Remote Sensing of Biotic Stress in Crop Plants and Its Applications for Pest Management

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Chapter 16
Remote Sensing of Biotic Stress in Crop Plants and Its Applications for Pest Management

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Abstract Remote sensing (RS) of biotic stress is based on the assumption that stress interferes with photosynthesis and physical structure of the plant at tissue and canopy level, and thus affects the absorption of light energy and alters the reflectance spectrum. Research into vegetative spectral reflectance can help us gain a better understanding of the physical, physiological and chemical processes in plants due to pest and disease attack and to detect the resulting biotic stress. This has important implications to effective pest management. This review provides an overview of detection of various biotic stresses in different crops using various RS platforms. Previous work pertaining to the use of RS technique for assessing pest and disease severity using different RS techniques is briefly summerized. The available sources of ground based, airborne and satellite sensors are presented along with various narrow band vegetation indices that could be used for characterizing biotic stress. Using relevant examples, the merits and demerits of various RS sensors and platforms for detection of pests and diseases are discussed. Pest surveillance programs such as field scoutings are often expensive, time consuming, laborious and prone to error. As remote sensing gives a synoptic view of the area in a non-destructive and non-invasive way, this technology could be effective and provide timely information on spatial variability of pest damage over a large area. Thus remote sensing can guide scouting efforts and crop protection advisory in a more precise and effective manner. With the recent advancements in the communication, aviation and space technology, there is a lot of potential for application of remote sensing technology in the field of pest management.

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16.1 Introduction

Plant stress is defined as a significant deviation from the optimal conditions for plant growth that could cause harmful effects when the limit of plants' ability to adjust is reached (Larcher 1995). Plant stress can affect almost every part of a plant, although typically one or few plant structures are influenced depending on the age and the source of stress. In case of biotic stress, the mechanism of damage by the pest largely influences the physiological response of plants, which is in turn gets manifested into typical symptoms. Plants may respond to pest and disease stress in a number of ways, including leaf curling, wilting, chlorosis or necrosis of photosynthetic plant parts, stunted growth, or in some cases reduction in leaf area due to severe defoliation. Major types of pest damage mechanisms are classified as germination reduction, stand reduction, light stealing, assimilation rate reduction, assimilation sapping, tissue consumption and turgor reduction (Boote et al. 1983; Aggarwal et al. 2006). While many of these responses are difficult to visually quantify with acceptable levels of accuracy, precision, and speed, these same plant responses will also affect the amount and quality of electromagnetic radiation reflected from plant canopies. Thus, remote sensing instruments that measure and record changes in electromagnetic radiation may provide a better means to objectively quantify disease stress than visual assessment methods. Furthermore, the effects of many pest/disease infestations are often not noticeable to the human eye, until it reaches an advanced stage when it becomes too late to control the outbreak. Remote sensing provides an alternative cost effective method to obtain detailed spatial information for entire crop fields at frequent intervals during the cropping season (Datt et al. 2006). Additionally, remote sensing can be used repeatedly to collect sample measurements non-destructively and non-invasively (Nilsson 1995; Nutter et al. 1990; Nutter and Litterell 1996).

Pests and diseases cause serious economic losses in yield and quality of many cultivated crops, which is estimated at 14% of the total agricultural production (Oerke et al. 1994). Timely detection and assessment of their damage symptoms is very crucial. Traditionally, pest and disease assessment of crop plants is being done by a visual approach i.e., relying up on human eye and brain to assess their incidence. However the problem with the traditional approach is that they are often time consuming and labour intensive. Recent advances in the field of radiometry and other remote sensing technologies offer ample scope for exploiting these technologies towards developing an alternate means that can enhance or supplement the traditional approaches. Precise knowledge of areas where pest or disease activity has started would enable the farmer to apply just the right amounts of pesticides to the affected areas, thereby yielding both economic and environmental benefits (Datt et al. 2006).Though there are several distinct regions in the electromagnetic spectrum. In this review we restricted to the 'optical region' as this is the most extensively studied and widely used for remote sensing of biotic stresses in crop plants. Optical remote sensing makes use regions of visible, near infrared and short-wave infrared sensors. Several reviews were published from time to time on remote sensing of biotic stress (Jackson 1986; Riley 1989; Hatfield and Pinter 1993; Nilsson 1995;

Everitt et al. 2003; West et al. 2003; Yang et al. 2004; Kelly and Guo 2007). This review is an attempt to provide updated and comprehensive, if not exhaustive information on this topic.

16.2 Principle of Operation

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object under investigation. When electromagnetic energy is incident on any feature on the earth surface, three energy reactions with the feature are possible: reflection, absorption and/or transmission (Lillesand et al. 2004). The portion of energy reflected, absorbed or transmitted will vary for different earth features depending on their material type and condition. Even within a given feature type, the portion of reflected, absorbed and transmitted energy will vary at different wavelengths. Thus, two features may be distinguishable in one spectral range and be very different in another wavelength band. Because many remote sensing systems operate in the wavelength regions in which reflected energy predominates, the reflectance properties of earth surface are very important. The reflectance characteristics of earth surface features may be quantified by measuring the portion of incident energy that is reflected (Panda 2005). Reflectance is measured as a function of wavelength and is called spectral reflectance. A graph of the spectral reflectance of an object as a function of wavelength is termed as 'spectral reflectance curve' (Fig. 16.1).

The configuration of spectral reflectance curve gives us the insights into the spectral characteristics of an object and has a strong influence on the choice of

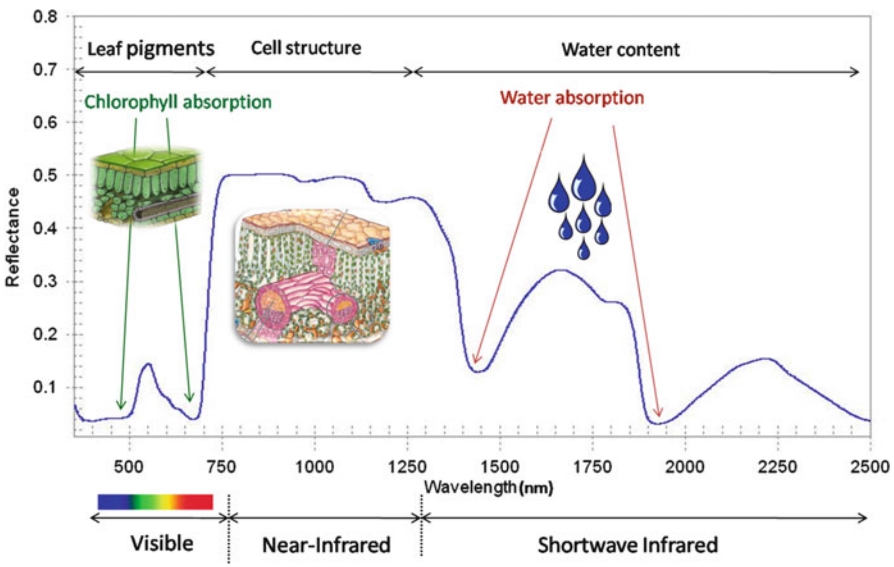

Fig. 16.1 Typical spectral reflectance curve of healthy vegetation depicting different absorption peaks

wavelength regions in which remote sensing data need to be acquired for particular application. Physical and physiological basis for the reflectance of visible and near infrared radiation from vegetation has been extensively studied (Knipling 1970; Zhang et al. 2003). Reflectance spectra of crop canopies are known to be a function of canopy optical properties with contributions from biophysical and biochemical attributes of vegetation, viewing geometry of detector, illumination conditions of the surroundings, and background effects (Asner 1998; Barrett and Curtis 1992; Goel 1998; Myneni et al. 1989). The three dimensional orientation of biophysical attributes of vegetation provides a better architecture for photon reception from incident radiation, yet creates variation in the spectral characteristics. The biochemical components of the plant parts also influence plant reflectance spectra (Buschman and Nagel 1993; Baret et al. 1994; Kupiec and Curran 1995).

