HYPERSPECTRAL RADIOMETRY: AN INTRODUCTION AND METHODOLOGY

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Preface

Remote sensing is one of the advanced study having good scope in near future. Previously, Multispectral Remote sensing involves the study of spectral bands in broad band width, but now Hyperspectral Remote sensing replaced it with narrow bandwidth.

The purpose of remote sensing in entomology is to detect and estimate the pest damage by calculating equations using regression coefficient. The sensors used in satellites were used in taking the data on pest damage so that comparision in large area becomes easy. Keeping this view, spectral remote sensing related to different pest damage.

While compiling this book I have referred various references related to entomology in Remote sensing, I have tried to put our level best to put information in one book related to every aspect of I acknowledge our humble indebtness to all those authors from whose works material has been drawn. Maximum care has been taken to maintain the correctness of the matter compiled. Though all sincere and careful efforts have been made to check, correct and prevent typographical or other types of mistakes, it is neither claimed nor be claimed that there is no deficiencies. I express my immense sense of gratitude, indebtedness and heartfelt thanks to my chairman Dr. M.R. Srinivasan, Professor, Department of Agricultural Entomology, TNAU, Coimbatore, India for his valuable guidance, whole hearted help, constant encouragement, timely advice and unending benevolence throughout the course of this investigation. Amidst his busy schedule, he allocated much of his time for commendable guidance throughout the research work. I shall be failing in my duty if I do not indicate his critical examination of the script and valuable additions and omissions thus enhancing the value of the research work carried out. I also express my heartfelt thanks to his family members for their continuous support and affection towards me. I thank all those who have directly or indirectly helped to bring out this book most successfully.

Criticism and suggestions for the improvement of present book from worthy teachers and students will be gratefully acknowledged. Feedback may be sent to emailranjithagurram@gmail.com.

Ranjitha.G

DEDICATED TO

My Beloved Parents

RAMACHANDRAN.G, RAJYALAKSHMI.G

My brother, RAKESH. G

My Sister-in-law, Dr. RAMYA.G

My Nephew, AAHISH.G

And

My Chairman, Dr. M.R.Srinivasan,

Professor (Entomology),

TNAU, Coimbatore

INTRODUCTION

Early detection of insect pest infestation is an essential step to take up timely management measure. Remote sensing can be useful in detecting crop damage over a large area in a short time period. It is necessary to conduct ground level study to establish the relationship between actual pest infestation and the data obtained through satellite remote sensing. Recording the ground truth with the help of multispectral or hyperspectral spectroradiometer can allow detection, identification and estimation of various crop stresses through analysis of their spectral signatures (Fitzgerald *et al*., 2004) in a non-destructive way.

Hyperspectral remotely sensed data provide hundreds of contiguous narrow spectral bands, forming spectral curves of the scene components of interest. Analyses of the shapes of these spectra allow discrimination of the scene component (Blackburn, 1998a). The utility of hyperspectral data to diagnose pests and diseases can improve detection speed and provide opportunity for non-destructive sampling (Apan *et al*., 2005). Moreover, with the launch of new hyperspectral remote sensing satellites by India, the focus of current research has shifted to making maximum use of the new technology to the benefit of Indian farming community.

Another area of application of the spectral signatures of crop stresses is precision farming. Nowadays ground based spectral sensors aid in finding the intra-field variations in crop stresses so as to apply remedial measures using variable rate applicators only to those points that need the inputs such as pesticides, growth promoters and fertilizers (Liaghat and Balasundram, 2010). Traditionally, in order to obtain greater production, larger quantities of agricultural inputs have been applied, resulting in greater environmental pollution. In this respect, precision farming with the site-specific application of agricultural inputs, can lead to an overall reduction in chemical inputs without affecting agricultural production (Tomer *et al*.,1997; Christensen *et al*., 1998).

In the last decade, with the advent of remote sensing techniques, plant protection scientists have worked to detect crop damages caused by insect pests and diseases in various crops such as cotton, rice, wheat, sugarcane, pulses and vegetables (Mageshwaran, 2012;Apan *et al*., 2004;Mirik *et al*., 2006a;Chen *et al*., 2007) using these techniques. The technique involves recording of spectral reflectance at canopy level using hyperspectral spectroradiometer and comparing the data obtained from healthy and pest infested plants. The reflectance data from different spectral bands namely blue, green, red and near infra red (NIR) from healthy and infested plants are subjected to mathematical analysis to calculate vegetation indices which can also help in detecting and estimating the crop damages.

In fact, a few studies have been made to identify damages caused by cotton aphids and spider mite, tarnished plant bug through remote sensing techniques (Reisig and Godfrey 2006;Sudbrink *et al.*, 2003). These studies have been made to find out the spectral bands reflecting damage caused by individual pests. Very few studies have been conducted in the past to differentiate among different pests damaging a crop using spectral reflectance. Hence, a detailed analysis of the spectral reflectance characteristics of damages caused by cotton pests under field conditions help to diagnose pests, discriminate among them, estimate the level of loss and thus help to devise better management strategies.

