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Original Research Article

Hypesectral Remote Sensing Technique for Estimation of Magnesium in Cotton Canopies

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A B S T R A C T

Magnesium is one the most important growth limiting factors in cotton crop production. The use of remote sensing is deemed particularly and practically suitable for assessing the nutrient stress and implementing site specific management strategies because it presents unique advantage of repeatability and accuracy. A field survey was conducted in cotton during Kharif, 2016 to a) determine the optimum spectral bands for discrimination of Magnesium content using hyper spectral data. b) study the relationship between the spectral bands and the leaf Magnesium content. Spectral measurements and leaf samplings were simultaneously done at flowering and boll formation stages. The field observation of reflectance was measured using hand held spectroradimeter (350-1050 nm). Stepwise discriminant analysis and regression analysis were done and identified the spectral bands. Stepwise discriminant analysis was used to identify the most influencing bands for discrimination of leaf Mg. The identified spectral bands were 499 nm in blue, 564 in green, 600 and 610 nm in red, 701, 741 and 773 in NIR regions. It was observed that among the three models tested for determination of leaf Mg in cotton canopies, simple ratio (R_{773}/ R_{499}) had the highest R value (0.821) for leaf Mg. The Reflectance values at 701 nm selected through SRA used to estimated leaf Mg. The SRA and GNDVI had the R values of 0.793 and 0.747, respectively. Hence, out of three models tested for estimation of leaf magnesium content in cotton canopies, simple ratio developed using R_{773}/ R_{499} was found to be superior.

Keywords

Remte sensing technique, Estimation of magnesium

Introduction

In many studies, precision farming are focused on Mg application rate and timing for high yield and crop quality (Weiss *et al.*, 2001). Conventional chemical analyses are usually made to determine nutrient element status of plants using laboratory techniques. Analysis of leaf samples in crop plants is usually undertaken with the objectives of diagnosing nutrient deficiencies and imbalances and evaluating the effectiveness of the current nutrient management programs (Miles, 2010). But, conventional laboratory analysis is expensive, laborious and time consuming. Furthermore, in many cases, the results of the laboratory analyses are sent to the cotton growers after the cotton picking, hence, significantly reducing any benefit to the farmer in terms of nutrient management. Determination of leaf biochemical content by remote sensing could be used as an alternative method and could reduce the problems of laboratory analyses (Mutanga *et al.,* 2004). The spectral reflectance can be effectively used to discriminate the nutrient stress in cotton. Ground based systems play an important role in remote sensing.

Canopy structure and pigment status of cotton were the most important factors affecting the canopy spectral reflectance. The selection of optimum wavebands from the spectral (blue, green, red and NIR) regions had been performed in a number of cases, focused mainly on how to improve the correlation between spectral indices and crop biophysical/biochemical variables. But, studies were focused on how to increase the sensitivity of the spectral bands to Mg stress.

Hence, an experiment was conducted to a) determine the optimum spectral bands for discrimination of Magnesium content using hyper spectral data. b) Study the relationship between the spectral bands and the leaf Magnesium content.

Materials and Methods

In order to identify the multi-nutrient deficiencies through hyper spectral remote sensing, a field survey was conducted during kharif, 2016 at flowering and boll formation stages in cotton. The field survey was conducted to collect the spectral reflectance and leaf samples (n = 30). The leaf samples were used to estimate the Fe contents.

The results of the leaf analysis and spectral reflectance are presented hereunder. The spectral reflectance was measured using GER 1500 portable spectro radiometer which has 512 channels ranging from 350-1050 nm with 1.5-3.2 nm bandwidths. The spectral reflectances were collected during flower formation (82 days after sowing) and boll formation stage (98 days after sowing) in cotton. The data were pooled for further analyses. The spectral readings of cotton were recorded in bright sun between 11.00 am to 12.00 noon. At the time of spectral reflectance measurement, four to five representative leaves of cotton were collected from the experimental plot for the estimation of total Iron. The leaf sample collected from each treatment and estimated as per the standard analytical method. Collected plant samples were shade dried and then in hot air oven (60^0C-70^0 C) for 36 hours and ground. The leaf samples were digested with triacid (Nitric acid: Sulphuric acid: Perchloric acid, 9:2:1) for estimation of leaf Mg (Piper, 1966).