Rapid and accurate quantification of early symptoms are important from a pest management point of view, and efforts at remotely detecting plant stress due to disease or insect activity utilize principles of biophysical remote sensing (Jensen 1983). Plant stress usually results in an increase in visible reflectance (due to a decrease in chlorophyll and a resulting decrease in absorption of visible light), and a decrease in NIR reflectance from changes in the internal leaf structure (Hatfield and Pinter 1993). Use of remote sensing techniques for detection crop pests and diseases is based on the assumption that stress induced by them interferes with photosynthesis and physical structure of the plant and affects the absorption of light energy and thus alters the reflectance spectrum of the plants (Riley 1989; Hatfield and Pinter 1993; Moran et al. 1997). Natural growth processes (e.g. increase of biomass, development, maturation, senescence, plant architecture and natural fluctuations in hydraulic properties) and the related biochemical changes, such as concentration of chlorophyll and other pigments, also have an impact on the amount of solar energy that is reflected, absorbed, and transmitted by plants (Carter 1993; Lillesand et al. 2004; Ustin et al. 2002). Thus, research into vegetative spectral reflectance can help better understand the physiological, chemical and physical processes in plants and to detect plant stress when remedial action may still be effective.

16.3 Types of Remote Sensing Platforms

Remote sensing platforms can be field-based (ground based), or mounted on aircraft (airborne) or satellites (space borne). Ground-based platform, such as handheld spectroradiometer, is typically used for ground truth study. Airborne RS is flexible and able to achieve different spatial resolutions with different flight altitudes. Satellite RS is generally for small scale (large area) study but it often times cannot meet the requirement of spatial resolution in applications. However, with recent advent of high resolution sensors, there is lot of potential for large scale (small area) field applications. Depending on the band width, number of bands and contiguous nature of recording spectral scanner scan be of two types viz., multispectral or broad band and hyperspectral or narrow band (Table 16.1). Multispectral scanners

Table 16.1 Spatial and spectral characteristics different satellite sensors

Satellite/Sensor	No of bands	Band width (μm)	Spatial resolution (m)	Temporal resolution (days)
Multispectral				
Landsat-1,2,3 MSS	4	0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–1.1	56 × 79	16
Landsat-4,5 TM	7	0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90, 1.55–1.75, 10.4–12.5, 2.08–2.35	30	16
Landsat-7 ETM+	8	0.52–0.90 (p)	15	16
		0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90, 1.55–1.75, 10.4–12.5, 2.08–2.35	30	
ASTER	14	VNIR: 3 bands (0.52–0.86)	15	16
		SWIR: 6 bands (1.6–2.43)	30	
		TIR: 5 bands (8.125–11.65)	90	
ALI	10	0.48–0.69 (p)	10	16
		VIS: 4 bands (0.433–0.69)	30	
		NIR: 3 bands (0.775–1.30)		
		SWIR: 2 bands (1.55–2.35)		
SPOT-4	5	0.43–0.47, 0.50–0.59, 0.61–0.68, 0.79–0.89, 1.58–1.75	2.5–20	26
SPOT- 5				
-HRG	6	0.48–0.71 (p)	2.5–5	26
		0.43–0.47, 0.50–0.59, 0.61–0.68, 0.79–0.89, 1.58–1.75	10–20	
-HRS	5	0.49–0.69 (p)	5–10	26
		0.45–0.52, 0.61–0.68, 0.78–0.89, 1.58–1.75	1,000	
RESOURCESAT-1 (IRS-P6)				
-AWiFS	4	0.52–0.59, 0.62–0.68, 0.77–0.86, 1.55–1.70	56	5
-LISS III	4	0.52–0.59, 0.62–0.68, 0.77–0.86, 1.55–1.70	23	24
CBERS -2				
- CCD	5	0.51–0.73 (p), 0.45–0.52. 0.52–0.59, 0.63–0.69, 0.77–0.89	20	26
-IR MSS	4	0.50–1.10 (p), 1.65,2.22, 11.45	80–160	26
-WFI	2	0.66, 0.83	260	5
NOAA-14-AVHRR	5	0.58–0.68, 0.72–1.1, 3.55–3.93, 10.5–10.5, 11.5–12.5	1,000	Daily
MODIS-TERRA	36	0.62–14.385	250–1,000	Daily

(continued)

Table 16.1 (continued)

Satellite/Sensor	No of bands	Band width (μm)	Spatial resolution (m)	Temporal resolution (days)
Hyperspectral				
EOS-Hyperion	196	VNIR – 427.55–925.85 nm (band 8–57) SWIR 932.72–2395.53 nm (band 79–224)	30	16
Hyperspatial				
IKONOS	4	0.45–0.90 (p)	1	5
		0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90	4	
QUICKBIRD	4	0.45–0.90 (p)	0.61	5
		0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90	2.40	
RESOURCESAT-1 LISS IV	3	0.52–0.59, 0.62–0.68, 0.77–0.86	5.8	5
Rapid Eye	5	0.44–0.51, 0.52–0.59, 0.63–0.68, 0.69–0.73, 0.76–0.85	6.5	1–5
WorldView-2	8	0.45– 0.80 (p)	0.46	2–5
		VIS: 6 bands (0.45–0.745)	1.85–2.07	
		NIR: 2 bands (0.77–1.04)		
CARTOSAT-2	1	0.52– 0.85 (p)	1	5
FORMOSAT-2	5	0.45–0.90 (p)	2	Daily
		0.45–0.52, 0.52–0.60, 0.63–0.69, 0.76–0.90	8	
KOMPSAT-2	5	0.5–0.9 (p)	1	14
		0.45–0.52, 0.52–0.6, 0.63–0.59, 0.76–0.90	4	
ALOS-AVNIR-2	5	0.52–0.77 (p)	2.5	2
		0.42–0.50, 0.52–0.60, 0.61–0.69, 0.76–0.89	10	

(p): panchromatic

sense several wavebands in a wider range of discrete wavelengths while hyperspectral scanners provide the opportunity to sense many very narrow wavebands over a wide range of wavelengths with much greater number of sensors. Multispectral systems measure energy in specific, strategically restricted portions of the electromagnetic spectrum while hyperspectral systems measure several consecutive wavebands across a specified region of the electromagnetic spectrum. However, a major limitation of broadband RS products is that they use average spectral information over broadband widths resulting in loss of critical information available in specific narrow bands (Blackburn 1998a, b; Thenkabail et al. 2002). Most hyperspectral sensors acquire radiance information in less than 10 nm bandwidths from the visible to the SWIR (400–2,500 nm) (Asner 1998). For example, the spectral shift of the red-edge (670–780 nm) slope associated with leaf chlorophyll content, phenological state and vegetation stress, is not accessible with broadband sensors (Collins 1978; Horler et al. 1983). Recent developments in hyperspectral RS or imaging spectrometry have provided additional bands within visible, NIR and shortwave infrared (SWIR) which are useful for biotic stress detection (Pena and Altman 2009; Yang 2010; Jones et al. 2010).

