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Original Research Article

Hypesectral Remote Sensing Technique for Estimation of Iron Content in Cotton Canopies

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A B S T R A C T

Iron is one the most important micronutrient element in physiology of crop. 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 crop during 2016 to a) determine the optimum spectral bands for discrimination of Iron content using hyper spectral data. b) study the relationship between the spectral reflectance and the leaf Iron content. Spectral measurements and leaf samplings were simultaneously done at flowering and boll formation stages. The reflectance was measured in cotton crop using hand held spectroradimeter (350-1050 nm). The estimated leaf Fe content and spectral reflectance values were processed using stepwise discriminant analysis and regression analysis. As a result of the statistical analysis, it is identified the spectral band 738 nm which discriminates the iron stress in cotton. There was a linear relationship between the leaf Fe and spectral reflectance, with the coefficient of determination (R) of 0.855. Hence, it can be stated that hyper spectral will serve as an alternative and reliable technique of estimating the iron content in cotton canopy.

Keywords

Remote sensing technique, Iron content

Introduction

In many studies, precision farming are focused on Fe 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 reflectance, spectral indices and crop nutrients. But, a few studies were focused on how to increase the sensitivity of the spectral bands to leaf N and chlorophyll contents. Hence, an experiment was conducted to a) determine the optimum spectral bands for discrimination of iron content using hyper spectral data. b) study the relationship between the spectral bands and the leaf iron 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.

Spectral measurement

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.

Leaf sampling and analysis

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 Fe (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 Fe) and the spectral reflectance values were dependent variables.

Stepwise regression analysis was done to derive the relationship between the Leaf Fe and spectral reflectance of the most influencing spectral bands for discrimination of Iron 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 spectral bands selected for Fe discrimination and leaf analysis data were presented below.

Leaf iron analysis

The laboratory analysis of the leaf sample samples for iron content was done. The iron content of cotton leaf samples at flower formation (82 DAS) varied from 116 – 270 mg kg^{-1} with the mean value of 201 mg kg^{-1}. The iron contents of cotton leaf samples at boll formation (98 DAS) varied from 62 – 270 mg kg^{-1} with the mean value was 82 mg kg^{-1}. As per the Steve Philips (2009), optimum leaf iron content was 100 - 300 mg kg^{-1} in cotton. The present study revealed that 8 observations were deficient (66 – 74 mg kg^{-1}) and 22 observations were optimum (116 – 270 mg kg^{-1}) in leaf Fe content. The iron deficient cotton leaves exhibited an inter-veinal chlorosis. The mean value of iron content in cotton leaves had declined from flowering to boll formation stage. This is in agreement with Rochester (2007) who indicated a large proportion of Fe taken up by the crop were redistributed into the developing bolls and removed in seed cotton.

Spectral band selection

The stepwise discriminant analysis tests the strength of spectral data in separating or discriminating the Iron stress. The spectral bands of least wilks' lambda were selected for discriminating Fe stress and presented in the Table 1. The most influencing spectral bands for discrimination of Fe levels in cotton canopies were 496 and 499 nm in blue, 524 and 571 nm in green, 601, 608 and 694 nm in red and 701 nm in NIR regions. The identified bands were again analysed through stepwise regression Stepwise regression selected 571 nm and 608 nm in the predictive equation. The rest of the bands were 496 and 499 nm in blue, 524 and 571 nm in green, 601, 608 and 694 nm in red and 701 nm were excluded in the regression analysis as it was relatively less sensitive to the Fe stress.

Blackmer *et al.*, (1994) reported that the reflectance near 550 and 710 nm were better for detecting corn N deficiencies compared with reflectance at other wavelengths. In general, the Fe 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 Discriminant Analysis (SDA)

The spectral reflectance and leaf Fe contents taken during the kharif, 2016 (n = 30) were used for analysis. The leaf Fe content was classified into 2 class viz., class-1 (< 100 mg kg^{-1}) and class-2 (> 100 mg kg^{-1}). The classified independent variables (leaf Fe) were dummy numbered as 0 and 1.Number of independent variables observed under class-1 and class-2 were 18 and 12, respectively. The spectral reflectance from the spectral regions were grouped into 400-499, 500-599, 600-680, 681-780 and 741-950 nm. The reflectance values of grouped bands and leaf iron contents were subjected to stepwise discriminant analysis for identification of spectral bands. The identified bands are used for further analysis to estimate leaf iron levels. The identified bands had a Wilks' lambda value from 0.190 to 0.387 at 1% level of significance. The least Wilks' lambda was observed in green region (524 nm) and the highest value among the selected bands was in red region (496 nm). The identified spectral bands were in the order of 496 and 499 nm in blue, 524 and 571 nm in green, 601, 608 and 694 nm in red and 701 nm in NIR regions. The iron deficiency could have decreased the chlorophyll concentration and absorbance, increased reflectance, and shifted red edge position towards shorter wavelengths. Thus, leaf iron contents were indirectly responsible for modifications in leaf spectral properties. These results are in conformity with Davis *et al.,* (1986) and Nenova and Stojanov (1993) in corn and sunflower, respectively.