In order to exploit the advancement in the field of remote sensing of crop health status using hyperspectral radiometry, studies have to be conducted with the following objectives,

- To study the spectral reflectance characteristics of healthy and pest damaged crop and compile a spectral library of damage symptoms caused by sucking pests of cotton.
- To determine the best spectral bands relevant to pest detection.
- To explore possibility of estimating pest damage levels based on spectral properties of cotton crop showing varied levels of pest infestation.

Remote sensing

Remote sensing is increasingly identified as a relatively inexpensive source of data for site specific crop management (Moran *et al.*, 1997). In the past two decades, vast scientific developments have taken place in the areas of remote sensing and its applications in pest damage detection. To make use of the techniques effectively, it is essential to provide precise remote sensing methods to detect changes in crop condition caused by insect pests.

Remote sensing is the technique of deriving information about objects on the surface of the earth without physically coming into contact with them (De Jong and Van de Meer, 2006). This process involves making observations using sensors (cameras, scanners, radiometer, radar etc.) mounted on platforms (aircraft and satellites or at ground level), and recording the observations on a suitable medium (images on photographic films and videotapes or digital data on magnetic tapes).

Remote sensing – applications

Remote sensing has been used in agriculture for many decades (for example, the review of Moran, *et al*., 1997). One of its earliest applications was on crop disease assessment. It provide a better means to objectively quantify disease stress than visual assessment methods, and it can be used to repeatedly collect sample measurements non-destructively and non-invasively. In agriculture, possible applications of remote sensing are in the management of soil resource inventory, estimation of cropped area and production, scheduling of irrigation, detection of many stresses like water, nutrients, salinity, pests and diseases etc., and estimation of evapo-transpiration apart from modeling crop growth and yield using remotely sensed inputs.

Remote sensing for precision farming

Remote sensing has the potential to be used as an effective and inexpensive technique to identify pest and disease affected plants in a field scale, mainly because affected plants have different spectral response compared to healthy plants (Zhang *et al*., 2002). In particular, precision farming needs cost and time effective methods for identification of various crop types in order to evaluate crop condition and recommend suitable measures (Lutman and Perry, 1999)

There is a rapidly growing interest in methods for automatic plant identification in agricultural research. The spatial variability of pest infestations in field is obtained by analysing the hyperspectral data which offers a better understanding of field conditions and pest-plant interactions, which in turn useful for site-specific pest management. Using this data, correct amount of pesticides can be applied to the right places at the right time. It also helps in applying the pesticide in the areas of fields most affected, thus decreasing the damage to beneficial insects. However, such applications require pre-established ground truths for data verification and validation so that operation is directed more efficiently and economically**.**

The aerial sketch map would identify the causal agent and the general region where this activity is taking place, but remote sensing when used to identify disturbance caused by defoliation would provide for more precise mapping of the actual areas of defoliation.

Advantages

Remote sensing is an economical, exhaustive, simple and fast. It is used as early warning system against possible threats (like natural calamities). The remotely sensed data provide considerable potential for estimating agricultural area and yield forecasting at local, regional, and global scales (Khajeddin and Pourmanafi, 2007; Serra *et al.*, 2007). Spectral remote sensing is an useful tool for non-destructive estimation of plant growth and biophysical parameters (Takebe *et al.*, 1990) associated with pathogens and insect pests.

Multispectral remote sensing

Earlier, multispectral remote sensing (with broadband data) have been applied to monitor crop growth status for various purposes (Shibayama and Akiyama, 1991; Cloutis *et al.*, 1996). Multispectral data was useful in identifying reflectance obtained from crop due to incidence of pests and diseases, (Summy *et al.*, 1997), weeds (Brown *et al.*, 1994), and mites (Penuelas *et al.*, 1995; Fitzgerald *et al.*, 1999a, 1999b) but due to its limited spectral coverage, multispectral remote sensors may not be able to uniquely identify the damage-causing stressor. Multispectral satellite data helped to generate NDVI (Normalised Difference Vegetation Index),which can be correlated with the landuse, landcover, soil moisture, soil quality and groundwater quality to estimate the deterministic yield of Bt cotton crops.

Hyperspectral remote sensing

Hyperspectral remote sensing is a technique that utilises sensors operating in hundreds of narrow contiguous spectral bands, which offers potential to improve the assessment of crop diseases and pests. Relationships between spectral characteristics and symptoms of infestations must be adequately investigated based on ground studies, before the development of the remote sensing algorithms and management schemes, thus helps to play an effective role in crop pest management (Yang *et al.*, 2007). It is a precision tool that can detect plant health through analysis of their spectral signatures (Reisig and Godfrey, 2007).