The data the RS sensors capture is often characterized by four kinds of resolutions viz., (i) spatial (the smallest resolvable unit on the ground, also called the pixel), (ii) spectral (how sensitive is the sampled spectra), (iii) temporal (how often the data can be captured) and (iv) radiometric (the ability to discriminate very slight differences in reflected or emitted energy) (Kelly and Guo 2007). The common pixel sizes (spatial resolution) are wide-ranging across different satellites (Table 16.1). Weather satellites have pixel resolutions larger than 1 km; the AVHRR sensor, an early multispectral sensor still in use has a 1 km pixel size; the series of Landsat sensor have 30 m pixels, and there are a range of newer commercial satellites (e.g. Quickbird and IKONOS) that have near and under 1 m spatial resolution. Sub-meter resolution imagery is increasingly common, especially with the use of aircraft-borne sensors. The spectral information contained in imagery can include multispectral (<10 bands of spectra, covering the visible and NIR portion of the spectrum), hyperspectral (10s to 100s of bands, covering a wider range of the spectrum) and thermal spectra (covering longer wave infrared emittance spectra) (Kelly and Guo 2007). A new RS product, RapidEye, is now available with 5-m spatial resolution with a red-edge band. This red-edge band, which is the region of rapid change in reflectance of chlorophyll in the near infrared range, can improve the accuracy for mapping plant diseases (Santoso et al. 2011).

16.4 Concept of Spectral Vegetation Index

A vegetation index (VI) can be defined as a dimensionless, radiation based measurement computed from the spectral combination of remotely sensed data. Numerous vegetation indices, broadband as well as narrowband, have been developed to detect plant stress (Carter 1994). Single wavebands are often good indicators of biochemical constituents, but are subject to variability caused by environmental factors such as illumination differences including solar angle and background scattering. Vegetation indices also lead to data dimensionality reduction and therefore might be helpful in terms of data processing and analysis. Such indices are also able to overcome the limitations of single band applications by minimizing external factors, and therefore correlate more closely with vegetative biochemical constituents (Delalieux et al. 2009). VIs also enhances sensitivities to green vegetation spectral signals and reduces external effects such as noise related to soil and atmospheric influences (Zhao et al. 2005). Ratios can be simple two band ratios or can include a combination of bands. Several researchers have proposed several ratios for different applications (Tables 16.2 and 16.3). These VIs can be divided into four broad groups (Mirik 2001). (i) Ratio-based VIs: They are based on the ratio between red and NIR reflectance.

Table 16.2 Sensitive bands and spectral indices for different kinds of biotic stresses in different crops

S.No.	Crop	Pest	Platform	Spectral resolution	Optimum bands (in nm)/ indices/technique used	Reference
1.	Wheat	Leaf rust, yellow rust	Space borne	Multispectral (Landsat)	NDVI	Nagarajan et al. (1984)
2.	Peanut	Leaf spot	Ground based	Multispectral	800 nm	Nutter (1989), Aquino et al. (1992)
3.	Bentgrass	Blight	Ground based	Multispectral	760,810 nm	Raikes and Burpee (1998)
4.	Wheat	Cereal aphid	Ground based	Hyperspectral	NPCI	Riedell and Blackmer (1999)
5.	Apple	Scald	Ground based	Hyperspectral	550 & 700 nm; BRI	Chivkunova et al. (2001)
6.	Rice	Panicle blast	Ground based & Airborne	Hyperspectral	485,675 nm; (R470/R570);(R520/R675);(R570/R675);(R550/R970); (R725/R900)	Kobayashi et al. (2001)
7.	Alfalfa	Leaf spot	Ground based	Multispectral	810 nm	Guan and Nutter (2002)
8.	Wheat	Yellow rust	Ground based	Hyperspectral	543,630,750, 861 ± 10 nm	Bravo et al. (2003)
9.	Rice	Leaf blast	Ground based	Multispectral	(R550/R675), (R570/R675)	Kobayashi et al. (2003)
10.	Cotton	Armyworm	Ground based & Airborne	Multispectral	NDVI	Sudbrink et al. (2003)
11.	Sugarcane	Orange rust	Space borne	Hyperspectral (Hyperion)	DWSI	Apan et al. (2004)
12.	Rubber	Corynespora	Space borne	Multispectral (IRS 1 C)	NDVI	Ranganathan et al., 2004
13.	Cotton	Spider mite	Airborne	Hyperspectral (AVIRIS)	SMA	Fitzgerald et al. (2004)
14.	Tomato	Late blight	Ground based Airborne	Hyperspectral Multispectral (ADAR)	5-index feature vector method	Zhang et al. (2005)
15.	Wheat	Greenbug	Ground based	Multispectral	694, 800 nm	Yang et al. (2005), Yang et al. (2009)
16.	Rice	Sheath blight	Airborne	Multispectral (ADAR)	RI, SDI	Qin and Zhang (2005).
17.	Mustard	Alternaria	Space borne	Hyperspectral (Hyperion)	DWSI	Datta et al. (2006)
18.	Wheat	Powdery mildew and take-all disease	Ground based	Hyperspectral	490_{780}, 510_{780}, 516_{1300} and 540_{1300} nm	Graeff et al. (2006)