Data Analysis

Stepwise discriminant analysis was carried out to classify the spectral bands based on the strength of the data. The dummy variables (1 and 2) were assigned for grouping the dependent variable (Leaf Mg) and the spectral reflectance values were dependent variables. Stepwise regression analysis was done to derive the relationship between the leaf Mg and spectral reflectance of the most influencing spectral bands for discrimination of Magnesium stress in cotton. These analyses were performed by using SPSS 19.0 (Chicago, IL, USA) software.

Results and Discussion

The hyper spectral data (350-1050 nm) were collected from different stages (flowering and boll formation) of the cotton crop growing in open field. The leaf samples analysis and the spectral bands selected for Mg discrimination were discussed hereunder.

Leaf magnesium analysis

The results showed that the leaf magnesium content ranged between 0.41 percentage and 0.98 percentage with the mean value of 0.61 percentage at flowering (82 DAS) stage. Similarly, leaf magnesium content at boll formation (98 DAS) stage ranged between 0.11 percentages and 0.39 percentages with the mean value of 0.26 percentages. Leaf Mg contents were comparable to the observation made by Steve Philips (2009) who reported that optimum leaf magnesium content was 0.30 - 0.75 percentage in cotton. The present study revealed that 6, 19 and 5 observations were deficient (0.11 – 0.29 %), optimum (0.30 – 0.72 %) and excess (0.77 – 0.98 %), respectively in leaf Mg content.

Stepwise Discriminant Analysis (SDA)

Stepwise discriminant analysis was used to identify the most influencing bands for discrimination of leaf Mg and presented in Table 1. The identified spectral bands were 499 nm in blue, 564 nm in green, 600 and 610 nm in red, 701, 741 and 773 nm in NIR regions. A relationship between spectral reflectance, particularly visible absorption and magnesium might be due to their effect on the photosynthetic process in plants (Mutanga *et al.,* 2013).

In general, the N deficiency usually decreases the leaf chlorophyll concentration resulting in an increase in leaf reflectance in both green centered (550 nm) and red edge (700-720 nm) ranges (Daughtry *et al.,* 2000; Zhao *et al.*, 2003). The significance of some of the spectral bands are presented in Table 2.

Stepwise regression analysis

Stepwise regression was used to study the relationship between leaf magnesium content and reflectance value of the identified bands. The stepwise regression selected 701 nm out of the subjected bands and formed an empirical formula. The empirical formula was used to predict the leaf magnesium content in cotton leaves. The model used the reflectance values at 701 nm. The predictive equation for leaf magnesium is given below.

$$Y = 0.959 – 0.019 X$$

Where,

Y = Leaf magnesium (%)
X = Reflectance (%) at 701 nm

The leaf magnesium contents were calculated using the predictive equations obtained. The estimated and predicted magnesium contents were plotted in scatter diagram with 1: 1 line. The relationship between the estimated and predicted magnesium is shown in Fig.1. The stepwise regression equation used the 701 nm for prediction of leaf Mg, with the R value of 0.793. This finding is in agreement with the Mutanga *et al.,* (2004) in forage crops. The present result also supported by Menesatti *et al.,* (2010) who determined the leaf Mg in citrus leaves using spectral reflectance. Basayigit and Senol (2009) and Ordonez *et al.,* (2013) also estimated the leaf Mg contents in cherry and vine leaves, respectively using stepwise regression analysis.

Vegetation indices

In this study, simple ratio was developed using reflectance value of bands from NIR to blue, NIR to green and NIR to red region. The leaf magnesium content was correlated with simple ratios of identified bands. The correlation co-efficient (r) for leaf Mg are presented in Table 3. Among the simple ratios, the simple ratio developed using 773 and 499 nm had the highest correlation co-efficient (r = 0.906) with leaf magnesium.

Linear regression was formed with simple ratio (R_{773}/R_{499}) and leaf Mg. The relationship between leaf magnesium content and simple ratio index (R_{773}/R_{499}) was studied and presented in Fig.17. The co-efficient of determination (R) for leaf Mg was 0.821. The linear regression equation for estimation of leaf magnesium is given below.

$Y = -0.234 + 0.069\ x$,

Where,

Y = Leaf magnesium (%)
x = Simple Ratio Index (R773/ R499)

Leaf magnesium was also analyzed with the existing vegetation indices namely Green Normalized vegetation Indices (GNDVI) and presented in Fig.18. The Fig.18 illustrated that there was a significant relationship between the leaf Mg and GNDVI. The leaf magnesium content was estimated by the linear regression between leaf Mg content and GNDVI. The co-efficient of determination (R) for leaf Mg was 0.747. The linear regression equation for estimation of leaf Mg is given below.