The development of hyperspectral remote sensing has satisfied the demand in providing qualitative and quantitative details of vegetation spectrum and help in assessing and evaluating crop condition parameters (Yoder and Pettigrew-Crosby, 1995; Blackburn, 1998a). It also increases our ability to accurately map the vegetation attributes (Kumar *et al.*, 2001). The utility of hyperspectral data to diagnose pests and diseases of vegetables can improve detection speed and provide opportunity for non-destructive sampling (Apan *et al.*, 2005). Compared to traditional methods, vegetation stress caused by heavy metals can be detected by hyper-spectral remote sensing in a quicker, exact, and more comfortable way especially on a large scale (Broge and Mortensen, 2002; Yang *et al.*, 2007).

Advantage of hyperspectral sensors over multispectral sensors

The broadband multispectral sensors may be helpful in discriminating diseased and healthy crops, but the best results for identifying diseases were obtained with hyperspectral information (Moran *et al.*, 1997).

The spectral data from the current generation of earth orbiting satellites carrying broad band sensors such as Landsat Thematic Mapper (TM), Le Syste´me pour l'observation de la terre (SPOT) high resolution visible (HRV), and the Indian Remote Sensing (IRS) Linear Imaging Self-Scanning have limitations in providing accurate estimates of biophysical characteristics of agricultural crops (Fassnacht *et al.,* 1997; Thenkabail *et al.* 1995; Wiegand *et al.* 1991; Wiegand and Richardson 1990), natural vegetation (Friedl *et al.,* 1994), and in quantifying other terrestrial ecosystem characteristics, such as soil characteristics; stress due to weeds, water and nitrogen deficiencies or excess; crop phenology; and fallow, forest, and agricultural interactions (Moran *et al.* 1994; Running, 1989).

Spectral reflectance and spectral signature

When electromagnetic radiation falls upon a surface, some of its energy is absorbed, some is transmitted through the surface, and the rest is reflected back. Surfaces also naturally emit radiation. The reflected and emitted radiation from the surface is recorded with the help of a digital sensor. Since the intensity and wavelengths of this radiation reflected or emitted is a function of the surface, each surface is being processed with a characteristic 'spectral signature' (Lillesand and Kiefer,1987). If an instrument can identify and distinguish between different spectral signatures, then it will be possible to map the extent of surfaces using remote sensing.

Canopy spectral reflectance obtained due to biophysical and biochemical attributes of vegetation, which were influenced by factors such as geometry of detector, illumination conditions of the surroundings, and background effects were studied by Asner (1998). Similarly, leaf spectral reflectance and their spectral curves are obtained as a result of physical and biochemical properties of leaves, which are influenced by the integration of genetic, developmental and environmental factors (Mohammed *et al.*, 2000). Pathogens and pests can induce physiological stresses and physical changes in plants, such as chlorosis or yellowing (reduction in plant pigment), necrosis (damage on cells), abnormal growth, wilting, stunting, leaf curling, etc. Incidentally, these changes can alter the reflectance properties of plants.

In the visible portion of the electromagnetic spectrum (approx. 400nm to 700nm), the reflectance of green healthy vegetation is relatively low due to strong absorption by pigments (e.g. chlorophyll) in plant leaves. If there is a reduction in pigments due to pests or diseases, the reflectance in this spectral region will increase. At about 700nm to 1300nm (NIR portion), the reflection of healthy vegetation is significantly high. With a disease or pest that damaged the leaves (e.g. cell collapse), the overall reflectance in the NIR region is expected to be lower. Spectral reflectances of leaves or canopies, in both the visible and near-infrared region provide information on their structure, physiology and chemistry (Kumar *et al*., 2003; Jorgensen *et al*., 2006).

Vegetation indices

Spectral vegetation indices (VI) are mathematical combinations of different spectral bands mostly in the visible and near infrared regions of the electromagnetic spectrum. They are derived using the reflectance properties of vegetation. Each of the VIs is designed to accentuate a particular vegetation property. Most of them are called broadband VIs because they are based on combinations of reflectance in the red (R) and that in the near infrared (NIR) spectral bands (Elvidge and Chen, 1995) such as normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) in the detection of crop stress (Vigier *et al*.,2004; Yang *et al*.,2009).

The main purpose of spectral vegetation indices is to enhance the information contained in spectral reflectance data, by extracting the variability due to vegetation characteristics (e.g. LAI, vegetation cover) and to minimize soil, atmospheric, and sun-target-sensor geometry effects. Spectral vegetation indices constitute a simple and convenient approach to extract information from remotely sensed data, due to their ease of use, which facilitates the processing and analysis of large amounts of data acquired by satellite platforms (Govaerts *et al*., 1999; Myneni *et al.,* 1995).

Significant advances have been achieved in the understanding of the nature and proper interpretation of spectral vegetation indices (Myneni *et al*., 1995; Pinty *et al.,* 1993) and theoretical frameworks have been proposed to support the development of indices optimized for particular applications/ sensors (Verstraete *et al.,* 1996; Gobron *et al*., 2000).