19.	Vegetables	Silver leaf whitefly, soft rot, leaf spot, caterpillar damage	Ground based	Hyperspectral	Silverleaf index,Broccoli soft rot index, Bacterial leaf spot index, Sunburn index	Datt et al. (2006)
20.	Cotton	Aphid, spider mite	Airborne, Space borne	Multispectral (SAMRSS, QuickBird); Hyperspectral (AV-NIR)	NIR are more sensitive	Reisig and Godfrey (2006)
21.	Wheat	Green bug	Ground based	Hyperspectral	AI	Mirik et al. (2006a)
22.	Wheat	Green bug	Ground based	Hyperspectral	DSSI	Mirik et al. (2006b)
23.	Peanut	Late leaf spot	Ground based	Multispectral	700–850 nm	Prabhakar et al. (2006)
24.	Wheat	Aphid	Airborne	Multispectral	NDVI	Elliott et al. (2007)
25.	Wheat	Powdery mildew and leaf rust	Airborne and Space borne	Hyperspectral (HyMap) Multispectral (QuickBird);	SMA, MTMF, NDVI	Franke and Menz (2007)
26.	Tomato	Leaf miner	Ground based	Hyperspectral	800 to1100 nm, 1450 and 1900 nm	Xu et al. (2007)
27.	Rice	Brown plant hopper, leaf folder	Ground based	Hyperspectral	426,1450 nm, linear correlation intensity analysis	Yang et al. (2007)
28.	Rice	Leaf folder	Ground based	Hyperspectral	757,445 nm	Yang et al. (2007)
29.	Forest trees	Gypsy moth	Space borne	Multispectral (MODIS)	NDVI, EVI, NDWI, NDII	Beurs and Townsend (2008)
30.	Forest tress	Pine beetle	Space borne	Multispectral (Landsat)	NDMI	Goodwin et al. (2008)
31	Rice	Brown spot	Ground based	Hyperspectral	(R702/R718), (R692/R530), (R692/R732)	Liu et al. (2008)
32.	Wheat	Sunn pest	Ground based	Hyperspectral	NDVI, SIPI	Genc et al. (2008)
33.	Pine	Bark beetle	Space borne	Multispectral (Landsat)	LAI	Coops et al. (2009)
34.	Conifer	Aphid	Space borne	Hyperspectral (Hyperion)	ARI	Pena and Altman (2009)

(continued)

Table 16.2 (continued)

S.No.	Crop	Pest	Platform	Spectral resolution	Optimum bands (in nm)/ indices/technique used	Reference
35.	Wheat	Aphid	Airborne	Multispectral	Unsupervised classification, spatial pattern analysis	Backouloua et al. (2010)
36.	Rice	Bacterial leaf blight	Ground based	Hyperspectral	943 and1039 nm, MLR	Yang (2010)
37.	Tomato	Bacterial leaf spot	Ground based	Hyperspectral	Partial least squares (PLS) regression, stepwise multiple linear regression (SMLR)	Jones et al. (2010)
38.	Wheat	Streak mosaic	Space borne	Multispectral(Landsat TM)	Maximum likelihood classifier	Mirik et al. (2011)
39.	Oil palm	Stem rot	Space borne	Multispectral (QuickBird)	ARVI, GNDVI, GBNDVI, NDVI, SAVI, SR	Santoso et al. (2011)

R: Reflectance

Table 16.3 Narrow band vegetation indices for use in biotic stresses detection

S. No.	Index	Formula	Reference
1.	Normalized Difference Vegetation Index (NDVI)	(R800 – R670)/(R800 + R670)	Rouse et al. (1974)
2.	Red Edge Position (REP)	700+40(RRE – R700)/(R740 – R700) RRE=(R670+R780)/2	Guyot and Baret (1988)
3.	Chlorophyll Index (CI)	(R415 – R435)/(R415+R435)	Barnes (1992)
4.	Photochemical Reflectance Index (PRI)	(R531 – R570)/(R531+R570)	Gamon et al. (1997)
5.	Simple Ratio (SR)	R695/R420	Carter 1994
6.	Normalized Pigment Chlorophyll Index (NPCI)	(R680 – R430)/(R680+R430)	Penuelas et al. (1995a)
7.	Structure Insensitive Vegetation Index (SIPI)	(R800–R445)/(R800+R680)	Penuelas et al. (1995b)
8.	Green Normalized Difference Vegetation Index (GNDVI)	(R750 – R550)/(R750+R550)	Gitelson et al. (1996)
9.	Optimized Soil-Adjusted Vegetation Index (OSAVI)	(1+0.16) (R800 – R670)/(R800+R670+0.16)	Rondeaux et al. (1996)
10.	Water Index (WI)	R900 nm/R970 nm	Penuelas et al. (1997)
11.	Red-edge Vegetation Stress Index (RVSI)	(R714 nm+R752 nm)/2–R733 nm	Merton and Huntington (1999)
12.	Modified Chlorophyll Absorption Reflectance Index (MCARI)	[(R700 – R670)–0.2 (R700 – R550)] (R700/R670)	Daughtry et al. (2000)
13.	Transformed Chlorophyll Absorption Reflectance Index (TCARI)	3 [(R700 – R670)–0.2 (R700 – R550)(R700/R670)]	Haboudane et al. (2002)
14.	Ratio of TCARI and OSAVI	TCARI/OSAVI	Haboudane et al. (2002)
15.	Browning Reflectance Index (BRI)	(1/R550 – 1/R700)/(R750)	Chivkunova et al. (2001)
16.	Anthocayanin Reflectance Index (ARI)	$(R550)^{-1} - (R700)^{-1}$	Gitelson et al. (2001)
17.	Zarco Tejada and Miller (ZTM)	R750/R710	Tejada et al. (2001)
18.	Modified red edge Normalized Difference Vegetation Index (mNDVI705)	(R750 – R705)/(R750+R705 – 2*R445)	Sims and Gamon (2002)
19.	Disease Water Stress Index 2 (DWSI-2)	R1660/R550	Apan et al. (2004)
20.	Damage Sensitive Spectral Index-2 (DSSI 2)	(R747 – R901 – R537 – R572)/(R747 – R901)+(R537 – R 572)	Mirik et al. (2006a)
21.	Aphid Index (AI)	(R761 – R908)/(R712 – R719)	Mirik et al. (2006b)
22.	Broccoli soft rot index	(D725 – D700)/(D725+D700)	Datt et al. (2006)
23.	Bacterial lea spot index	(R550 – R640)/(R550+R640)	Datt et al. (2006)
24.	Sunburn Index	(R450 – R680)/(R450+R680)	Datt et al. (2006)

R: Reflectance at corresponding wavelength (nm); D: First order derivative at corresponding wavelength (nm)

The normalized difference vegetation index (NDVI) (Rouse et al. 1974) and ratio vegetation index (RVI) (Pearson and Miller 1972) are the most commonly used ratio-based VIs. (ii) Orthogonal VIs: Defined by a line in spectral space for identification at bare soils. The transformed soil-adjusted vegetation index (TSAVI) (Baret et al. 1989), second soil adjusted vegetation index (SAVI2) (Major et al. 1990) and modified second soil-adjusted vegetation index (MSAVI2) (Qi et al. 1994) are examples of orthogonal VIs. (iii) Derivative VIs: First and second-order derivative greenVIs introduced by Elvidge and Chen (1995). (iv) Atmospheric corrected indices: Such as the visible atmospherically resistant index (VARI) (Gitelson et al. 2002).