Stepwise Regression Analysis (SRA)

Stepwise regression selected 571 and 608 nm in the linear equation, with the co-efficient of determination (R) of 0.827. A statistically significant relationship was found between the leaf iron contents and the spectral reflectance values at 571 and 608 nm in cotton canopies. These results are supported by Basayigit *et al.,* (2015) in cherry leaves through statistical analysis (R = 0.753), laboratory analysis results and spectral reflectance values.

The predictive equation for leaf iron is given below.

$$Y = 246.24 – 17.93 X1 + 13.03 X2$$

Where,

Y = Leaf iron (mg kg^{-1})
X1 = Reflectance (%) at 571 nm
X2 = Reflectance (%) at 608 nm

The leaf iron contents were calculated using the predictive equations obtained. The estimated and predicted iron contents were plotted in scatter diagram with 1: 1 line. The relationship between the estimated and predicted iron is shown in Figure 1. The co-efficient of determination (R) for leaf iron was 0.827. Menesatti *et al.,* (2010) also supported the above findings. They reported that leaf Fe content in citrus plants was predicted using VNIR spectrophotometric analysis. Consequently, this investigation produced a significant R value (0.946) for leaf Fe. VNIR spectroscopy was also successfully employed for determining Fe content in rice by Shao and He (2013). Similar findings were reported by Huang *et al.,* (2004) in winter wheat crop using spectral reflectance.

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 Fe was correlated with simple ratios of identified bands. The results are presented in Table 3. Among the simple ratios, the ratio developed using 701 and 601 nm had the highest correlation co-efficient (r = 0.837) with leaf Fe. Linear regression was formed with simple ratio (R_{701}/ $R7_{601}$) and leaf Fe. The relationship between leaf iron content and simple ratio index (R_{701}/ R_{601}) was studied and presented in Figure 2. The co-efficient of determination (R) for leaf Fe was 0.701. The linear regression equation for estimation of leaf Fe is given below.

$$Y = - 244.90 + 224.80 x,$$

Where,

Y = Leaf iron (mg kg^{-1})
x = Simple Ratio Index (R701/ R601)

Leaf iron was also analyzed with the existing vegetation indices namely Green Normalized vegetation Indices (GNDVI) and presented in Figure 3. The Figure 3 had illustrated that there was a significant relationship between the leaf iron and GNDVI. The leaf iron content was estimated by the linear regression between leaf iron content and GNDVI. The co-efficient of determination (R) for leaf iron was 0.760. The linear regression equation for estimation of leaf iron is given below.
$$Y = -122.90 + 455.40 x$$

Where,

Y = Leaf iron (mg kg^{-1})
x = GNDVI

It was observed that among the three models tested for determination of leaf Fe in cotton canopies, the highest (0.827) co-efficient of determination (R) was obtained by stepwise regression analysis. The simple ratio and GNDVI had the R value of 0.701 and 0.760, respectively. Hence, out of three models tested for estimation of leaf iron content in cotton canopies, regression equation using the reflectance value at 571 nm and 608 nm was found superior to simple ratio and GNDVI.

The present study has identified the most influencing spectral bands for discrimination of Fe levels in cotton canopies were 496 and 499 nm in blue, 524 and 571 nm in green, 601, 608 and 694 nm in red and 701 nm in NIR regions. Stepwise regression selected 571 nm and 608 nm in the predictive equation. The highest (0.827) co-efficient of determination (R) for leaf Fe was observed by SRA. Simple ratio (R_{701}/ R_{601}) and GNDVI had the R value of 0.701 and 0.760, respectively.

Hence, out of three models tested for estimation of leaf iron content in cotton canopies, regression equation using the reflectance value at 571 nm and 608 were found superior to simple ratio and GNDVI.