Ratio Vegetation Index (RVI) or Simple Ratio (SR)

Ratio-based index (RVI) also known as simple ratio (SR) which is the ratio of NIR and Red band (Jordan.,1969). The SR is the ratio of the highest reflectance and absorption bands of chlorophyll. It is both easy to understand and effective over a wide range of conditions. It saturates in dense vegetation when leaf area index (LAI) becomes very high. SR is defined by the following equation:

- $RVI = \frac{RNIR}{RRED}$

where, RRED and RNIR are reflectance in the red and near infrared wavelength bands, respectively. The value of this index ranges from 0 to more than 30. The common range for green vegetation is 2 to 8 (Tucker, 1979; Sellers, 1985).

Normalized Difference Vegetation Index (NDVI)

- NDVI is one of the oldest, most well-known and most frequently used Vegetative Index.
- NDVI has been widely used for crop stress detection because of its high correlation with vegetation parameters such as biomass and green leaf area (Curran, 1980). NDVI is often used for plant stress detection.
- NDVI is the normalized difference of green leaf scattering in NIR and chlorophyll absorption in red region. The combination of its normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions (Sims and Gamon, 2002; Mirik *et al*., 2006a; Yang *et al*., 2009). It can, however, saturate in dense vegetation conditions when LAI becomes high. NDVI is defined by the following equation:
- $NDVI = \frac{(RNIR-RRED)}{(RNIR+RRED)}$

  where, RRED and RNIR are reflectance in the red and near infrared(NIR) wavelength bands, respectively. The value of this index ranges from -1 to 1. The common range for green vegetation is 0.2 to 0.8 (Sellers, 1985; Lillesand and Kiefer, 1987).
- The NDVI and SR are fundamentally the same. one can be readily calculated from the other without additional information.

- $NDVI = \frac{(RVI-1)}{(RVI+1)} \quad SR = \frac{(NDVI+\ )}{(NDVI-\ )}$

  While NDVI has the advantage of the fixed range from -1 to 1, SR is sometimes preferred for its better sensitivity and more linearity with biophysical parameters (Chen, 1996; Chen and Cihlar, 1996).

Wiegand *et al.* (1991) studied the relationship of a number of vegetation indices with cotton (*Gossypium hirsutum* L.) grown in salt-affected soil and found a significant relationship between yield and seasonal accumulated NDVI (i.e., the sum of daily NDVI values). A significant positive relationship was found between yield and NDVI.

Green Red Vegetation Index (GRVI)

- Motohka *et al.* (2010) suggested a new index called green red vegetation index (GRVI), which can show small changes in vegetation condition during crop growth.
- $GRVI = \frac{(RGREEN-RRED)}{(RGREEN+RR\quad)}$

  where, RGREEN and RRED are reflectance in the green and red wavelength bands, respectively.
- In terms of the balance between green reflectance (520–590 nm) and red reflectance (620–680 nm), we can find three groups of spectral reflectance patterns for major components of ground cover.

  1. Green vegetation (conifers, deciduous trees, and grass): green is higher than red
  2. Soils (brown sand, silt, and dry clay): green is lower than red
  3. Water/snow: green and red are mostly the same.
- GRVI decreases in response to the changes in canopy vegetation even in the middle of the growing period when the apparent change of leaf colors and leaf density are small. GRVI keeps changing during the entire growing period, whereas NDVI stops changing in the middle of the growing period at a saturation value. This suggests that GRVI is better for detecting subtle disturbance in the middle of the growing period. GRVI (-6 to +10 Percent sensitivity) is superior in discriminating damage caused due to aphids on cotton. (Ranjitha G and M R Srinivasan; 2014)

Green Normalized Difference Vegetation Index (GNDVI)

Green normalized difference vegetation index (GNDVI) was proposed by Gitelson *et al.* (1996). For calculating GNDVI, red light is replaced by a green wavelength band in the formula to calculate NDVI. This index also acts as indicator of plant condition (Sembiring *et al.*, 1999).

- $GNDVI = \frac{(RNIR-RGREEN)}{(RNIR+RGREEN)}$

  Where, RNIR and RGREEN are reflectance in the NIR and green wavelength bands, respectively.

Soil Adjusted Vegetation Index (SAVI)

- The soil adjusted vegetation index (SAVI) was developed by introducing a parameter L into the calculation of NDVI. This parameter is determined by the position of the convergence point. In SAVI, it is taken as a constant of 0.5, while in SAVI1, an improvement is made by allowing L to vary with the condition of the surface, using other indices because the convergence point is in fact not fixed (Qi *et al.*, 1994).

  $$SAVI = \frac{(RNIR - RRED)(1 + L)}{(RNIR + RRED + L)}$$

  Where, RNIR and RRED are reflectance in the NIR and red wavelength bands, respectively.

- To minimize the impact of soil background, the soil-adjusted vegetation index (SAVI) (Huete,1988) and modified soil adjusted vegetation index MSAVI are used (Qi *et al.* 1994).