These VIs have been shown to be quantitatively and functionally related with canopy parameters such as the leaf area index (LAI), aboveground biomass, chlorophyll and other leaf pigment content and vegetation fraction. Research results indicate these VIs have potential applications in agriculture in general and for monitoring pests and diseases in particular (Riedell and Blackmer 1999; Elliott et al. 2007; Franke and Menz 2007; Coops et al. 2009; Pena and Altman 2009). Sensitive bands identified by various workers and VIs used to detect biotic stresses caused due to specific pests and diseases are summarized in Table 16.2. It can be inferred that damage by different pests on the same host requires different band combinations for their detection. Sensitivity of the spectra to the stress are crop and pest specific as it varies depending on the nature of damage induced by the pest.

16.5 Ground Based Remote Sensing of Biotic Stress

Spectroradiometry is the technique of measuring the spectrum of radiation emitted by a source. In order to do this the radiation must be separated into its component wavebands and each band measured separately. It is achieved by diffraction grating technique within the spectroradiometers to split the radiation entering the system into its constituent wavebands. A suitable detector is then used to quantify the radiation of each wavelength (ASD 1999). The field spectroscopy concerns *in situ* measurement of the reflectance of composite surfaces. Increasingly, spectral data are being incorporated into process-based models of the Earth's surface and atmosphere, and it is therefore necessary to acquire data from terrain surfaces, both to provide the data to parameterise models and to assist in scaling-up data from the leaf scale to that of the pixel (Milton et al. 2009). In most cases, the reflectance of a vegetation canopy or a soil surface is presented as a 'reflectance factor'. Nicodemus et al. (1977) introduced the concept of a reflectance factor, being the ratio of the radiant flux actually reflected by a sample surface to that which would be reflected into the same reflected-beam geometry by an ideal (lossless) perfectly diffuse (Lambertian) standard surface irradiated in exactly the same way as the sample. Spectralon has become established material of choice for recording reference spectra (U.S. National Institute of Standards and Technology, NIST). Milton et al. (2009) provided an exhaustive review of developments in the field of field spectroscopy and its applications.

Evidently, a limiting factor of ground based remote sensing is that their applicability is for small areas when compared with aircraft and satellite sensors. However, using hand-held spectrometers to quantify the unknown spectral characteristics of un-infested and infested plant canopies due to insect feeding at a small-scale is needed because hand-held remote sensing devices have better temporal, spectral, and spatial resolutions, as well as the accuracy of collecting reflectance data over per unit area. Reflectance data obtained by hand-held instruments over small-areas provide information to understand spectral interactions between insect pests and their host plants, as well as fundamental ground-truth for interpretation of RS data measured from satellite and aircraft. Therefore, a logical initial step is to use a field spectrometer for understanding the spectral response of crop stress (Mirik et al. 2006b). Over the years several other studies have characterized stress in crop plants using multi and hyperspectral hand held radiometers.

16.5.1 Ground Based – Multispectral

There are number of studies on use of multispectral radiometers for pest and disease detection. Maize leaves infected with dwarf mosaic virus showed significantly lower reflection even before visible symptoms could be noted, when compared to healthy leaves (Ausmus and Hilty 1971). Such a change in reflectance characteristics was used to make an early diagnosis of disease symptoms. Changes in citrus soft scale infestation levels were detectable because the honeydew excreted by the scale insects was an excellent growth medium for a sooty mold fungus that showed very low reflectance in both the visible and NIR wavelength regions and tended to accumulate as the season progressed (Gausman and Hart 1974). Infection of *Sclerotina* stem rot in oil seed rape, net blotch disease in barley and barley stripe disease (Nilsson 1991) were studied using ground based radiometry. The highest correlations with disease severity were found in the NIR bands, while some effects were traced to the visible bands. High correlations were also reported between disease incidence and the NIR to red and the green-to-red reflectance ratios.

Sharp et al. (1985) monitored the onset of stripe and stem rust using a radiometer and four VIs based on broad Multi Spectral Scanner (MSS) channels. Yellow rust infested winter wheat was successfully detected (classification error of 2.1 per cent) in field using four wave band spectrograph (Bravo et al. 2003). Ibragimov et al. (1994) reported that changes in the spectral characteristics in the visible and near-infrared region were related to rust infections and they were registered under laboratory and field conditions. Correlations were found between quantitative and qualitative changes of spectral characteristics, the type of rust infection and disease intensity in wheat. There have also been reports of field experiments using ground-based radiometers to assess the severity of watermelon disease (Blazquez and Edwards 1986), various leaf and root diseases (Nilsson 1991), anther smut disease in *Silene dioica* (Nilsson and Carlsson 1994), barley stripe disease (Nilsson and Johnsson 1996) and Rhizoctonia blight in creeping bentgrass (Raikes and Burpee 1998a, b), early blight of tomato (Lathrop and Pennypacker 1980) and aphid damage in broccoli (Costello 1995).

Kobayashi et al. (2001) used multi spectrometer reading to examine the progression of rice panicle blast disease, *Magnaporthe grisea* Barr and found that early stages of disease infestation, changes in visible reflectance are most indicative of the disease, and as the disease progresses, changes in NIR reflectance are more useful. Remote sensing provided a more precise method to estimate impacts of foliar pathogens on alfalfa and it was conclusively demonstrated that percent reflectance had better relationship than the destructive and more labour intensive visual estimation of defoliation caused by the pathogen (Guan and Nutter 2002). A strong relationship between defoliation and canopy reflectance and pod yield in the peanut late leaf spot pathosystem was found (Nutter and Litterell 1996) and subsequent intensity of peanut leaf spot disease was successfully assessed using a ground based multispectral radiometry (Nutter et al. 1990; Aquino et al. 1992).

Riedell and Blackmer (1999) investigated the effects that sucking insects have on leaf reflectance by infesting wheat seedlings with aphids (*Diuraphis noxia* Mordvilko) or greenbugs (*Schizaphis graminum* Rondani). Compared with healthy plants, the leaves from infested plants had lower chlorophyll concentrations and displayed significant changes in reflectance spectra at certain wavelengths viz., 500–525, 625–635, and 680–695 nm. The band centered at 694 nm and the vegetation indices derived from bands centered at 800 and 694 nm were identified as most sensitive to damage due to greenbug (*Schizaphis graminum*) infestation in wheat and broad Landsat TM bands and derived vegetation indices also showed potential for detecting the stress (Yang et al. 2005). It was found that infrared spectral region between 700–850 nm was found to be sensitive to leaf spot disease in peanut (Prabhakar et al. 2006). They observed the percent reflectance in 700–800 nm range of spectrum was higher for healthy plants when compared to diseased plants. Additionally many broad band indices were tested for their ability to differentiate disease severity. However, low level of disease intensity could not be detected using multispectral reflectance. Use of multispectral radiometry for assessment of Rhizoctonia blight in creeping bentgrass (Raikes and Burpee 1998a, b) and insect infestation in soybean have been proved (Board et al. 2007). It was also demonstrated that using multispectral radiometry it was possible to differentiate stress caused by Russian aphid and greenbugs in wheat (Yang et al. 2009).

