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DETECTION AND CLASSIFICATION OF THE PLANT DISEASE AND STRESS USING HYPERSPECTRAL IMAGE ANALYSIS TECHNIQUES

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Abstract:

Plant stress detection is one of the important and critical aspect in order to improve crop yield. Abiotic stress and biotic stress can affect plant growth, including water, salt, temperature, light exposure and nutrient availability. Existing methods are based on manual monitoring of field symptoms by the experts on the field which is laborious, time consuming, error prone expensive and hard to repeat. These field-based methods are also dependent upon visible signs of the stress which leads to late diagnosis of the stress. Hyperspectral remote sensing provides effective means of detecting biotic and abiotic stress even before the appearance of visual symptoms. Early detection of disease leads to early intervention in order to prevent and control the spread of the stress. By following these advancement decision makers can effectively implement and modify crop management techniques. This paper reviews the potential of hyperspectral remote sensing in prevention, detection and quantification of plant stress.

Key Words: Biotic Stress, Abiotic Stress, Precision Agriculture

Introduction:

In country like India where agriculture is dominant, precise detection and timely identification of plant disease and stress is posing a challenge. Existing methods are based on manual monitoring of symptoms by experts on field which is time consuming, expensive, laborious, error prone and difficult to repeat. Manual detection techniques are solely dependent upon disease or stress showing visible symptoms which often exhibits middle to late stage of the infestation which leads to late diagnosis. Further, causality assessment and confirmation of disease or stress can be done by specific diagnostic tests. Diseases in plants usually start in a smaller patch or region which can be challenging to detect in early stages with manual techniques. Early detection of disease leads to early intervention in order to control and prevent the spread of the disease. Decision makers can effectively change crop management practices. Such precision agricultural practices can also ensure targeted application of pesticides and herbicides which has beneficial impact on the environment, ecosystems and finances. Therefore, replacement of manual processes with more automated, objective and sensitive methods is a need of the hour. Multiple remote sensing approaches have been explored which includes multi spectral, hyperspectral, thermal, chlorophyll fluorescence techniques.

For efficient crop management and plant health monitoring detection of biotic or abiotic stress should be done before the appearance of the visible signs. Image analysis techniques demonstrate autonomous and non-invasive methods to detect biotic and abiotic stresses. Many studies attempted recently examine

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machine learning for stress phenotyping, exploring phenotyping for stress identification, classification and quantification using various remote sensing sensors (Singh et al., 2016). Extraction and interpretation of the information based on the feature extraction through image analysis provides an important base for the research in the identification and quantification of plant stress. Recent advances have led these techniques to hyperspectral imaging in which imager captures the target in more than three bands as captured in the traditional imaging techniques. The subsequent analysis of these images is known as hyperspectral imaging analysis.

In this review, field based and laboratory-based application of hyperspectral imaging in detection of plant stress is described extensively. It also covers the implementation of the hyperspectral remote sensing in early detection and categorization of the plant stress. Finally, this review also involves pros and cons of this technology.

Hyperspectral Imaging Technology:

Hyperspectral remote sensing is defined as the simultaneous acquisition of images in many narrow, contiguous spectral bands (Goetz et al., 1985). Hyperspectral sensors are designed to acquire detailed images of the target in hundreds of narrow spectral bands. Hyperspectral remote sensing sensors capture light in the range of 400 nm to 2500 nm which includes visible, near infrared (NIR) and shortwave infrared (SWIR) frequency bands. In contrast, multispectral remote sensing sensors acquire data in relatively small number of broad spectral bands. Hyperspectral sensors are also referred as imaging spectrometers (Teke et al., 2013). Hyperspectral images are a three-dimensional cube where the X and Y dimensions specify the image dimensions and Z defines the spectral wavelength. Each pixel in the hyperspectral image represents the spectral reflectance which is the amount of energy received by the sensor from the sun after reflecting from the Earth's surface. Hyperspectral sensors are able to capture spatial and spectral signatures of the target which reveal valuable information and characteristics of the target.

Typical Leaf Spectral Signature and Effect of Stress:

The primary goal of using hyperspectral remote sensing is to recognize and analyze features of the target by non-invasive and accurate method. This can be achieved by understanding the spectral properties of the object which are known as signatures. In the field of remote sensing, it can be achieved by using reflectance measurements hence it is known as spectral reflectance.

Spectral reflectance of the plant leaf reveals many characteristics and hence to better understand the properties typical reflectance spectra is divided into three main broad regions (Gates et al., 1965).