Damage Specific Spectral Index (DSSI)

Mirik *et al.* (2006a, 2006b) recorded wheat canopies reflectance data by a hyperspectral field spectroradiometer and digital camera and illustrated that damage sensitive spectral indices (DSSI), SR, NDVI were strongly related to damage by greenbug.

$$DSSI = \frac{(R719 - R873 - R509 - R537)}{(R719 - R873) + (R509 - R537)}$$

Where R stands for Reflectance at the given wavelength

Sensitivity

Sensitivity Band (SB)

- Sensitivity at a given wavelength or band was computed by using the following formula (Carter,1993)

$$Sensitivity\ band = \frac{R_{inf} - R_{ctrl}}{R_{ctrl}} \times 100$$

Where R_{inf} - canopy reflectance of infested plants, R_{ctrl} - canopy reflectance of control plants.

Sensitivity Index (SI)

Sensitivity for given vegetation index was calculated by using the following formula:

$$Sensitivity\ VI = \frac{VI_{inf} - VI_{ctrl}}{VI_{ctrl}} \times 100$$

Where VI_{inf} - vegetation index of infested plants; VI_{ctrl} - vegetation index of control plants

Detection of pests and diseases

Pests and diseases cause serious economic losses in yield and quality of cultivated plants. Thus, the detection and assessment of their symptoms is essential in commercial agriculture. Traditionally, disease and pest damage assessment in plant populations is being done by visual approach, i.e. relying upon the human eye and brain to assess the incidence of disease or pest in crops. However, the problem with the traditional approaches is that they are often time-consuming and labour intensive. Therefore, there is a need to develop different approaches that can enhance or supplement traditional techniques.

Although the broadband multispectral sensors may be helpful in discriminating diseased and healthy crops, the best results for identifying diseases were obtained with hyperspectral information (Moran, *et al.,* 1997). Thus, there are indications that the use of hyperspectral sensing can be valuable to disease/pest detection and crop damage assessment.

Detection of pests

The reflectance and physical-chemical parameters of cotton leaves infested by aphid *Aphis gossypii* Glover (Homoptera: Aphididae) were analyzed and compared in different cotton growth periods and varieties. There was an increase in thickness and Chlorophyll b content and a decrease in Chlorophyll a, Chlorophyll a+b and carotenoid content in leaves affected by aphids. In visible region, the reflectance of cotton leaves affected by aphid increased initially and decreased later in different cotton growth periods and varieties with increasing severity levels. However, in NIR region, it has shown discrepancy in varieties. The wavelengths 434 nm and 648 nm can be used as sensitive and optimal band for aphid infested cotton leaves. Among all estimation models, a model of (R589-R648)/ (R589+R648) had the best estimation precision to estimate severity levels of leaves infested by aphid (Chen *et al*., 2010). However, it is observed that in spider mite- and aphid-infested cotton leaves, there was an increase in reflectance in the near infrared wavelength at approximately 850 nm in comparision to uninfested leaves which is in contrast to other reports (Reisig and Godfrey, 2007).

Decrease in Chl *a* pigment was more significant than Chl *b* in the infested plants and the ratio of Chl *a*/*b* showed a decreasing trend with increase in LH severity. Regression analysis revealed a significant linear relation between LH severity and Chl (R^2 = 0.505**), and a similar fit was also observed for RWC (Relative water content) (R^2 = 0.402**). Regression analysis of several ratio indices formulated with two or more of these sensitive bands led to the identification of new leaf hopper indices (LHI) with a potential to detect leafhopper severity. These new indices along with 20 other stress related hyperspectral indices compiled from literature were further tested for their ability to detect LH severity. Two novel indices LHI 2 and LHI 4 proposed in this study showed significantly high coefficients of determination across locations (R^2 range 0.521 to 0.825**) and hence have the potential use for detection of leafhopper severity in cotton (Prabhakar *et al.,*2011)

When spectral reflectance of cotton leaves infested with spider mite *Tetranychus turkestani* (Acarina: Tetranychidae) was measured using ASD Leaf clip, chlorophyll contents decreased, the carotenoid contents increased, spectral reflectance increased in both sides of green peak and there was a significant decrease at 748- 863 nm of NIR region with increase in infestation. The red edge of the infested cotton leaves remarkably moved to short wavelength. The slope of red edge (Dλ_ red), ratio of the slope of red edge to the minimum slope (Dλ_ red /Dλ_ min) and the area of red edge (∑Dλ _ 680 - 750) increased with the increase of infestation level. The red edge is a good indicator of spider mite infestation in cotton leaves (Chen *et al*., 2007).

When reflectance data was taken with spectroradiometer at cotton leaf level as well as from an aerial image (at canopy level) to identify variability in plant growth and correlation with larval densities of beet armyworm (BAW) *Spodoptera exigua* (Hubner) (Lepidoptera: Noctuidae) and cabbage looper *Trichoplusia ni* (Hubner) (Lepidoptera: Noctuidae), it is observed that at leaf level, there was a lower near-infrared reflectance values from BAW damaged leaves than from healthy leaves. At canopy level observations, BAW infestations appeared to be associated with lower NDVI values. The study was unsuccessful to detect cabbage looper damage (Sudbrink *et al*. 2003).

