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A Review on Remote Sensing in Successful Crop Disease Monitoring and Management

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Abstract:- Remote sensing is promising technology which can analyse spectral properties of the earth surface from various distances ranging from satellites to ground based platforms. Remote sensing playing huge role in agricultural crop production including crop protection. The data helps to find out the variability in reflectance spectra of plants resulting from the occurrence of various pests and diseases, nevertheless technical constraints and issues inherent to variability in host–pathogen interactions. The spectral sensors like multispectral, hyper spectral sensors and magnetic sensors cameras collect electromagnetic information to derive large scale information related to earth surface and atmosphere and data obtained here is digital. Quantified and manipulated by using computers. remote sensing have lot of scope in detecting and monitoring the diseases so that it reduces risk and minimize the damage.

Keywords:- *spectral sensors, Electromagnetic images, host-pathogen interaction, Disease detection and monitoring.*

I. INTRODUCTION

The global demand for agricultural products exceeds the supply. The ultimate aim is to manage the production of agricultural commodities more efficiently without modern technologies it is not easy to reach this trend (Mahleinet al., 2012).The innovative technologies like remote sensing contributes as promising technology to achieve successful crop protection. A large number of alien species like bacteria, viruses, fungi, nematodes, phytoplasmas ,weeds affect the crop production globally and they travel undisturbed to long distances through goods and people including planting materials spreading all over the world and causes serious losses to agriculture (Brasier CM .2008).Remote sensing technology useful in measuring and recording the emission of electromagnetic radiation from the target area and the sensor instruments. Thevarious sensor instruments used here are cameras, electromagnetic scanners, Video cameras and radar systems. Its working depends on the electromagnetic energy and the interaction between the radiation and ground targets (Yang and Everitt 2011)

II. PRESENT AND FUTURE TREND IN PLANT DISEASE DETECTION

The accuracy in the estimation of plant disease incidence and severity and the negative impacts of plant pathogens on agricultural produce are important for field crop, horticulture, plant breeding and improving fungicide efficacy .The common methods used for the detection and diagnosis of the plant diseases are Visual observation of characteristic symptoms, Microscopic evaluation of morphological features as well as molecular ,serological and other microbiological techniques (Book et al.2010,Nutter 2001).These methods used in the disease diagnosis and scientific research. The recent decades focusing on molecular and serological techniques which revolutionized the identification and quantification of the plant pathogens and diseases (Book et al.2010,Martinelli et al.2014,Word et al 2004).

A. Role of Time and space in the Pathogenesis and development of Plant diseases

The plant pathogens are detected in environment and host such as soil, water and air are required to quantify the pathogen inoculums and assessment of management approaches for the diseases, estimation of pathogen variation and evolution of new races and selection of sources of resistance and resolve the components of complex diseases induced by two or more pathogens and interactions between them and interrelationships between the plants and pathogen insight in to the phenomenon of pathogenesis and gene functions (Narayanaswamy et al.2011). In nature the pathogens are constantly changing and evolving new pathogenicity to overcome host defence and evolving plants to pathogen attack.

These type of co-evolutionary interactions happening with in ecological settings and favourable for the pathogen evolution and development (Iranzo J, Lobkovsky A E, Wolf Y I, Koonin E V. 2015.

Immunity, suicide or both Ecological determinants for the combined evolution of anti-pathogen defence systems. BMC Evolutionary Biology, 15, 324)

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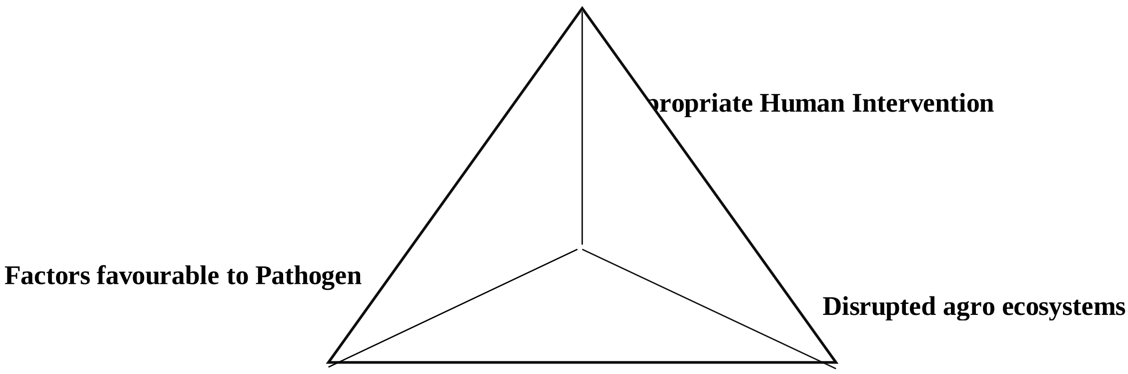
Factors Adversing Plant Ecosytem