16.5.2 Ground Based – Hyperspectral

Hyperspectral imaging spectrometers measure crop canopy reflectance in hundreds of narrow bands across the solar spectrum. Such high-resolution data or “spectral signatures” are able to detect subtle changes in plant chemistry and physiology caused by disease development or other stress factors (Datt et al. 2006). Malthus and Madeira (1993) investigated spectral reflectance properties of faba bean infected by *Botrytis* disease over the wavelengths range of 400–1,100 nm. The most significant changes in the spectral reflectance associated with the disease were a flattening of the response in the visible region and a decrease in the near-infrared reflectance shoulder at 800 nm. Both responses were attributed to collapse of leaf cell structure as the fungus spread. Riedell and Blackmer (1999) reported that feeding due to Russian wheat aphid resulted in a reduction in the leaf dry weight and area in the third and fourth leaves, and a reduction in total chlorophyll concentration in all leaves. Leaf reflectance in the 625–635 nm and the 680–695 nm ranges, as well as the normalized total pigment to chlorophyll-a ratio index (NPCI) were significantly correlated with total chlorophyll concentrations in plants damaged due to green bug and Russian wheat aphids. Yang and Cheng (2001) measured spectral characteristics of rice plants at various levels of infestation by the brown plant hopper, *Nilaparvata lugens*. There were significant differences in reflectance among infestations at wavelengths of 755 and 890 nm. Particularly spectral parameters such as the NDVI and cumulative reflectance may also be used to discriminate levels of hopper infestation. Later Yang et al. (2007) identified sensitive narrow bands for damage caused by rice brown plant hopper and leaf folder. They studied the damage due to these pests using both narrow and broad-band spectral indices.

Hyperspectral images of healthy and yellow rust infected wheat plants taken with an imaging spectrograph under ambient lighting conditions were found to classify diseased and healthy plants in the field using a quadratic discriminating model based on the reflectance of four wavebands (543 ± 10 nm, 630 ± 10 nm, 750 ± 10 nm and 861 ± 10 nm) with high coefficient of determination (Bravo et al. 2003). Several studies have demonstrated the utility of hyperspectral in diagnosing the pest and disease infestations in vegetable crops (Apan et al. 2005; Datt et al. 2006), rice and castor (Prabhakar et al. 2008) and citrus canker disease (Burks et al. 2009). By characterization of the spectral properties of wheat plants infested by green bug (Mirik et al. 2006a, 2006b) and Russian aphid *D. noxia* (Mirik et al. 2007) using a ground based hyper spectral spectrometry new indices and algorithms for estimating these pests on wheat has been suggested. By comparing leaf reflectance measurements in the visible and near-infrared, a reduction in chlorophyll was detected in the early stages of disease development in *Nicotiana debneyi* plants infected with tomato mosaic virus, even though visible symptoms were not apparent until several days later (Polischuk et al. 1997). While Delalieux et al. (2007) differentiated leaves of plants infected with apple scab (*Venturia inaequalis*) based on leaf reflectance in narrow wavebands. These results indicated that the specific wavelengths that yielded the best discrimination power were dependent upon the number of days following infection, as well as the plant cultivar (resistant or not). Discern differences in hyperspectral signatures were used to differentiate healthy palm oil leaves from Ganoderma infected leaves (Shafri and Anuar 2008).

Muhammed (2005) characterized hyperspectral crop reflectance data for estimating fungal disease severity in wheat and established a procedure with low computational load that were suitable for real-time applications. Specific differences in vegetation indices and wavelength intervals were observed between leaf roll virus-infected grape leaves and uninfected leaves in the green peak (near 550 nm), the near infrared (near 900 nm) and in the mid-infrared (near 1,600 and 2,200 nm).

Further analysis suggest that different vegetation indices and/or individual wavelength bands may differ in their ability to detect leaf roll disease in grapes depending on whether there are visible symptoms in the virus-infected leaves (Naidu et al. 2009). Using ground based hyperspectral radiometry Datt et al. (2006) developed narrow-band indices specific to pest and disease damage vegetable crops like silver leaf white fly in pumpkin, bacterial rot in broccoli, bacterial leaf spot in lettuce and caterpillar damage in cabbage

Devadas et al. (2008) tested different narrow band indices to discriminate three rust diseases on wheat and found no single index was capable of discriminating all three rust species on, but sequential application of selected indices would provide for the required species discrimination under laboratory conditions and thus, could form the basis for discrimination of rust species in wheat under field conditions. Genc et al. (2008) tested different hyperspectral indices for detection of sunnpest (*Eurygaster integriceps*) on wheat and found NDVI and SIPI as more suitable for assessing their damage levels. Ray et al. (2010) demonstrated the use of hyperspectral indices based on narrow bands to differentiate healthy and blight infested potato plants. Ultraviolet, visible, and near infrared reflectance spectroscopy was used to determine the disease severity of tomato leaves infected with bacterial leaf spot, *Xanthomonas perforans* and identified wavelengths around 750–760 nm as significant and seem highly related to the disease (Jones et al. 2010). While Liu et al. (2008) estimated brown spot fungal disease of rice using hyperspectral reflectance data and identified sensitive bands specific to this disease. Jusoff et al. (2010) developed a signature library profile of leaf fall disease affecting rubber trees and opined that such studies certainly assists in the development of an early disease warning system using an airborne hyperspectral imaging system. Recently Sindhuja et al. (2010) reviewed the possibility of using spectral reflectance for detection of several plant diseases. Characterization of reflectance spectra of several biotic stresses on various crops during ground- truth studies so far provide crucial information required for interpretation of remote sensing data obtained from airborne and space borne platforms. Hence it is important that this kind of basic studies should be carried out using hand-held radiometry to all the important biotic stresses on which such information is not available so far. The narrow band hyperspectral radiometers provide more useful and meaningful results compared to multispectral radiometers, specially for biotic stress studies.

16.6 Airborne Remote Sensing of Biotic Stress

Studies on the use of airborne remote sensing for crop disease assessment started long time ago. For example, in the late 1920s, aerial photography was used in detecting cotton root rot (Taubenhaus et al. 1929). The use of infrared photographs was first reported in determining the prevalence of certain cereal crop diseases (Colwell 1956). William Collins and Sheng-Huei Chang, along with Hong Yee Chiu developed the first airborne spectrometer for vegetation stress applications based on variations in the wavelength position of the red-edge (Chiu and Collins 1978). In the early 1980s, Toler et al. (1981) used aerial colour infrared photography to detect root rot of cotton and wheat stem rust. In these studies, airborne cameras were used to record the reflected electromagnetic energy on analogue films covering broad spectral bands. Since then, RS technology has changed significantly. Everitt et al. (2003) provided an overview of aircraft remote sensing in integrated pest management with four exemplary examples viz., blackfly in citrus, silver whitefly in cotton, harvest ant infestations in rangelands and western pine beetle infestations in a forested area. They concluded that integration of remote sensing, GPS and GIS provide valuable tools that can enable resource managers to develop maps showing distribution of insect infestations over large areas. The digital imagery can serve as permanent data base for monitoring future contraction or spread of insect infestation over time. However, aircraft RS data may suffer from mismatching of the image pixels to the ground features, and also from the problem of spectral pixel mixing, which is the mixture of the signals from different objects such as soil, healthy and infested plants or vegetation, different species, and varying cover levels (Mirik et al. 2005). Nevertheless, airborne multi-spectral imaging system has a great potential for use in area wide pest management systems (Lan et al. 2007; Huang et al. 2008).