The literature available on detection of damage caused by other pests using hyperspectral sensors is tabulated below

S no	**Pest**	**Sensitive wavelength**	**Indices /Other information**	**Reference**
1	Brown plant hopper	755 and 890 nm	-	Yang and Cheng, 2001
		1813-1836 nm	-	Zhou *et al*., 2010a
		550- 760nm	Red edge indices R769 factor	Sun and Liu, 2010
		Double peak at 696 and 735 nm	-	Liu *et al*.,2010
2	Rice leaf folder	741nm	Yellow edge index	Huang *et al*., 2010
3	Rice White Backed Plant Hopper	779nm	-	Qiu *et al.,* 2008
4	Wheat Aphids	-	(R800/R450) (R950/R450)	Yang *et al.,* 2009
5	Wheat Greenbug	694nm 800nm	-	Yang *et al*. 2005
6	Wheat Aphids and green bugs	625-635 nm 680-694nm	NPCI	Riedell and Blackmer., 1999
7	Sugarcane Thrips *Fulmekiola serrata* Kobus	-	Red edge position	Abdel-Rahman *et al*., 2010
8	Cotton Thrips	508,551,691 and 710nm	Red band	Ranjitha *et al,* 2014
9	Cotton Leafhoppers	376,496,691,761,1124 and 1457nm		Prabhakar et al; 2011

10	Tobacco aphid	-	38% decrease in NIR	Qiao *et al*., 2007
11	Cowpea weevils *Callosobruchus maculatus* Fabricius	780-900nm 920-1000nm 1205-1560nm	-	Zhou *et al*., 2010b
12	*Egg plant 28-Spotted Ladybird beetle Epilachna vigintioctopunctata* Fabricius	732nm – 829nm	Red edge position	Apan *et al*., 2005
		1590-1766nm	Short infrared bands	
13	*Tomato Leaf miner Tuta absoluta Meyrick*	1450-1900nm	-	Xu *et al*.,2007
14	*Apple Mite Aculus schlechtendali*	-	SRPI(index) NPI -	Penuelas *et al*., 1995
15	*Eucalyptus Insect damage*	550nm 750nm	-	Stone *et al*., 2001

Disease detection

Remote sensing offers opportunities for detection of plant diseases, in addition to being used in detection of damages caused by insect pests. Hyperspectral imagery is new for measuring severity of plant disease and is still in the early phase of use for detection and quantification, but offers an interesting opportunities for application (Coops *et al*., 2003; Huang *et al*., 2007; Larsolle and Muhammed, 2007; Qin *et al*., 2008). Large-scale farming of agriculture crops requires real-time detection of disease for effective management. Hyperspectral remote sensing data generally have high spectral resolution, which could be very useful for detecting disease stress in green vegetation at the leaf and canopy levels (Liu *et al*., 2008).

Detection of diseases in various crops:

Information available on detection of diseases in various crops using hyperspectral radiometry is tabulated below

S no.	**Crop**	**Disease**	**Sensitive wavelength range/ region**	**Indices / other information**	**Reference**
1	Rice	Brown spot Bipolaris oryzae	-	R702/R718 R 692/R 530	Liu *et al.,* 2008
2	Maize	Maize dwarf mosaic (RNA virus)	NIR		Ausmus and Hilty, 1972
3	Field bean	Chocolate spot disease (*Botrytis fabae*)	-	First order derivative over visible and NIR regions	Malthus and Madeira,1993
4	Barley	Cereal powdery mildew (*Blumeria graminis*)	visible	-	Lorenzen and Jensen, 1989
5	Soybean	*Sclerotinia* stem rot	675–685 nm	**-**	Vigier *et al.* 2004
6	Tomato	Late blight (*Phytophthora infestans*)	NIR	-	Zhang *et al*., 2003
		Fungal "early blight" (*Alternaria solani*)	Red egde	-	Apan *et al.*,2005
7	Sugarcane	Orange rust disease	Combination of VNIR and	-	Apan *et al.*, 2004

			SWIR		
8	Tomato	fungal “early blight” (*Alternaria solani*),	690,720, 735 and 1142nm	-	Apan *et al.*, 2005

Detection of chlorophyll content

Detection of crop stress by remote sensing is based on the assumption that crop stress factors interfere with photosynthesis or the physical structure of the plant and affect the absorption of light energy which in turn alter the reflectance spectrum of the plants (Moran *et al.*, 1997). There is a loss of chlorophyll in the plants due to insect pest damage. Hence, it is essential to know the effect of chlorophyll content of leaves on spectral characteristics and also find methods to estimate chlorophyll content from spectral reflectance data. Spectral wavebands in the red edge (700–750 nm), red (630–690 nm) and green band (500–580 nm) regions are considered to be the three useful ranges for estimating chlorophyll concentration (Blackburn, 1998b; Zarco-Tejada *et al.*, 2001; Gitelson *et al.*, 2003). Red bands are the active chlorophyll absorption bands and NIR bands are active chlorophyll reflectance bands (Mirik 2006a and 2007). The reflectance in NIR region decreases, when there is a loss of leaf area, foliage density, and other changes in canopy characteristics (Gausman, 1974; Kollenkark *et al.*, 1982). The red-edge region is considered as a good estimator of chlorophyll-related stress (Curran *et al.*, 1995).

