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Research Paper

Selection of sensitive bands for assessing Alternaria blight disease severity grades in mustard crops using hyperspectral reflectance

KARUNESH K. SHUKLA[1], AJANTA BIRAH[1*], RAHUL NIGAM[2], A. K. KANOJIA[1], MUKESH KM KHOKHAR[1], BIMAL K BHATTACHARYA[2] and SUBHASH CHANDER[1]

[1]ICAR-National Research Centre for Integrated Pest Management, New Delhi-12, India.
[2]Space Applications Centre, ISRO, Ahmedabad, Gujarat, India.
**Corresponding author email-ajantabirah69@gmail.com*

ABSTRACT

Recent development in remote sensing technology using hyperspectral reflectance or spectroscopic data has enabled rapid and ongoing progression of monitoring, mapping, and surveillance for detection of disease and improved crop management. This study describes a spectroscopy-based methodology to escalate the efficiency of present surveillance practices for detection of disease infestation viz., Alternaria blight in mustard crop. The methodology uses ground-based hyperspectral data across the spectral bands 350-2500 nm at 1 nm intervals. Two different statistical procedures such as sensitivity analysis (correlation between reflectance, 1st and 2nd derivatives with disease severity grades) and continuum removal analysis was implemented for selection of sensitive bands. In this method, we explore the combinations of different selected sensitive spectral bands and regions to separate the disease affected mustard crops from the healthy ones. The objectives of this research is to develop a novel methodology for selection of bands sensitive to Alternaria blight affected crops. The development of such methodology will provide a reliable and stable method for researchers, and remote sensing practitioners to achieve faster technique with higher accuracy to map Alternaria blight affected crops.

Keywords: Hyperspectral, spectroscopic, spectral band, derivative, reflectance

Mustard (*Brassica juncea* L. Czern and Coss) is one of the important oilseed crops in India occupying, around 6.8 million hectares (ha) with a production of 9.1 million tones and an average yield of 1331 kg per ha (GOI, 2020). India ranks first in the area and production of mustard in the world; the average yield per hectare is low as compared to a few other oilseed *Brassica* producing countries. Such low yields are primarily due to its cultivation in substantial area after the harvest of rice under rainfed conditions and due to the spread of Alternaria blight. Among the major diseases of the oilseeds *Brassica*s, Alternaria blight caused by *Alternaria brassicae* is the most widespread and devastating disease of rapeseed-mustard, causing a major yield loss ranging 15–71% in productivity and 14.6–36% in oil content (Mallick et al., 2015) apart from adversely affecting seed quality causing discoloration and reduction in seed size. This perpetual situation demands accurate quantification and efficient management methodology for proper surveillance, detection, mapping, and monitoring of disease severity grades. Traditionally, the extent of disease and its severity are assessed by visual inspection of symptomatic plants, which is time consuming and labor intensive (Giblot *et al*., 2016). Furthermore, the ability of references to precisely detect plant disease can vary, and it is difficult to estimate the severity grade on a large scale by visual inspection with precision. Therefore, there is a need for an alternative method to replace the traditional method with high accuracy and rapid detection of the severity grade and extent of any disease affected crop. However, the response of above-ground plants to infection often affects the quantity and quality of electromagnetic radiation reflected from the plant canopy (Nutter *et al*., 2002). This suggests that hyperspectral remote sensing techniques may provide a more objective assessment of disease severity than readily available records and visual assessments. Hyperspectral data especially reflectance data was capable of detecting changes in plant biochemical and biophysical properties due to disease (Nigam *et al.,* 2019). In addition, hyperspectral remote sensing may provide greater resources to accurately estimate disease severity and extent than visual assessment methods, and it can be used to collect sample

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measurements repeatedly, non-destructively and non-invasively.

The symptoms of the disease first appear as black dots on the lower leaves, which later enlarge to develop into prominent, round, concentric spots of various sizes. As the disease progresses, the disease appears with small spots on the middle and upper leaves, when defoliation of the lower leaves occur. Alternaria blight infection on leaves and siliquae significantly reduces the photosynthetic area. The stage of infection on the siliquae adversely affects the general seed development, seed weight, seed color, percentage oil content in the seed, and seed quality (Chattopadhyay *et al*., 2015). The presence of disease or insect feeding on a plant or canopy surface causes changes in chlorophyll, chemical concentration, cell structure, nutrient and water uptake, and gas exchange, which leads to differences in colour and temperature that can modify canopy reflectance characteristics (Raikes and Burpee, 1998). It is possible to detect changes in crop health during the different growing season using remote sensing instruments (San *et al.,* 2022). Hyperspectral technology have made it possible to collect several hundred spectral bands in a single acquisition, thus producing much more detailed spectral data (Tan, 2016). There is no report regarding the use of hyperspectral reflectance data for the detection and measurement of Alternaria blight disease of mustard and its severity. This paper presents the methodologies for selection of sensitive spectral regions and bands to detect Alternaria blight disease severity grades using ground-collected hyperspectral data.