The visible spectrum ranges from 400 to 700 nm and represents the spectral signature of the leaf pigment chlorophyll, carotene and xanthophylls. This region of the spectral signature is characterized by low reflectance and high absorbance.

Internal structure of the leaf dominates the response in the near infrared (NIR) region which ranges from 700 to 1300 nm. Refractive index between the airspace and

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spongy mesophyll of the cell causes total internal reflection of the incident solar radiation resulting in very high reflectance (Gausman, 1974). This region also features two weak water absorption features at 950-970 nm and 1150-1260 nm wavelengths respectively(Sims and Gamon, 2002).

Spectral response in the shortwave infrared (SWIR) region is due to the internal structure of the leaf up to some extent. However, it is mainly dominated by the major water absorption bands at 1400 nm, 1900 nm and 2700 nm. Retrieval of leaf water content is widely studied by using NIR and SWIR spectra (Ceccato et al., 2002; Cheng et al., 2011). Water molecules present in leaves exhibit weak absorb radiation in the NIR (720-1000 nm) and strongly absorb in the SWIR (1400-1900 nm) region (Datt, 1999). Hence, SWIR region response is more sensitive and accurate towards measurement of the leaf water content (Datt, 1999).

Biotic and abiotic stress causes major changes in the standard leaf spectral signature. Reduced chlorophyll content due to stress results in the increased reflectance in the visible region. Structural damage to the leaf results in the low reflectance in the NIR region. Lowered water content in the leaf results in the weak absorption in the SWIR region.

Comparison of healthy and stressed leaf spectra can efficiently detect, analyze and quantify the stress in the vegetation.

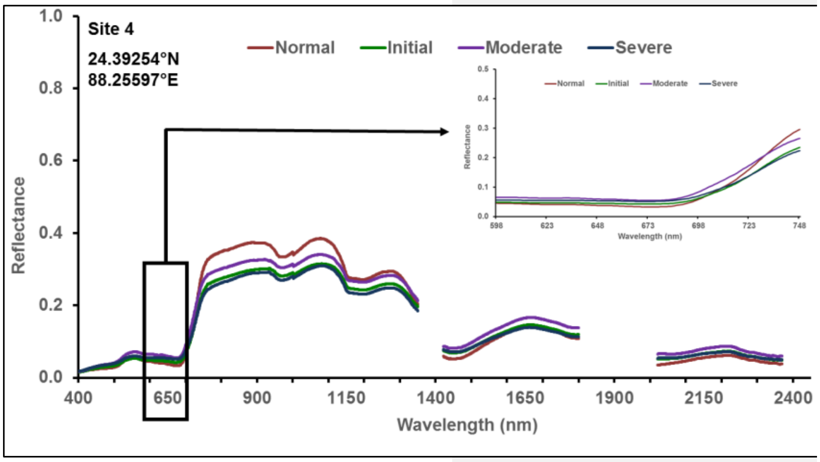

Figure 1 Spectral Signature of Wheat Crop Infested With Wheat Blast With Various Intensity

Applications for the detection and classification of healthy and diseased plants:

Use of Vegetation and Disease Indices for the stress detection:

Vegetation indices (VIs) are defined as combinations of spectral responses in different wavebands which emphasize a particular feature of the vegetation. The indices are ideally a sum, difference, ratio or other linear combination of reflectance factors or radiance observation from two or more wavelengths/wavelength intervals (Wiegand et al., 1991).Detection of plant biochemical and biophysical features affected due to biotic or abiotic stress can be accurately attributed as these indices are more sensitive than individual wavebands (Asrar et al., 1984).These indices also standardize the representation of the crop spectral signature which helps to compare the spectral response region to region and year to year and reduce the dimensionality of the data(Malingreau, 1989).

Penuela et al., 1993 introduced the water index (WI = R970/R900) which is used to assess the water status in the various crops (El-Shikha et al., 2007). There were two vegetation indices suggested based on the WI. One is NWI1= [R970-R900]/[R970+R900] and the other is NWI2= [R970-R850]/[R970+R850]. These two indices were useful in order to estimate grain yield of spring wheat genotypes under well irrigated and water deficit conditions. Other two indices with variations were proposed for the estimation under rainfed conditions with the use of slightly different wavebands. NWI3= [R970-R880]/[R970+R880] and NWI4= [R970-R920]/[R970+R920] were used for the estimation of grain yield of winter wheat (Prasad et al., 2007). The WI indices are used as NIR region wavelengths have deeper penetrability into the canopy which gives accurate estimation of the water content (Babar et al., 2006; Prasad et al., 2007; Gutierrez et al., 2010). Leaf water content and water potential has significant correlation with normalized difference water index (NDWI= [R860-R1240]/R860+R1240]) and normalized difference vegetation index (NDVI= [R900-R680]/[R900+R680]) (Stimson et al., 2005).