Detection of nutrient deficiency

A considerable research attention has been received in detecting nitrogen and water stress using remote sensing techniques. Multi-spectral radiometers and infrared thermometers have been successfully used to detect and quantify nitrogen deficiency in agricultural plants. (Blackmer *et al.*,1994; Sembiring *et al.*, 1999). For estimating N levels, spectral regions green(530–560nm), red (630–660) and IR(760-900 nm) are most preferred for rice (Wu *et al.,*2000) while the 550–710 nm region is preferred for maize (Blackmer *et al.*, 1996).

Detection of water stress

The reflectance can be used to derive indicators of crop conditions and to assess levels of water stress (Fernandez *et al.*, 1994). Infra red thermometers were used to detect change in the amount of thermal energy radiated by plants under water stress (Pinter, 1979; Michels *et al.*, 1999). Water stress has been studied using hand held multi-spectral radiometers (Mahey *et al.*, 1991) hyper-spectral spectroscopy (Fernandez *et al.*, 1994; Penuelas *et al.*, 1997). The difference between remotely sensed surface temperature and ground-based measurement of air temperature has been established as a method to detect water stress in plants (Jackson *et al.*, 1981). More recently, to improve remotely-sensed estimates of evapotranspiration, spectral vegetation indices were integrated with temperature (Moran *et al.*, 1994; Carlson *et al.*, 1995).

Thus, any change in the crop health status has been found to cause a specific pattern of change in spectral reflectance, which on characterization can help to detect and estimate the damage caused by pests.

METHODOLOGY

The naturally occurring pest infestation was studied in two plots demarcated as T_1 (Undamaged) and T_2 (Damaged) in existing crop. In the plot marked healthy or undamaged, the plants were protected from pest damage by spraying suitable insecticides periodically. In the plot marked damaged, no plant protection measures were taken up so as to allow natural build up of pest population. However, both the plots were kept free from plant diseases by careful monitoring and spraying fungicide/ bactericide whenever necessary. Three plants were tagged in each treatment to represent healthy (undamaged) and damaged categories of protected and unprotected plots respectively. These tagged plants served as replications for each treatment.

Observations to be recorded:

Pest population, Per cent pest damage, Per cent spectral reflectance have to be recorded at regular interval during active infestation by pest in different crops in tagged plants of both treatments.

In order to detect the presence of damage caused by pests using hyperspectral radiometry, the pest population and spectral reflectance were recorded in undamaged and damaged plants or plots. For studying correlation, ten plants with varying levels of pest damage / population were selected from damaged plot and population was recorded.

Per cent leaf damage

The spectroradiometer can read the plant canopy surface and detect damage caused by insect pests in terms of spectral reflectance and derived indices. It would be more scientific to estimate pest damage rather than pest population from spectral indices through correlation and regression studies. Hence, the per cent leaf damage was also calculated in addition to observing the pest population. The number of damaged leaves and the undamaged ones were recorded and percent infestation was determined using the following formula

$$Percent\ damage = \frac{Number\ of\ damaged\ leaves}{Total\ number\ of\ leaves} \times 100$$

The Spectral reflectance observations was recorded using a field portable Spectroradiometer.

Per cent spectral reflectance

The canopy spectral reflectance has to be collected by pointing the instrument at a distance of 30cm above the crop on clear sunny days between 10 am and 1 pm local time. The instrument was optimized and calibrated before the first measurement and after every five minutes onwards to adapt to the changing atmospheric conditions as mentioned by Luther and Carroll (1999) and Abdel-Rahman *et al* (2010).

The incident spectrum (reference) was periodically obtained from the light reflected by a barium sulphate standard panel before each set of measurements. The per cent reflectance spectrum was calculated as the ratio between the reflected spectra from target and the incident spectra (reference) of the canopy using the following formula.

$$Per\ cent\ reflectance = \frac{Reflectance\ from\ target\ (plant\ canopy)}{Reflectance\ from\ reference\ (barium\ sulphate\ panel)} \times 100$$

The spectral reflectance data, both absolute and per cent reflectance values were transferred from the Spectroradiometer to a personal computer as ASCII files with .asc extension utilizing a specific software supplied with the instrument. These files were later opened in a spreadsheet programme and further analyses were carried out. The 512 values of per cent spectral reflectance at approximately 1.5 nm bandwidth interval starting from 276.86 to 1093.50 nm (reflectance at 350 to 1050 nm ranges being more stable) were obtained for each plant and for all the plants in both treatments.

Spectral bands

The reflectance in blue, green, red and near infra red (NIR) bands were calculated for each plant by taking mean of reflectance values in wavelength ranges of 520-590nm, 620-680 nm and 770-860 nm respectively. The wavelength ranges used in our experiments for green, red and NIR were taken to match the bands in the LISS III, LISS IV (Linear Imaging Self Scanning Sensor) and AWiFS (Advanced Wide Field Sensor) sensors of latest Indian remote sensing satellites namely Resourcesat 1 and 2. The blue band was taken to match with LANDSAT 7's sensor Enhanced Thematic Mapper Plus sensor (ETM+).