$Y = -0.441 + 1.499\ x$

Where,

Y = Leaf magnesium (%);
x = GNDVI

It was observed that among the three models tested for determination of leaf Mg in cotton canopies, simple ratio ($R_{773}/\ R_{499}$) had the highest R value (0.821) for leaf Mg. The SRA and GNDVI had the R value of 0.793 and 0.747, respectively. Hence, out of three models tested for estimation of leaf magnesium content in cotton canopies, simple ratio developed using $R_{773}/\ R_{499}$ was found to be superior. The simple ratio of reflectance in near infrared (NIR) to blue region ($R_{773}/\ R_{499}$) of the electromagnetic spectrum, was highly related to magnesium content in cotton leaves. The co-efficient of determination (R) for leaf Mg was 0.821 (Fig. 2). The leaf Mg content was also predicted using GNDVI, the R values was 0.747 (Fig. 3). Similar results were reported by Masoni *et al.*, (1996) in barley, wheat and maize crops and Pradhan *et al.*, (2013) in wheat crops.

Stepwise discriminant analysis was used to identify the most influencing bands for discrimination of leaf Mg. The identified spectral bands were 499 nm in blue, 564 in green, 600 and 610 nm in red, 701, 741 and 773 in NIR regions. It was observed that among the three models tested for determination of leaf Mg in cotton canopies, simple ratio ($R_{773}/\ R_{499}$) had the highest R value (0.821) for leaf Mg.

The Reflectance values at 701 nm selected through SRA used to estimated leaf Mg. The SRA and GNDVI had the R values of 0.793 and 0.747, respectively. Hence, out of three models tested for estimation of leaf magnesium content in cotton canopies, simple ratio developed using $R_{773}/\ R_{499}$ was found to be superior.

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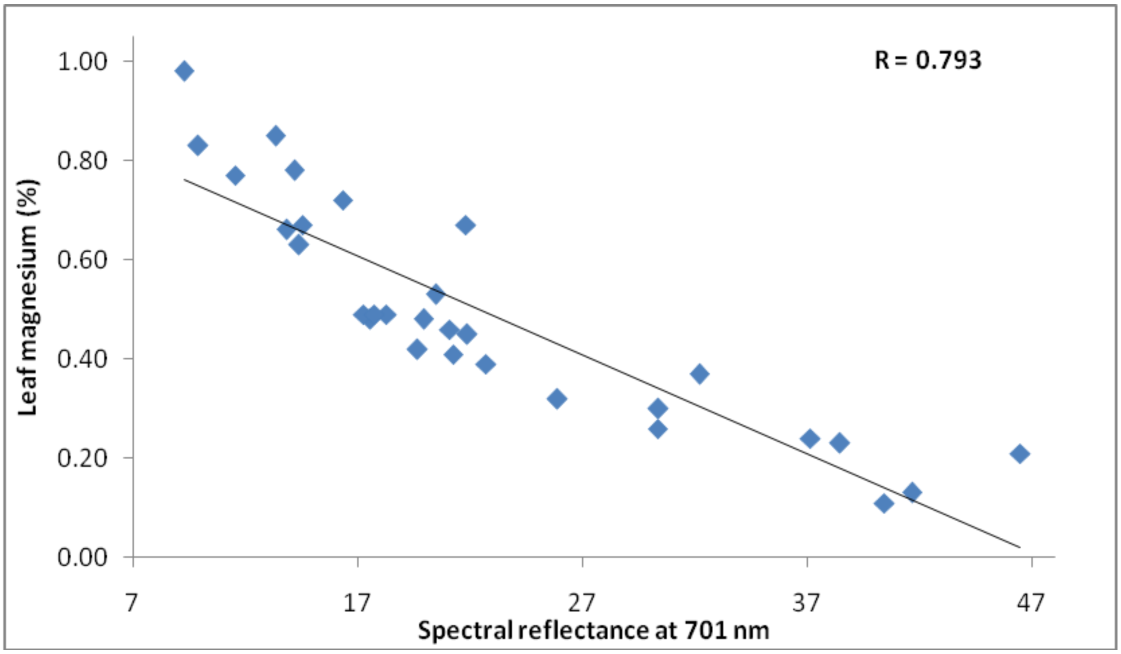

