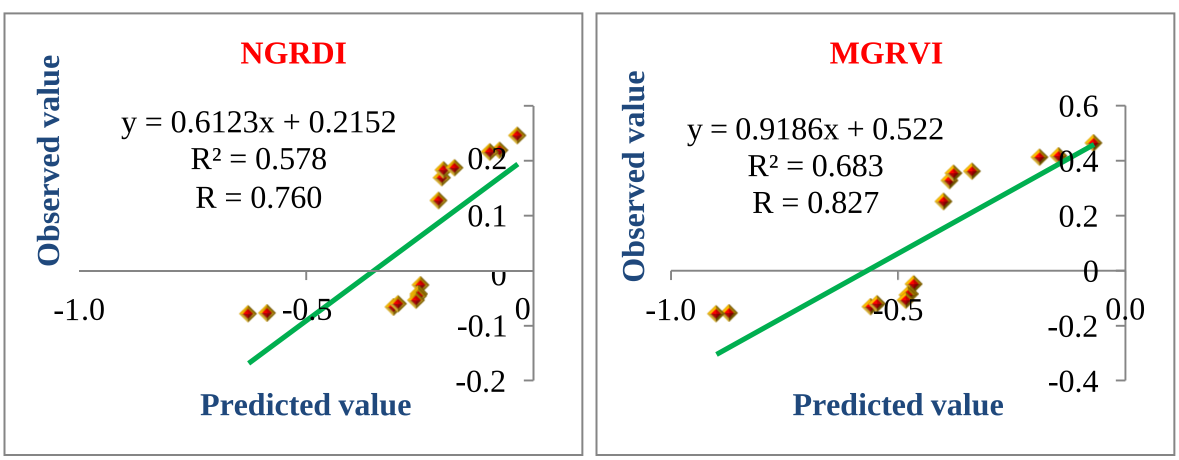


Fig 1. Hyperspectral reflectance of cotton at different wavebands



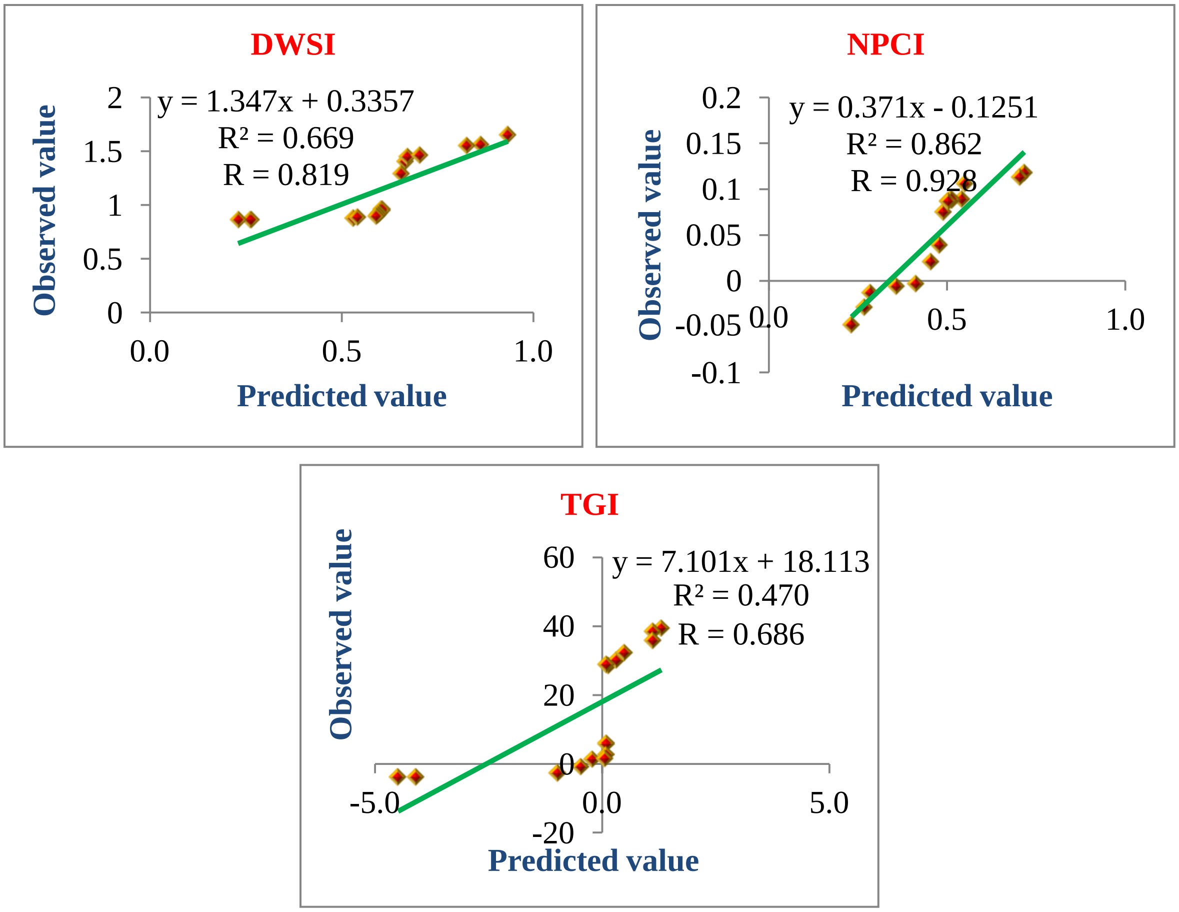


Fig 2. Relationship between NGRDI, MGRVI, DWSI, NPCI and TGI indices with hyperspectral data using Pearson correlation analysis

Conclusion

From this research, it was concluded that among the spectral vegetation indices used in this study Normalized pigment chlorophyll ratio index (NPCI) was found to be the most sensitive vegetation index for detecting the cotton reddening stress condition. This confirms that RGB sensors are most useful for mapping the stress severity using reflectance data (Tetila *et al.*, 2017). Accurate, real-time, and early identification of crop stress condition was beneficial for agricultural management systems.

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