From the reflectance values calculated for blue, green, red and NIR bands, various vegetation indices that would reflect the crop condition were worked out.

Spectral vegetation indices

Vegetation Indices (VIs) are combinations of surface reflectance at two or more wavelengths designed to highlight a particular property of vegetation. They are derived using the reflectance properties of vegetation described in plant foliage. Each of the VIs is designed to accentuate a particular vegetation property. All VIs require high-quality reflectance measurements from either multispectral or hyperspectral sensors.

Normalized Difference Vegetation Index (NDVI)

NDVI is the normalized difference of reflectance in NIR and red bands (Sellers, 1985; Sims and Gamon, 2002; Mirik *et al.*, 2006a; Yang *et al.*, 2009). NDVI is used to detect plant stress. Its values range from -1 to 1. NDVI can saturate at high leaf area index (LAI).

$$NDVI = \frac{(RNIR - RRED)}{(RNI \quad + RRED)}$$

Where RRED and RNIR are spectral reflectance values in red and NIR bands respectively.

Ratio vegetative index (RVI) (or) Simple Ratio (SR)

The RVI is the ratio of the highest reflectance and absorption bands of chlorophyll. As with the NDVI, it can saturate in dense vegetation when LAI becomes very high. The value of this index ranges from 0 to more than 30 (Sellers, 1985; Sims and Gamon, 2002; Mirik *et al.*, 2006a).

$$RVI = \frac{RNIR}{RRED}$$

Where RRED and RNIR are spectral reflectance values in red and NIR bands respectively.

Green Red Vegetation Index (GRVI)

Motohka *et al.* (2010) suggested a new index called green red vegetation index, GRVI which can show small changes in vegetation condition during crop growth. GRVI does not saturate at high LAI.

$$GRVI = \frac{(RGR \qquad - RRED)}{(RGRE \qquad + RRE \quad)}$$

Where RRED and RGREEN are spectral reflectance values in red and green bands respectively.

Mathematical and Statistical analyses

The indices and pest damage data have to subjected to the following mathematical and statistical analyses to get meaningful interpretation.

1. Band Sensitivity and Vegetation Index Sensitivity analyses
2. Factorial completely randamised design (fCRD)
3. Correlation and linear regression studies
4. Linear correlation intensity analysis

Band Sensitivity and Vegetation Index Sensitivity analyses

Sensitivity at a given wavelength or band was computed by using the following formula (Carter, 1993).

$$Band\ Sensitivity\ = \frac{R_{inf} - R_{ctrl}}{R_{ctrl}} \times 100$$

Where R_{inf} - canopy reflectance of infested plants, R_{ctrl} - canopy reflectance of control plants.

Similarly, sensitivity for given vegetation index was calculated by using the following formula:

$$Vegetation\ Index\ Sensitivity\ = \frac{VI_{inf} - VI_{ctrl}}{VI_{ctrl}} \times 100$$

Where VI_{inf} - vegetation index of infested plants; VI_{ctrl} - vegetation index of control plants. The band sensitivity and VI sensitivity analyses were performed for data obtained from field studies.

Corrected sensitivity:

The variation in light intensity between observations caused shifting of sensitivity curve along y-axis. In order to correct this, a corrected sensitivity was worked out as below. The reflectance in the wavelength range 350-370 nm was found to be unaffected by pest damage, based on preliminary observations. Hence, the average of sensitivity values between 350-370 nm was taken as zero. This was taken as correction factor and applied to sensitivity values at other wavelengths by adding or subtracting the correction factor. The corrected sensitivity values have been reported as the sensitivity values.

Factorial completely randamised design (fCRD)

The factorial Completely Randomized Design (fCRD) was calculated for the vegetative indices namely RVI, NDVI and GRVI and means were compared by Least Significant difference (LSD) at $p=0.05$.

Correlation and linear regression studies

The correlation between vegetation indices (namely NDVI, GRVI and RVI) and the per cent leaf damage caused by pests were worked out. Ten plants which had varying levels of pest infestation were selected. The percent damage and the corresponding vegetation indices were worked out for each plant, which were used in working out the correlation coefficient (r) and the coefficient of determination (R^2). The test of significance of the Correlation Coefficient was done as suggested by Rangaswamy (1995). A Linear Regression of the per cent damage on each of the vegetation indices was fit based on the varying levels of pest infestation in the ten tagged plants and the corresponding vegetation indices.

Linear correlation intensity analysis

Linear correlation intensity analysis was done to find out the wavelengths whose reflectance values had the maximum positive and negative correlation with pest damage. The correlation between pest damage and spectral reflectance in each of the 512 wavelength bands especially ranging from 350 to 1050 nm were worked out and these correlation values were plotted as a graph against the wavelengths to get the linear correlation intensity analysis graph. Similar to the band sensitivity analysis, this study will help to locate wavelengths most sensitive to pest damage.

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