Fig.1 Relationship between spectral reflectance (%) and leaf magnesium content (%) in cotton canopies

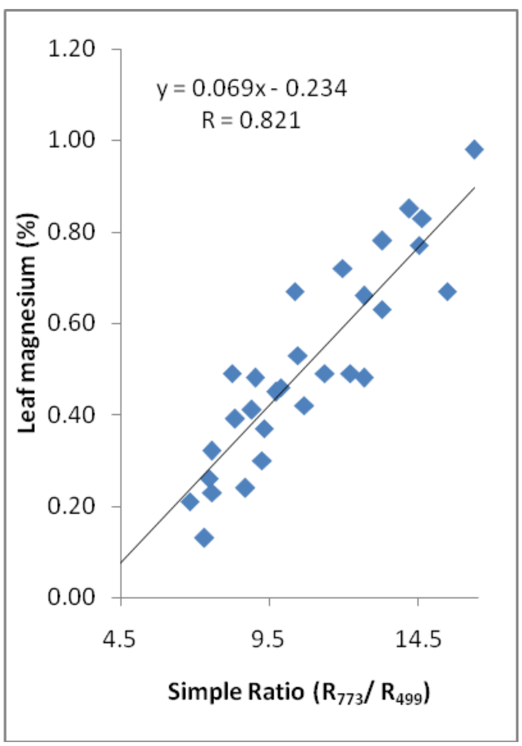

Fig.2 Relationship between leaf magnesium and R_{773}/ R_{499}

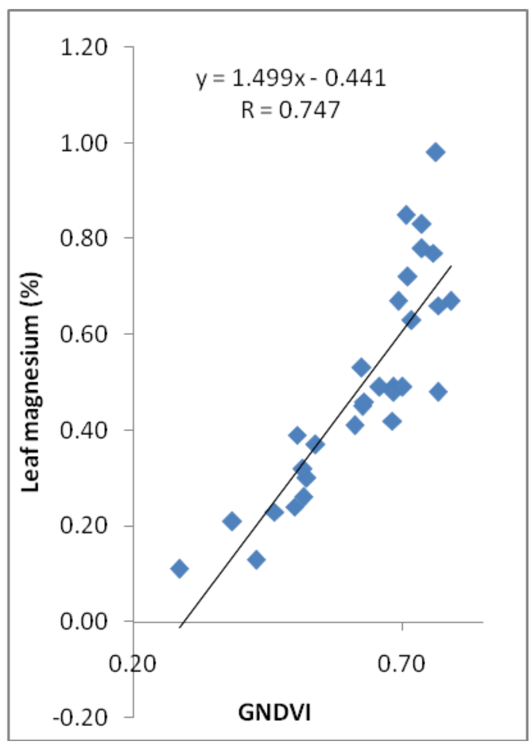

Fig.3 Relationship between leaf magnesium and GNDVI

Table.1 Spectral bands selected by stepwise discriminant analysis enabling maximum discrimination of magnesium stress in cotton

Spectral region	Magnesium
Blue	499
Green	564
Red	600, 610
Red Edge	701, 741, 773

Table.2 Selected wavebands for magnesium level discrimination and their significance

Spectral region	Wavelength (nm)	Significance
Blue	499	Light absorbed nit only by chlorophyll but also by carotenoids.
Green	564	Green band peak or the point maximal reflectance in the visible spectrum (Thenkbail *et al.*, 2000)
Red	600, 610	Absorption pre maxima
Red edge	701	Plant stress is best detected at red-edge bands centred around 705 nm and 735 nm (Elvidge and Chen, 1995)
NIR	741, 773	Early NIR. More sensitive to changes in chlorophyll content than a broad NIR Band

Table.3 Correlation between leaf magnesium (%) and simple ratio

Spectral Region	Bands (nm)	701 nm	741 nm	773 nm
Blue	499	0.106	0.895**	0.906**
Green	564	0.376*	0.846**	0.856**
Red	600	0.603**	0.885**	0.887**
	670	- 0.198	0.613**	0.643**
NIR	701	1.000	0.764**	0.777**
	741	- 0.805**	1.000	0.880**
	773	- 0.789**	0.689**	1.000

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