B. Science Behind the Remote sensing

Remote sensing means sensing the objects from distance. The American Society for Photogrammetry and Remote Sensing(ASPRS) defined Remote sensing is the art, science and technology of obtaining reliable information about the Physical objects and the environment and obtaining information without any physical contact Remote sensing technology may be ground, aerial and satellite based. Satellite remote sensing achieved success in aerial remote sensing during the 1960 with the explorer TRIOS (Telivision Infrared Observation Satellite) series, Corona and later with Landsat missions (Lettenmaier ,D.P,A lsdorf, D, Dozier .J, Huffman ,G.J ,Pan ,M,Wood ,E,F 2015 Inloads of Remote sensing into hydrologic science during the WRR era .Water Resource RES 51(9),7309-7342) .The remote sensing process intiated from sun (Passive remote sensing or from satellite itself (Active remote sensing). Radiations which are incident are absorbed, transmitted and reflected while interacting with the earth surface and these reflected radiations absorbed by satellite sensors and gives the information about the terrestrial components .These processes includes vegetation, hydrological cycles, water bodies, agriculture ecosystem and topography. The reflected radiations are recorded at various wavelengths of electromagnetic spectrum .Visible or optical spectrum (0.4-0.7µm) and near infrared (NIR)0.7-1.3µm),Middle infrared (MIR)1.3-3µm, and thermal infrared TIR at 3.0-14µm wavelength and microwave spectrum at 1mm-1m wavelength recorded.

C. Principles in monitoring plant diseases through remote sensing

The symptoms produced by diseases causing organism among different crops is observed by pathogen and its host interactions. To form a physical basis for their remotely sensed monitoring, this technology is not suitable to detect the pathogen which lack identifiable characteristics. On other side, soil borne diseases and root rotting pathogens that cause systemically infect the physiology of the host plants can be detected as well. The common symptoms like lesions, pustules and sori or necrotic tissues are caused by disease causing organisms. These symptoms varies among different diseases in their colour and shape. The abundance and canopy distribution of these lesions and pustules have a great influence on their detectability. (Cao et al., 2013; Moshou et al., 2004). The Hyper spectral remote sensing also used to detect destructed pigment systems viz., chloroplast and other organelles and variation shown in pigment contents[chlorophyll(Chl), carotenoid(Car) and anthocyanin] due to disease and insect pest attack(Girsham et al., 2010, Zhang et al., 2012). The loss of rigidity and drooping due to dehydration is the most common symptom of wilting not only shown by plant pathogens sometimes it can be confused with drought stress, piercing & sucking behaviour of insect pest [example., hoppers or aphids] (Cheng et al., 2010). In fact remotely sensed monitoring is used to capture the accumulation of symptoms.

D. The available remote sensing technology for monitoring plant diseases and pest

The remote sensing systems potentially applied for detecting various number of plant diseases and pest infestations performing with both passive and active radiation. The given data acquisition by RS system ranging from gamma ray to microwave. To make this data efficient many efforts have been made to apply different RS systems for capturing infection systems physiological responses and structural changes caused by plant pathogens and pests.(Hahn., 2009; Mahlein., 2015; Sankaran et al., 2010). Based on technical maturity and sensing principles the sensing systems can be generally classified into three types: [1] Visible and near Infrared spectral systems(VIS-SWIR) [2] Fluorescent and thermal systems [3] Synthetic aperture radar.

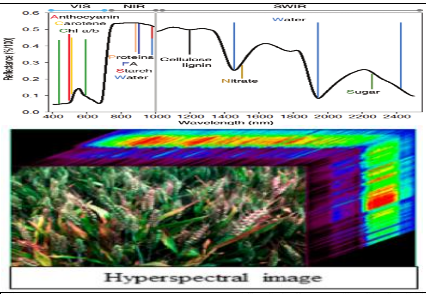
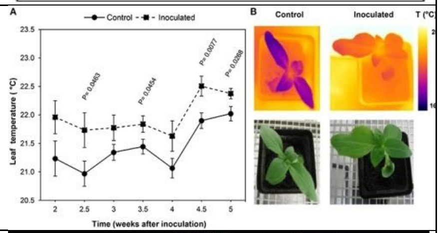
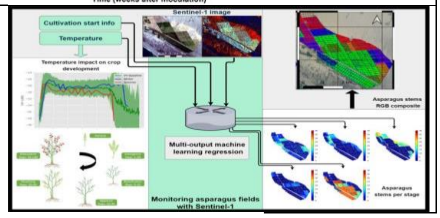
Remote sensing systems	Main characteristics	Merits and Demerits	Application capability	Pictorial representation
VIS-SWIR	Find out destruction caused by plant diseases & pest infestation by emittance in VIS-SWIR region.	Steady, provide authenticated monitoring results, but poor performance on early detection.	High[relative instruments & algorithms are available at relatively low price]	
Fluorescence and thermal	Records pre symptom physiological changes	Possess a capability to provide presymptom detection. But currently tough to apply in large area.	Medium[Lot of systems are available currently for research, which ar high cost with low applicability]	
SAR & Lidar	Records structural changes caused by disease and pests	Capable to indicate changes in plant morphology. The systems and case studies are presently lacking.	Low[Predominant ly remain at conceptual stage]	