Water status was assessed using NDWI from the airborne hyperspectral remote sensing data which is having a higher spatial resolution (Gao, 1996). To estimate plant water content relative to LAI, equivalent water thickness (EWT) and leaf biomass simple ratio water index (SRWI= R860/R1240) was found to be suitable (Zacro-Tejada et al., 2003). Many other spectral based water indices were developed such as normalized difference infrared index (NDII= [R820-R1600]/[R820+R1600] (Hardisky et al., 1983), normalized multiband drought index (NMDI= [R860-(R1640-R2130)]/[R860+(R1640+R2130)] (Wang and Qu, 2007).

Estimation of plant biochemical and biophysical parameters using narrow band vegetation indices have been a successful approach which helps to detect emerging stress in the early stage. These vegetation indices utilize the difference in the reflectance spectra of two spectral bands (Rouse et al., 1974).

Most useful wavelength ranges for the plant and vegetation spectra are visible and near infrared. This wavelength ranges can capture changes in the leaf pigmentation (400-700 nm) and mesophyll cell structure (700-1300 nm). Changes in the water content of a plant are efficiently depicted in the SWIR region which ranges from 1300 to 2500 nm.

Disease Identification:

Identification of disease or stress is the next and most important step after the detection of the appropriate wavelength ranges. One of the most useful approaches is spectral information divergence classification. This method compares the divergence between the observed spectra and reference-spectra. A library of the spectra or average spectra from the data can be provided as reference spectra. In this approach, smaller the divergence value then more similar the spectra are. If the value is larger than the set threshold then they are not classified as ~~a~~ reference-spectra.

This method provides approximately 95% classification accuracy.

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Quantifying the stress severity:

It is extremely important to quantify the stress for effective policy making and implementation. It can lead to efficient and timely implementation of the crop management and prevention of the spread. Quantification of stress poses challenge of accurate classification of the healthy and diseased plant. Under extreme stress conditions, classification becomes very difficult. However, there are many methods which can be useful for the accurate and precise quantification of the plant stress.

Spectral angle mapper (SAM) classifier is widely used for the quantification of the plant stress. This approach matches the pixel spectra to reference spectra to classify the pixels by calculating the angle between the spectra which are considered as n-dimensional vectors in space. SAM was successfully implemented for the assessment of severity of *Fusarium* head blight disease in wheat by Yuhas. The hyperspectral data range was 400-1000 nm and spectral resolution was 2.5 nm. Disease severity assessed by this approach with 87% classification accuracy.

Apart from SAM, there are many other techniques which help in accurate quantification of the plant diseases. Quadratic discriminant analysis, decision tree, multilayer perceptron, partial least square regression, fisher linear determinant analysis, artificial neural network, support vector machine, spectral information divergence are the techniques used for the quantification of plant stress. These techniques are implemented on the crops like wheat, avocado, sugar beet, celery, cucumber, barley and grapefruit for the better understanding of disease severity.

Hyperspectral Data Collection and processing:

Hyperspectral image data is consisting of narrow contagious spectral bands and hence large in size. Hyperspectral data processing takes long time for analysis if the whole spectrum is being analyzed. Hence, the analysis of the selected wavelengths gives faster and accurate solutions. However, hyperspectral data contains valuable information which cannot be captured by multispectral data therefore selection of wavelength regions should be done with extreme technical discretion and based on the objectives of the study. Selecting and storing most important fewer waveband regions results in smaller file size, reducing the amount of complex and redundant data and accuracy in results.

Conclusion:

In recent years, hyperspectral imaging techniques are widely used in the detection, classification and quantification of the plant stresses. Plant disease detection is one of the most important techniques in the management of crop plants in agriculture and horticulture. These techniques are specifically useful in the detection of early onset of stress and disease which is beneficial for farmers and as well as policy makers which helps to prevent crop loss and quality. Hyperspectral imaging techniques are non-invasive process where plants are scanned using hyperspectral imagers which make it cost effective, repeatable and accurate. Significant wavelength ratios help to indicate the plant stress and diseases significantly known as vegetation indices. Other classification techniques and modelling techniques are also useful for

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Hyperspectral imagery systems, software are essential aspects for the implementation of the precision agriculture. With the increasing population and depleting natural resources, hyperspectral precision agriculture becomes an important research area. This review describes the importance of these techniques and future aspects of the technology.

Comment [H10]: We need to add some current diseases being studied, some success story, some limitations

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