MATERIAL AND METHODS

Study area

The hyperspectral reflectance data were collected from Bharatpur district of Rajasthan state, India. This district is the largest mustard-growing district that covers about 48% of the total production of the Rajasthan state that again cares for about 45% of the total mustard seed produced in India (GOI, 2020). The mustard crop is grown in post-*rabi* (south-west monsoon) season (October to April). October and November are the post-rainy months, with around 3% and 0.4% of annual rainfall, respectively. December, January, and February months are the cooler months, with minimum and maximum mean daily temperatures ranging 7.3-10.3°C and 22.2-25.2°C, respectively. The temperature remains higher in the months of March and April as compared to the month of February. Maximum and minimum temperatures were 39°C (in April) and 7.4°C (in January) during crop season (October to April). Six locations were selected and considered for the ground measurements during the crop seasons 2016-17 and 2017-18.

Measurement of damage severity grade (DSG) of Alternaria blight

DSGs were measured for Alternaria blight affected mustard crops during the field survey at 45 days after sowing (DAS), 60 DAS and 75 DAS. Disease severity grade was estimated using disease rating scale of 0-5 (Bhat *et al*., 2013) based on visually estimated percentage of infected leaf area as follows:

0: no disease;

1: 0.1-25% infected leaf area;

2:25.01: 50% infected leaf area;

3: 50.01-75% infected leaf area; and

4: > 75.0% infected leaf area.

Measurements of hyperspectral reflectance data

Leaf reflectance was measured for different DSGs (0-5 grades) of Alternaria blight affected mustard crop with the help of hyperspectral reflectance measuring device; Analytical Spectral Device (ASD) FieldSpec-4.0, spectroradiometer. The device operates in the 350–2500 nm spectral region with a spectral resolution of one nm. All the measurements were taken under uncloudy condition between 1100 hrs and 1430 hrs Delhi local time using ASD spectrometer at 0.5 m above the leaf surface with 25^{o}-angle field of view. Twenty samples of each DSGs with four replicate measurements were collected from each site. The average spectra of replicates was used as the final spectra of an observation. Six hundred samples (100-100 samples from each site) were obtained as the final spectra of healthy and Alternaria blight affected crops.

Pre-processing and transformation of spectral data

Pre-processing of hyperspectral reflectance ASD data have to be done before further analysis. There are two steps of preprocessing. The first is to eliminate irregular values and absorption spectral bands (350-400 nm, 1350-1450 nm, 1790-1960 nm, 2360-2500 nm) and the second is to smooth the spectral curves. The spectral data were smoothed using Savitzky-Golay filter (Savitzky and Golay, 1964) with a five-point moving average to minimize instrumental and environmental noise before the data were further analyzed (Kobayashi *et al*., 2001). After pre-processing, the spectral derivative analysis (SDA) was applied and the first and second order derivatives of the spectra were calculated using the procedure of Savitzky and Golay (1964). Finally, the two procedures, sensitive and continuum-removal analysis were used to select sensitive spectral regions and bands concerning different DSGs.

Hyperspectral ASD data contain hundreds of contiguous spectral-bands, and they can provide more detailed information about crops than multi-spectral data that provides an opportunity to use sophisticated statistical procedures and algorithms. However, the large data size is already a problematic subject to deal with. The SDA algorithms can provide extraction of advantageous information from hyperspectral ASD data. It can also reveal the essence by partially sinking the atmosphere and environmental background of vegetation (shadows, soil, water, etc.) influences. In the study, reflectance, first, and second order derivatives of hyperspectral ASD data were used to determine the DSGs of mustard crops. The first order derivative (the slope) reveals information about the rate of change in reflectance with respect to wavelength, while the second order derivative provides the change in the slope per nm wavelength (Liu *et al*., 2008).