Table 1: Commonly developed RS systems used for detection & monitoring plant diseases & pests

Classification	Feature type	Characteristics	References
Special features	1.Real reflectance 2.Indices of vegetation 3.Imitative spectral features 4.Continuous removal spectral features 5.Wavelet features	1.Take out spectral variations caused by disease infection and pest infestation. Spectral features are having ability to describe either variation of bands reflectance intensity or changes in shape of spectral curves.	Sankaran et al.(2010); Huang et al.(2012); Xu et al.(2007); Zhang et al.(2012a); Luo et al.(2013); Zhang et al.(2014a)
Fluorescence and thermal parameters	1.Parameters emitted from laser induced fluorescence spectra. Eg.,F686/F740. 2.Parameters related with saturation pulse method. Eg., Fv/Fm,NPQ, ϕPSII,Fv'/Fm' 3.Absolute temperature Eg., T_{leaf} - T_{air}	1.Pre-symptomatic indicators of plant diseases & pests. The Fluorescence parameters quantify changes in photosynthetic system due to disease infection and pest infestation. The Thermal parameters indicate changes in plant transpiration intensity.	Tartachnyk et al.(2006); Kuckenberg et al.,(2009)Iqbal et al. (2012); Bauriegel et al. (2014); Stoll et al. (2008); Calderón et al. (2013)
:Image and landscape features	1.Colour co-occurrence method[CCM] based on texture features[Eg.,Variance, uniformity, mean, intensity, entropy, contrast, modus etc.] 2.Landscape characters Eg., Area, shape, class, clumpiness, index etc.	Takes out the spatial pattern at both micro and macro levels based on image processing. At a micro level feature takes out the distribution of scabs and spots on leaves. While at macro level features indicate the changes in pattern of landscape.	Pydipati et al. (2006); Yao et al. (2009); Backoulou et al. (2011); Backoulou et al. (2013); Kautz et al. (2011)
Habitat associated features	1.Tassled Cap Transformation [TCP] [i.e.,greenness,brightness,wetness] 2.Land Surface Temperature [LSD] 3.Vegetation indices [Eg.,TVI, SAV, PRI, WI, NDWI etc.]	Show habitat of plant diseases and pests. Some features[TCT-greeness, Vis reflect. Growing status of the plant], TCT-wetness gives environmental condition in the field	Zhang et al. (2013); Coops et al. (2009); Wolter et al. (2008); Brown et al. (2008); Bhattacharya and Chattopadhyay (2013)