16.6.1 Airborne – Multispectral

Hart and Meyers (1968) used colour-infrared (CIR) photography and hyperspectral reflectance data to identify citrus trees infected with brown soft scale insects (*Coccus hesperidum*). Airborne RS technology has been employed for detecting crop disease and assessing its impact on productivity (Heald et al. 1972; Henneberry et al. 1979; Schneider and Safir 1975). Wheat disease severity assessment has been advocated using airborne remote sensing (Kanemasu et al. 1974). Detection of coconut wilt disease is one of the earliest applications on use of airborne RS for pest detection from India (Dakshinamurti 1971). The recent advent of high spatial resolution aircraft-borne imaging instrumentation has demonstrated several applications in pest management. Such multispectral instruments typically capture reflectance in three visible and the NIR band, and thus their imagery is often used to map vegetation. One increasingly commonly used system is the high spatial resolution multispectral imaging system called Airborne Data Acquisition and Registration (ADAR), which has been used with some success to map and monitor crop health. The ADAR camera is digital, and captures reflectance in blue, green, red and near infrared. Because it can be mounted on aircraft, flight altitude and spatial resolution can be controlled. Qin and Zhang (2005) used multispectral ADAR imagery to detect rice sheath blight disease in Arkansas, USA. They had better success in discriminating severe infestation levels, and had more trouble discerning early stages of the disease. Broad band airborne multispectral imageries were successfully used to identify the differences in growth pattern induced by tarnished bug infestation (Willers et al. 1999, 2005), beet army worm and cabbage looper damage in cotton (Sudbrink et al. 2003) and citrus greasy spot disease in citrus (Du et al. 2008).

Study by Zhang et al. (2005) provided a method of identifying late blight infection on tomato fields in California and demonstrated the capability of utilizing multispectral images in monitoring crop growth and precisely managing diseases in fields. However they found that earlier detection of this disease can be difficult due to its similar spectral response to that of healthy plants, disease was identified when infection reached stage 3 or above. Elliott et al. (2007) used a three band multispectral imaging system, SSTCRIS on board a Cessna 17 air craft was used to differentiate varying levels of injury caused by Russian wheat aphid, *Diuraphis noxia.* They demonstrated that the multispectral RS data acquired by a relatively inexpensive and easy to use multispectral imaging system could detect aphid-induced stress in production winter wheat in the presence of other stress inducing variables (Elliott et al. 2007). Further, Backoulou et al. (2010) showed the potential of combining multispectral airborne imagery with spatial pattern recognition to identify and spatially differentiate the aphid (*Diuraphis noxia*) infestation in wheat fields, and also showed that patches of wheat stressed by *D. noxia*, drought, and agronomic conditions differed spatially with respect to size, shape, and spatial arrangement within a wheat field.

16.6.2 Airborne – Hyperspectral

Hyperspectral data recorded from low attitude flights usually have high spectral and spatial resolution, which can be very useful in detecting stress in green vegetation. An airborne visible infrared imaging spectrometer (AVRIS) image with 224 bands with the wavelength range of 0.4–2.5 μm was used to detect stress in tomatoes induced by late blight disease in California, USA (Zhang et al. 2003) and strawberry spider mite (*Tetranychus turkesni* U.N.) in cotton (Fitzgerald et al. 2004). Williams et al. (2004) developed hyper spectral signatures using airborne data that characterised individual tree species and health class which in turn may be used to classify hyperspectral images to produce maps of emerald ash borer host trees.

With the rapid developments in RS technology in recent decades, hyperspectral remote sensors, such as airborne visible infrared imaging spectrometer (AVIRIS), compact airborne spectrographic imager (CASI), multispectral infrared and visible imaging spectrometer (MIVIS), and hyperspectral mapping (HyMap) system, are now available to agricultural applications (Zhang et al. 2003). These sensors can provide quality images with high spatial and spectral resolutions required for precision agriculture (Fraser 1998; Treitz and Howarth 1999). Because of the high spectral resolution with a narrow band range of about 10 nm or finer, hyperspectral remote sensing images produce a complete spectrum for each pixel within the scene. These characteristics combined with high signal-to-noise ratio enable us to differentiate various vegetation stresses based upon spectra of small patches of ground surface (Rush 2002; Christ et al. 2000; Lelong et al. 1998). Muhammed (2005) developed a technique for rapid analysis of hyperspectral data to identify stress caused by fungal disease severity in wheat. Hence, cost effective air-borne hyperspectral remote sensing data, if made available to the users could play a key role in detection of biotic stress in several crops with a better temporal, spectral and spatial resolution compared to the available multispectral data from several satellite platforms.

16.7 Space Borne Remote Sensing of Biotic Stress

A large number of satellite remote sensing products are available at present. Each satellite has different spectral, spatial, temporal and radiometric resolutions (Table 16.1) and the choice of product depends on application. Some of the recent satellites with multispectral and hyperspectral sensors on board rapidly generate vast amounts of data in a cost effective manner and at higher spatial and spectral resolutions. However the use of these RS from satellite platform for detection of pests and diseases is limited owing to high spatial and temporal resolution of data required for this purpose (Table 16.2). More so, availability of cloud free data during the crop season is another issue that limits use of satellite RS for crop protection. Additionally, most of the successful applications for pest detection using space data are for forestry and some plantation crops where the spatial spread of the pest damage is large.

16.7.1 Space Borne – Multispectral

Moderate resolution imaging applications, beginning with the launch of the Landsat sensors in the 1970s, provided support for large scale plant disease and insect damage mapping and monitoring. Landsat 2 imagery was used to discriminate between cabbage and potato fields for subsequent evaluation of club root disease (Torigoe et al. 1992) and later Landsat MSS data was used to detect leaf rust disease (*Puccinia recondita* f. sp. *tritici*) and yellow rust (*Puccinia striiformis*) over large areas of wheat in Pakistan (Nagarajan et al. 1984). Fitzgerald et al. (1999) demonstrated that multispectral RS (MRS) would allow farmers to detect early infestation of mites in large scale cotton fields due to colour shifts and changes in canopy appearance over time. Areas identified on the map could be located with the help of portable GPS equipment by field scout, verify mite population in these areas and recommend regions in the field that require pesticide application. Preliminary analysis using IRS LISS III data showed the feasibility of discriminating fully damaged late blight potato fields from healthy ones (Arora et al. 2004). Similarly, successful evaluation of remotely sensed data (IRS-1-C) was conducted for detection, mapping and monitoring of rubber plantations affected by *Corynespora* and *Gloeosporium* fungi which causes leaf spot and leaf fall disease (Ranganath et al. 2004).