Sensitivity analysis

For the sensitivity of DSGs, the correlation between DSG and reflectance and derivative value at each wavelength from 400 nm to 2360 nm were analyzed using the method of Pearson and Lee

(1902). The sensitive bands are important to reduce data redundancy while selecting the optimal band segment. Therefore, it is important to precisely select the most sensitive bands. In this study, the sensitive spectral regions to discriminate healthy and disease affected crops were selected based on corresponding reflectance, first and second order derivative values and their correlations with DSGs at a level of 65% significance.

Continuum removal

A continuum is a polyline made by joining those vertices on the original spectral curve using a line that requires an exterior angle of more than 180^o of polyline at those vertices. Continuum removal is essentially a process of baseline extrapolation of the normal curve, fitting a smoothed curve to the general trend based on the absorption spectral bands. This method can perform normalized reflectance spectra, to allow comparison of individual absorption features from a common baseline (Kokaly and Clark, 1999). The continuum is a convex hull fitted to the top of a spectrum using straight-line segment that connects the local spectra maxima. The first and last spectral band data are on the hull; so the first and last spectral bands in the output continuum removed reflectance data file are converted to 1.0.

RESULTS AND DISCUSSION

Spectral response

After pre-processing, spectral response of different severity grades were plotted over spectral range 400-2500 nm. Fig.1a showed the dynamic changes in leaf reflectance under different severity grades. As the disease severity grades increased, the spectral response in visible region escalated mainly in the red portion; the spectral response was more in the higher DSG leaves than in those with lower disease severity grades. In this region, the spectral response was mainly influenced by leaf pigment content; plant chlorophyll was almost damaged at all the locations due to Alternaria blight in the mustard crops (Fig.1b). Kobayashi *et al.,* (2003) reported that diseases reduced the plant chlorophyll content. In the NIR and SWIR regions, the spectral response of lower DSG of infected leaves was smaller than in the higher DSGs of infected leaves with an increase in the DSG as Alternaria blight infection on leaves and siliquae significantly reduced the photosynthetic area and the leaf water content.

Sensitive spectral regions and bands for DSG

Sensitive bands are crucial to reduce data redundancy when using hyperspectral data. Therefore, it is more important to select the most sensitive spectral bands/regions. In the study, sensitivity analysis and continuum removal methods were simultaneously used to select the sensitive bands/regions. Field-based reflectance of mustard crop and its first and second order derivatives at each spectral band was patchily correlated with the disease severity grades (0-4) over the entire spectral range (400-2360 nm) (Fig. 2a, b and c). It is obvious that there was increase in magnitude with increasing infection grades. Spectral response and its first and second order derivatives were found to be significantly correlated with DSG. It was found that correlation was higher in visible and red edge regions whereas a lower correlation was found in the SWIR region The sensitive spectral regions to discriminate healthy and Alternaria blight affected crops were identified based on corresponding reflectance, first and second order derivative values and their correlations with DSG more than 65% significance. By plotting the reflectance, 1st and 2nd order derivatives and their correlations with disease severity grades, the sensitive spectral ranges of diseases severity was assessed and calculated (Fig. 2). The spectral regions 636-649 nm, 676-684 nm, 690-693 nm, 717-728 nm, 757-760 nm and 766-769 nm (Fig. 2, Table 1) showed significant changes in reflectance and derivatives (1st and 2nd order) and higher correlation (r>0.65) with DSGs were sensitive to separate different severity grades of Alternaria blight affected crops. These selected spectral bands were neither related to the known water absorption spectral bands at 970, 1200, 1400, 1450, and 1940 nm nor with the leaf pigment absorption spectral bands at 430, 460, and 660 nm (Horler *et al*., 1983; Curran, 1989; Filella and Penuelas, 1994; Kumar *et al*., 2001; Ge *et al*., 2019; Gholizadeh and Kopacková, 2019). The correlation was also high over the spectral regions 1140-1350 nm and 1440-1790 nm with reflectance and DSG but lower with the derivatives.