Table 2: Remote sensing characteristics for monitoring plant diseases and pests

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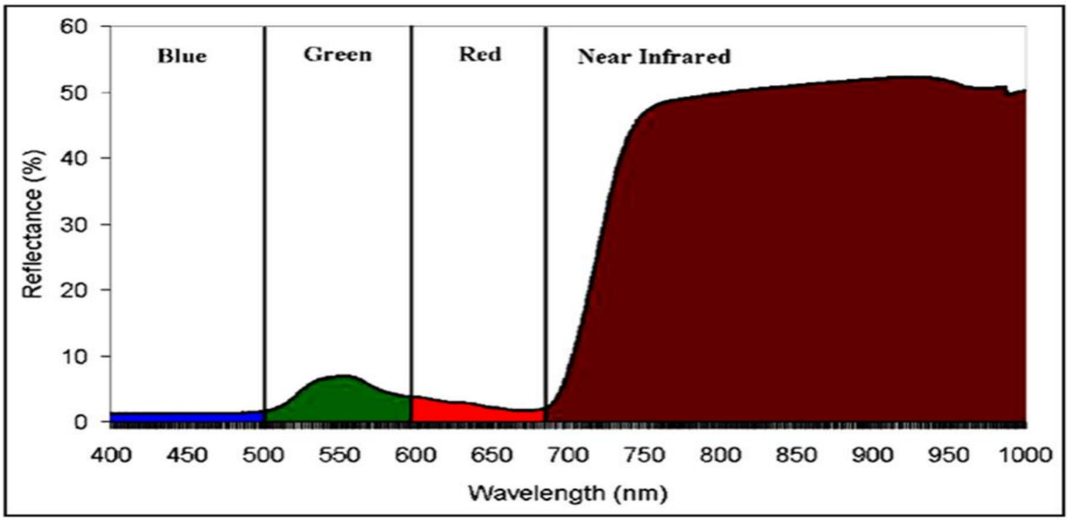
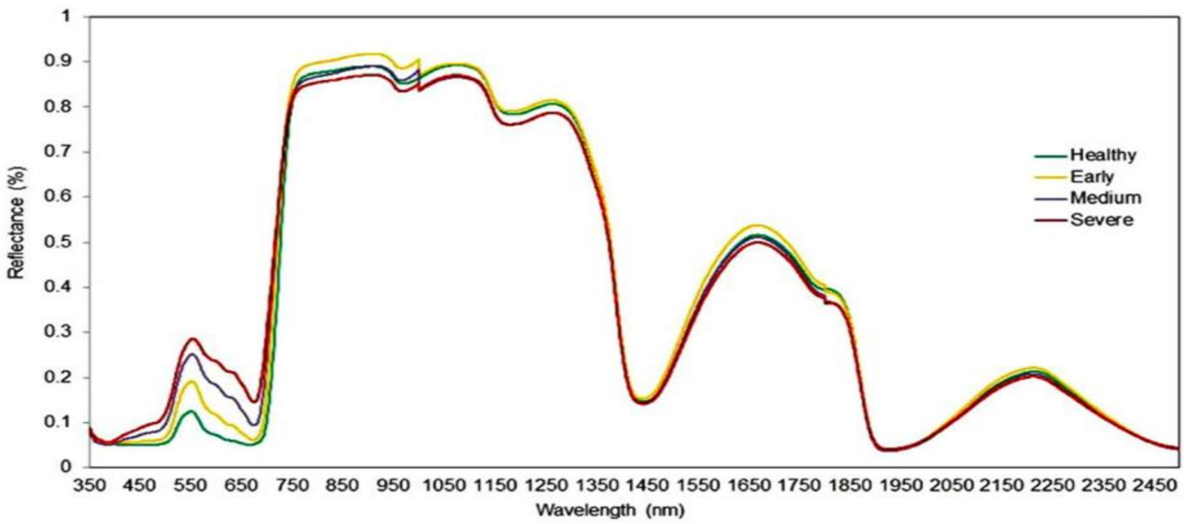
E. Remote sensing applications in successful plant protection

Crop security against plant infections is significant. Modern challenges stood up with logical inquiries against this concern. Naturally and neighbourly feasible arrangements are progressively requested. The accurate detection of primary infection and disease dynamics is very important to make decision for a subsequent management practice. Remote sensing technology provides a optical sensors can give accurate and objective discovery of plant infections. These approaches considered as key elements in plants phenotyping (Kuska&Mahlein. 2018). The passing of electromagnetic energy of the sun to the plants results in reflection, absorption or transmission based on wavelength of the energy and characteristics of individual plants. The visible aerial photography in the detection of viral diseases was first used and investigated for potato and tobacco crops by Bawden (1933) & Colwell (1956). Although using infrared imaging to discriminate against disease related changes that occurs in cereal crops internal leaf structure. The following mechanisms applied on broad spectrum of different diseases in crops such as potato blight (Brenchley 1968), bacterial blight of beans(Jackson & Wallen 1975), cotton root rot (Toler et al., 1981), sheath blight of rice (Qin et al., 2003). The spectral sensors recently applied have been contributed site specific disease management. For example yellow rust detection and quantification in wheat crop was investigated using hyperspectral technology(Kuska and Mahlein 2018). The hyperspectral camera is organized in field experiments on two measuring platforms: [1]Ground – based vehicle [2] Unmanned aerial vehicle. These sensors measure light reflected during pathogen infection and disease development in severities of yellow rust in wheat field and detection of crop canopy by using spectral sensors especially in the electromagnetic spectrum from 400 – 2500 nm. The observation through air borne imaging and high spatial resolution satellite devices have been used for crop plant diseases and assessment of impact on productivity (Qin and Zhang 2005; Sankaran et al 2010; Rani and Jyothi 2017; Zheng et al 2018).