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

Spectral region	Iron
Blue	496, 499
Green	524, 571
Red	601, 608, 694
Red Edge	701

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

Spectral region	Wavelength (nm)	Significance
Blue	496, 499	Light absorbed nit only by chlorophyll but also by carotenoids.
Green	524, 571	Green band peak or the point maximal reflectance in the visible spectrum (Thenkbail *et al.*, 2000)
Red	601, 608, 694	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)

Table.3 Correlation between leaf iron (mg kg^{-1}) and simple ratio

Spectral Region	Spectral Bands (nm)	701 nm
Blue	496	0.295
	499	0.364
Green	524	0.691*
	571	0.764**
Red	601	0.837**
	608	0.826**
	694	0.103**
NIR	701	1.000

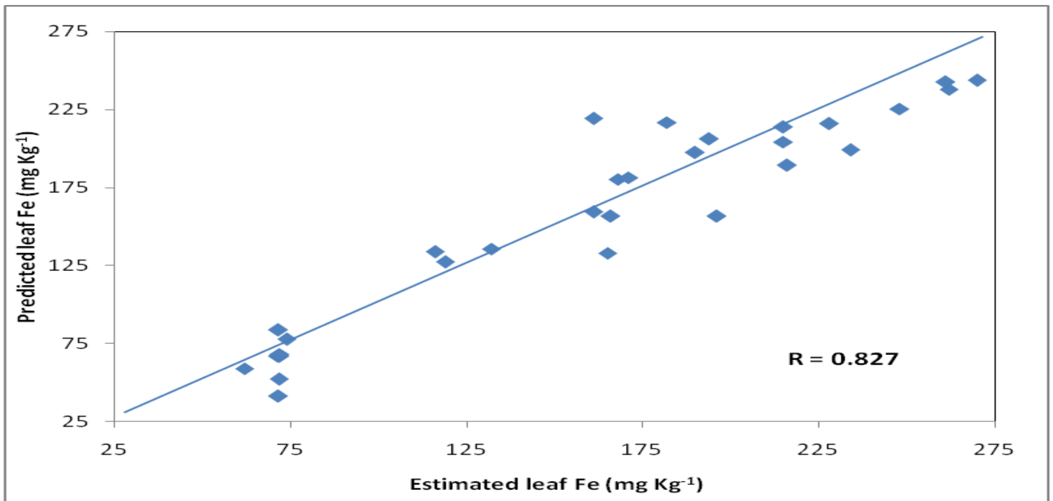

Fig.1 Relationship between estimated and predicted leaf iron content (mg kg^{-1}) in cotton canopies

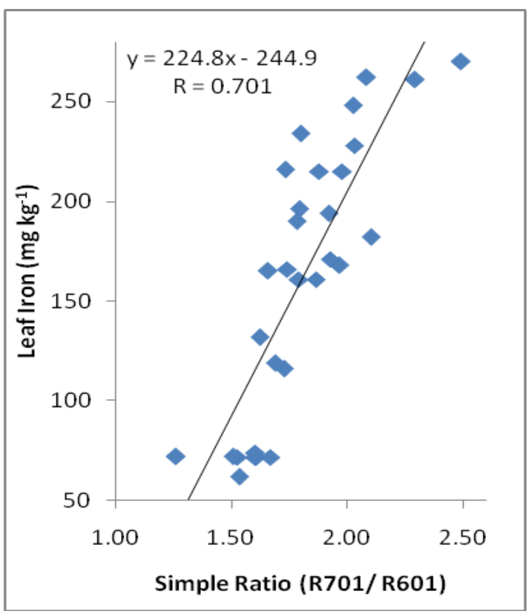

Fig.2 Relationship between leaf iron (mg kg^{-1}) and (R_{701}/ R_{601})

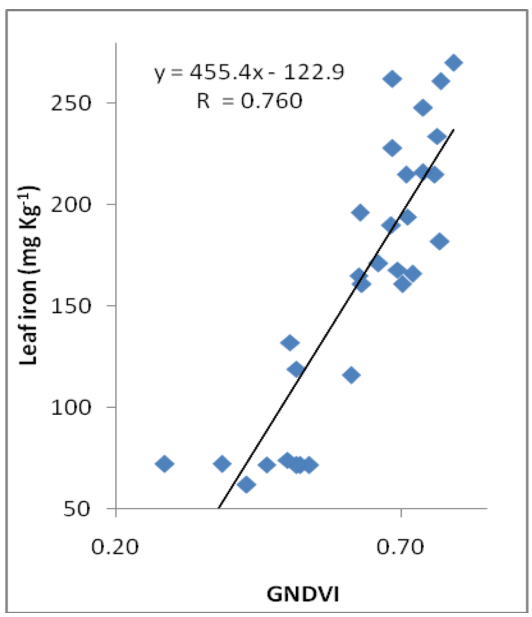

Fig.3 Relationship between leaf iron (mg kg^{-1}) and GNDVI

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