Nutter et al. (2002) used a combination of Landsat 7 and high spatial resolution multispectral imagery to map damage caused by soybean cyst nematode (*Heterodera glycines*). While other researchers have used Landsat (Nelson 1983; Vogelmann and Rock 1989; Goodwin et al. 2008) and SPOT (Buchheim et al. 1984; Ciesla et al. 1989; Sirois and Ahern 1989) satellite imagery with coarse spatial resolutions to detect and assess insect damage to forests. It has been demonstrated that by using Landsat TM data it is possible to assess mountain pine beetle (*Dendroctonus ponderosae*) in western Canada (Goodwin et al. 2008) bark beetle damage in pine forests (Coops et al. 2009). A spatial model has been developed using Landsat imagery and field observations based on environmental factors such as topography and soil types to predict densities of wheat aphid, *Diuraphis noxia* (Merrill et al. 2009). Recently using Landsat TM data, Mirik et al. (2011) separated healthy and diseases (streak mosaic) wheat fields by maximum likelihood classifier method with an overall classification accuracies of 89.47–99.07%. Currently, this method appears to be one of the best for identifying and mapping disease incidence over large and remote areas by offering a repeatable, inexpensive, and synoptic strategy during the course of a growing season.

Ji et al. (2004) evaluated the potential of hyper spatial data from MODIS to monitor locust outbreaks in China and showed that the NDVI reliably distinguished between before and peak damage situations for each category of damage. Areas where NDVI decreased could be clearly mapped and classified into light, moderate, and heavy damage categories. High resolution multi-spectral data from QuickBird were generally used to detect in-field heterogeneities of crop vigour but are only moderately suitable for early detection of crop infections by diseases. However QuickBird imagery was used for detecting citrus orchards affected by sooty mould (Fletcher 2005) and wheat diseases caused by powdery mildew (*Blumeria graminis*) and leaf rust (*Puccinia recondita*) (Franke and Menz 2007). A regional level spatial distribution model of aphid (*Lipaphis erysimi*) growth in Indian mustard using satellite based remote sensing data has been developed (Bhattachrya et al. 2007 and Datta et al. 2008). They employed near surface meteorological parameters derived from National Oceanic and Atmospheric Administration (NOAA) Television and Infrared Operational Satellites (TIROS) Operational Vertical Sounder (TOVS) data and field observations of pest infestation. Second order polynomials fits between peak aphid count and TOVS cumulative air temperature were produced in Northern India i.e., Bharatpur and Kalyani.

It was shown that daily MODIS data on an annual time can be used to monitor insect defoliation due to gypsy moth in North American forests for patches larger than 0.63 sq km (Beurs and Townsend 2008). A recent study by Santoso et al., (2011) investigated the potential of high resolution QuickBird satellite for detecting and mapping basal stem rot disease (*Ganoderma boninense*) in oil palms. Six vegetation indices derived from VIS and NIR were used for to identify palms infected by the disease and image segmentation effectively delineated areas infected by the disease with a mapping accuracy of 84%.

16.7.2 Space Borne – Hyperspectral

Satellite based imaging sensors, equipped with improved spatial, spectral and radiometric resolutions offer enhanced capabilities over those of previous systems. The Hyperion sensor, on board the EO-1 satellite provides continuation of broad spatial coverage with increased spectral sensitivity (over 200 bands from 0.4 – 2.5 nm) that can help in plant disease or pest damage discrimination. Inclusion of the moisture sensitive bands in the longer wavelength region (1,660 nm) from the Hyperion data increased the ability to map orange rust disease (*Puccinia kuehnii*) on sugarcane in Australia, when compared to the use of visible and NIR reflectance bands alone (Apan et al. 2004). They proved that substantial change in leaf water content or pigmentation of stressed crop can be detected due to decrease in reflectance in middle infrared bands (1,200–2,500 nm) and due to shift in red edge in near infrared red bands (600–750 nm). They further formulated new indices viz., 'Disease Water Stress Indices' (DWSI) which produced the largest correlations with the stress, indicating their superior ability to discriminate sugarcane areas affected by orange rust disease. Later, using the same central wave lengths at 550, 680, 800 and 1,600 nm and also the same vegetation index (DWSI), Datta et al. (2006) successfully detected disease severity in mustard crop in India using Hyperion data. Pena and Altman (2009) explored the suitability of vegetation indices derived from satellite hyperspectral data for identifying stress symptoms induced by the invasion of cypress aphid (*Cinara cupressi* Buckton) in central Chile. In their studies strongest correlations were recorded for two anthocyanin reflectance indices and the photochemical reflectance index. Hence vegetation indices derived from hyperspectral images are potentially very useful in the detection, assessment and monitoring of the damage caused by the aphid. Satellites provide synoptic view of large areas with valuable data for land use classification. Application of space borne satellite data for biotic stress detection so far is mostly for forest pests and diseases and to a limited extent in field and plantation crops. The major constraints for its wide use in biotic stress of agricultural crops appear to be spatial and spectral resolution of the satellite sensors and availability of cloud free optical RS data during the season. Hopefully the next generation satellites would address some of this issues.

16.8 Conclusions

Over the years lot of information has been generated on characterizing biotic stress using hand held multi spectral radiometry. With the advent of hyperspectral radiometry, it has been possible to have insights into more details and better understanding of the crop stress induced by insect pests and diseases. It was also feasible to differentiate between biotic and abiotic stresses with reasonable accuracy using hyperspectral radiometry. Reflectance data obtained by ground based remote RS provides vital information to understand spectral interactions between pests damage on the host plants and also to collect fundamental ground-truth information required for interpretation of remote sensing data obtained from space borne and airborne platforms. Satellite remote sensing provides sufficient data for large scale studies, but it has limitations such as temporal and spatial resolution, and more importantly, availability of cloud free data. On the other hand, airborne systems have a higher resolution and time flexibility and provide sufficient lead time for dissemination of crop protection advisory. Though application of airborne RS for biotic stress has been in vogue in several developed countries, it is yet to find wide usage in many of the developing countries. One of the main reasons could be the high cost involved, availability of suitable sensors, small farm holdings and diverse cropping systems.

Hence it is challenging to make airborne hyperspectral remote sensing a reality in these countries.

Limited availability of fine spatial resolution, near real-time data has slowed the application of satellite RS in the past, but now with the launch of new generation satellites this might not be a limiting factor. The narrow bands in the hyperspectral sensors are able to measure the characteristic absorption peaks of plant pigments and other related parameters more precisely and thereby provide better information related to plant health. But availability of hyperspectral data from satellite platforms is still in its infancy. Nevertheless, airborne and space borne remote sensing can provide spatial variability of biotic stress and a synoptic view of the large area in a non-destructive and non- invasive way. Hence it can supplement many of the on-going field surveillance programs, which is often expensive, time consuming, laborious and many at times error-prone. It has been proved that RS technology can provide accurate and reliable information to guide decision-making in crop protection and hence have great potential for use in pest management.

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