The above analysis shows that the difference of spectral response is significantly different for various severity grades, but they are obviously diverse in different spectral regions (visible, red edge, NIR and SWIR); comparatively, the spectral difference in the NIR region is the most obvious. Especially, derivative spectra including the first and second order derivatives can more precisely

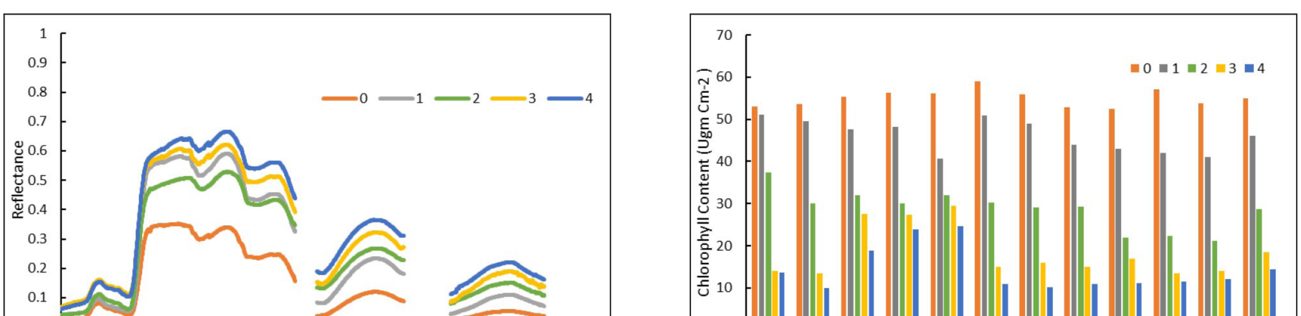

Fig.1: Comparison of (a) spectral response and (b) chlorophyll content of different severity grades of Alternaria blight affected crops

Table 1: Sensitive spectral regions and bands to discriminate Alternaria blight disease affected mustard crops

Sensitivity analysis					Continuum analysis	
SSRs				SSBs	SSRs	SSBs
Reflectance wavelength (nm)	*1st order derivative (nm)*	*2nd order derivative (nm)*	*Common*			
400-408	548-555	501-512	636-649	**648**	400-560	**424**
630-659	636-649	620-623	676-684	**682**	561-750	**712**
670-730	676-704	626-652	690-693	**692**	750-760	**757**
1140-1350	711-728	670-684	717-727	**720**		
1440-1790	757-760	690-693	757-760	**757**		
	764-769	717-727	766-769	**767**		
	814-815	754-763				
	868-890	766-771				
	904-912					

Where, SSRs: Sensitive spectral regions, SSBs: Sensitive spectral bands

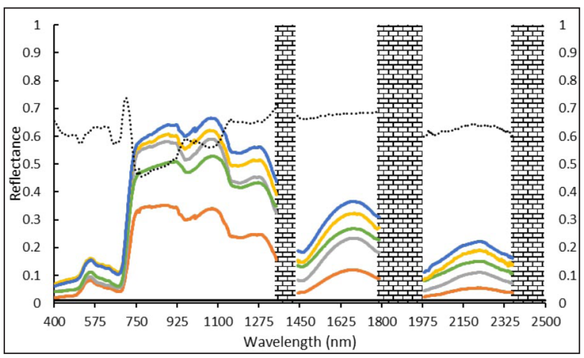

Fig. 2a: Spectral reflectance of different severity grades and their correlation

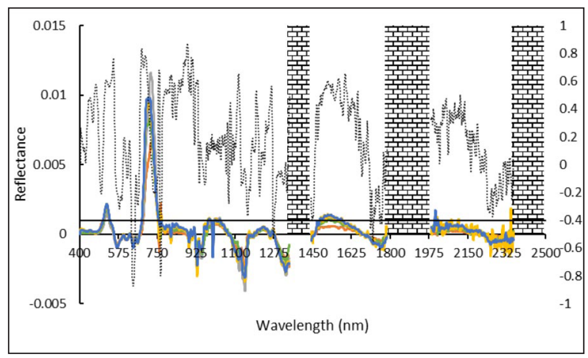

Fig. 2b: 1st order derivative spectral reflectance of different severity grades and their correlation

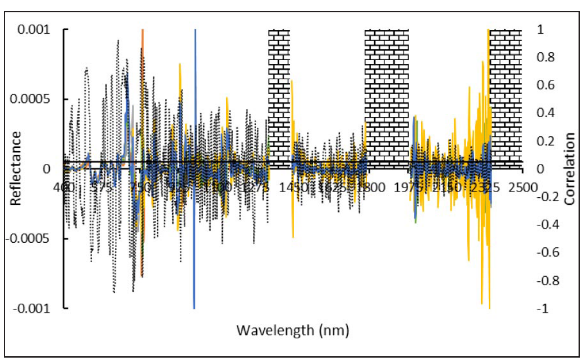

Fig. 2c: 2nd order derivative spectral reflectance of different severity grades and their correlation