Graf 1: Identical spectral curve of healthy plant (Rani et al 2018)



Graf 2: Healthy, Early, Medium, Severely infected maize leaves showing spectral images (Dhau et al. 2018a)

Plant & diseases	Goals*	Scales	Methods & results	Accuracy of classification	References
Sugarbeet& powdery mildew/rust/*Cercospora* leaf spot	Identification of disease	Leaf area	Spectral angel mapper[SAM]	Powdery mildew 97.23% at 14 dai; 61.70% for rust in sugar beet at 20 dai; Cercospora leaf spot 98.9% at 8 dai.	Mahlein 2012
Wheat & head blight of *Fusarium*	Identification of disease	Spike portion	Support Vector Machin[SVM] with reflectance & spectral vegetation indices[SVIs]	SVIs & reflectance two classes showing 95% & 99%; multiple classification of SVIs and reflectance showing 76% & 77%.	Alisacc 2018
Citrus & bacterial canker in citrus	Severity classification of the disease[asymptamatic,early& late symptoms]	Leaf area, fruit & plant	Neutral network radial basis function[RBF]; KNN with SVIs.	RBF gives 94%, 96% & 100%, Three levels of KNN showing 94%, 95%, 96% and detection of canker at fruit scale gives 92% & 100%.	Abdulridha 2019
Soyabean & charcoal rot	Identification of the disease	Stem	Three dimensional convolutional neural network [3D CNN]	95.73%	Nagasubramaniyan 2017
Wheat & yellow rust	Identification & mapping of the disease	Plot/Canopy	Linear regression model	___	Huang 2012

Table 3: The involvement of hyperspectral image classification for plantdisease detection, identification, and mapping

Plant and disease	Formula*	Sensors	Scales	Methods & Algorithms	References
Lemon Myrtle & Myrtle rust	LMMR =$\left(\frac{\rho 545}{\rho 555}\right)$ 5 3 × ρ1505 ρ2195	Spectral evolution PSR+3500	Leaf	D.A: Random-forest-based for feature selection	Heim 2019
Grapevine &FlavescenceDorée	SDI = −0.5 × ρ1770 + (ρ2208+ρ2019) (ρ2208−ρ2019)	FieldSpec 3 ASD	Leaf	D.A.: Genetic algorithm[GA] for feature selection	Al-Saddik 2017
Sugarbeet*Cercospora* leaf spot	CLS = (ρ698−ρ570) (ρ698+ρ570) − ρ734	ImSpector V10E	Leaf	D.A:RELIEF-F for feature selection	Mahlein 2013
Sugarbeet powdery mildew	PMI = (ρ520−ρ584) (ρ520+ρ584) + ρ724	ImSpector V10E	Leaf	D.A:RELIEF-F for feature selection	Mahlein 2013
Fusarium head blight in winter wheat	FCI = 0.25 × [2 × (ρ_{668} − ρ417) − ρ539]	UHD 185	Kernel	D.A:Instability index-spectral angel mapper[ISI-SAM] for feature selection	Zhang 2019

Table 4: Construction of special SDIs based on hyperspectral data

F. *Future aspects*

Plant pathogens contribute to prominent economic and post-harvest yield losses in agriculture production sector globally, specifically under the climate change influence in recent years. Many effective methods for plant disease detection monitoring and assessment have been collectively invented. In addition to this, visually professional interpretation, biochemical analysis and pathogen logical analysis should be developed in future. Non-invasive technologies like hyperspectral technology paying more attention in these days so challenges and developmental trends associated with hyperspectral technologies for plant detection framework should be studied and also integration analysis of satellite scales should be focused. After implementation of targeted hyperspectral satellite missions, big data collections, pre-processing and analysis results in the real time dynamic monitoring of plant disease at the regional, national and global scales and large scale data integration is achieved. The future may develop multisource RS data and multisource fusion of the data for successful plant disease monitoring and management.

III. CONCLUSION

The review concludes recent advance in farther detecting innovation in RS technology gives increasing and developing application in various agricultural approaches mainly focus on crop disease and pest management. The interpretation and revolution of information technology, data analysis for high technological applications that allows huge benefits in growing and supporting input knowledge for development of many research fields focused in this review. The remote sensing technology became general purpose data for broad community of users having diverse requirements. Remote sensing technology became one of the most prominent, promising, well trusted technology that supports integrated crop protection[IDM & IPM]. It also helps in investigating different environmental factors suitable for pathogen development and results in study of disease epidemiology. However, development in manufacture and operating of remote sensing system to decrease the cost and increase the efficiency of output imaging is a demand.

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