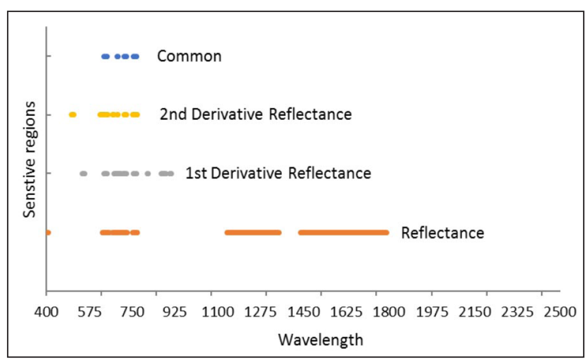

Fig. 2d: Senstive spectral regions of different analysis methods

Where, Orange: 0, gray: 1, green: 2, yellow: 3, blue: 4, dotted line: correlation, building blocks: spectral band segment removed from the analysis, and solid black line: significance level at 0.01

Fig. 2: Sensitive spectral regions over the spectral range 400-2500 nm

illustrate the spectral characteristics of healthy and disease affected crops. The investigation shows that the absolute value of derivative spectra generally rise with the increase in severity grade, which is nearly consistent with the method of Liu *et al.,* (2008). The correlation values of reflectance and derivative with severity grades is high in the visible range and generally low in NIR and SWIR regions.

The continuum removal technique can normalize spectral response to range between 0 and 1. Therefore, it provides the comparison of individual absorption features from a shared reference line. There are five regions viz., 400-560 nm, 561-750 nm, 750-760 nm, 930-1100 nm and 1110-1350 nm with changes in different severity grades (Fig. 3). However, the values of blue bands centered at 424 nm are less than that of red edge centered at 712 nm and 757 nm. Comparatively, the bands centered at 965 nm and 1205 nm have to be abandoned because of water absorption bands (Ge *et al.,* 2019; Gholizadeh and Kopacková, 2019) and less

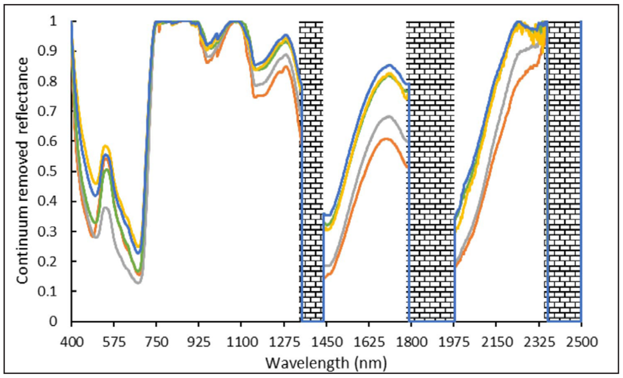

Fig. 3: Continuum removed reflectance of different severity grades of Alternaria blight affected mustard crops. Where, Orange: 0, gray: 1, green: 2, yellow: 3, blue : 4, dotted line : correlation, building blocks: spectral band segment removed from the analysis, and solid black line: significance level at 0.01

payload information, respectively. In these absorption regions, the regional variation of 400-560 nm spectral range is largest than that of four other regions, which indicate that this region will have a better effect in differentiating the severity grades of Alternaria blight affected mustard crops. Table-1 lists the selection results of sensitive spectral regions and bands. It is obvious that they are extremely similar, except that it has one more region and band of sensitive analysis than continuum removal. The phenomenon shows that there is no relationship between the selection of sensitive, bands and the algorithms. Zhang *et al.,* (2017) reported that the spectral shape and magnitude analysis (e.g., spectral derivative, continuum removal, transformed features, continuous wavelength features, etc.) are advantageous for distinguishing between healthy and pest-infested crop spectra.

CONCLUSION

This study is aimed at characterizing the spectral reflectance of mustard crop affected by Alternaria blight. The study revealed the potential of hyperspectral remote sensing not only for characterizing mustard crop affected by Alternaria blight but also for locating sensitive bands to assess appropriate severity grades. Difference in spectral reflectance was clearly visible for different disease severity grades. Spectral transformation to 1st and 2nd order derivatives, correlation and continuum removal led to locate the most sensitive spectral ranges for the disease severity grades. Therefore, sensitive bands have great potential to be upscaled for use through some recently developed multispectral camera on airborne platform.

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Data availability: To be provided on reasonable request.

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