

Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques

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Thesis submitted to the
Odisha University of Agriculture and Technology
in partial fulfilment of the requirements for the degree of
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(Entomology)

By
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2022



**ODISHA UNIVERSITY OF AGRICULTURE AND TECHNOLOGY
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Date: 30th July '22

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This is to certify that the thesis entitled “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenée) damage in rice using ground based hyperspectral remote sensing techniques” submitted in partial fulfilment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY IN AGRICULTURE (ENTOMOLOGY)** to the Odisha University of Agriculture and Technology, Bhubaneswar is a faithful record of *bonafide* and original research work carried out by **BHUBANANANDA ADHIKARI**, Adm. No. 02 ENT/Ph.D./16 under my guidance and supervision. No part of the thesis has been submitted for any other degree or diploma.

It is further certified that the assistance and help received by him from various sources during the course of investigation has been duly acknowledged.

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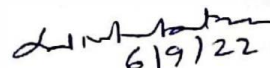
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CERTIFICATE-II

This is to certify that the thesis entitled “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques” submitted by BHUBANANANDA ADHIKARI, Adm. No. 02 ENT/Ph.D./16 to the Odisha University of Agriculture and Technology, Bhubaneswar in partial fulfilment of the requirements for the degree of **DOCTOR OF PHILOSOPHY IN AGRICULTURE (ENTOMOLOGY)** has been approved by the students’ advisory committee and the external examiner.

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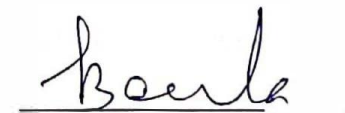
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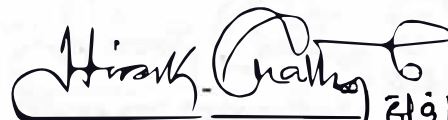
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ABBREVIATIONS

ABBREVIATIONS	DESCRIPTION
%	: Per cent
°C	: Degree Celsius
@	: At the rate
VIS	: Visible
NIR	: Near infrared
SWIR	: Short wave infrared
nm	: Nano meter
C.D.	: Critical difference
NRRI	: National Rice Research Institute
mg	: Milligram
hrs.	: Hours
CR	: Continuum removal
OUAT	: Odisha University of Agriculture and Technology
ICAR	: Indian Council of Agricultural Research
BPH	: Brown plant hopper
LF	: Leaf folder
SE _m	: Standard Error of Mean
<i>et al.</i>	: And others
<i>Viz.</i>	: Videlicet (namely/that is to say)
<i>i.e.</i>	: (<i>Id est.</i>) That is
CV	: Coefficient of variation
GIS	: Geographic Information System
QGIS	: Quantum GIS
UAV	: Unmanned Aerial Vehicle
VRT	: Variable Rate Technology
MATLAB	: Matrix Laboratory
ENVI	: Environment for Visualizing Images
SVM	: Support Vector Machine
VI	: Vegetative Index
NDVI	: Normalized Difference Vegetation Index

ABBREVIATIONS	DESCRIPTION
LAI	: Leaf Area Index
PRI	: Photochemical Reflectance Index
PSRI	: Photochemical Senescence Reflectance Index
REP	: Red Edge Position
UV	: Ultra Violet
YSB	: Yellow stem borer
FCC	: False Colour Composite
ROC curve	: Receiver Operating Characteristic curve
LR	: Leaf Roller
SAC	: Space Application Centre
ISRO	: Indian Space Research Organisation
<i>.xls</i>	: Microsoft Excel spreadsheet file
<i>.asd</i>	: Temporary backup created by Microsoft Word
<i>.txt</i>	: Text Document file
RF	: Random Forest
Fig.	: Figure
MT	: Million tonnes
<i>chl</i>	: Chlorophyll
LH	: Leaf hopper
AdaBoost	: Adaptive boosting
ARCGIS	: Aeronautical Reconnaissance Coverage Geographic Information System

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ABSTRACT

Field and laboratory experiments on “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques” were undertaken during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 at ICAR-NRRI, Cuttack. The spectral signature from the differentially infested canopy and leaves of rice var TN1 were assessed using ASD Field Spec hyperspectral spectroradiometer. The spectral curve obtained from the pre-processed data indicated higher reflectance of healthy vegetation than the rice plants infested by *C. medinalis* in visible and near infrared region. Derivative analysis was adopted to find out the particular spectral bands with maximum per cent change in first order derivatives. The continuum removed spectra were also obtained using ENVI software and the specific wavelengths with the absorption dips were identified. The central wavelengths identified from derivative analysis and continuum removal were subjected to unpaired ‘t’ test for testing of significance up to 100 nm interval. Seven spectral bands *i.e.*, 515, 582, 673, 732, 815, 898 and 1131 nm were found most sensitive to infestation of *C. medinalis* from both canopy and leaf level. The healthy leaves had highest concentration of total chlorophyll (3.95 mg/g) and carotenoid (0.36 mg/g) whereas these concentrations were found lowest *viz.*, 1.467, 0.207 mg/g in severely infested rice leaves (Grade 5). The phenol content was highest (4.79 mg/g) in severely infested rice leaves due to *C. medinalis* but it was lowest (3.25 mg/g) in the healthy leaves. The correlation between different biochemical components and identified sensitive bands revealed that four spectral bands *viz.*, 515, 582, 597 and 672 nm were found sensitive due to chlorophyll absorption. Similarly, the spectral band of 1131 nm was found sensitive for phenol absorption whereas for the carotenoid absorption the spectral 515 and 582 nm bands was found sensitive. Feature selection study was carried out using MATLAB by the Random Forest Elimination tool to reduce the dimensionality of the spectral data. The spectral band combination of five bands *viz.*, 515, 582, 673, 732 and 815 nm was found to be the best band combination with highest percentage of accuracy (86.33) which could differentiate the damage by *C. medinalis*. Studies on five spectral vegetation indices calculated based on spectral reflectance for detecting stress in rice infested by *C. medinalis* revealed that the values of Normalized Difference Vegetative Index (NDVI), Leaf Area Index (LAI) and Photochemical Reflectance Index (PRI) were highest in the healthy rice vegetation and were 0.77, 3.20 and 0.17, respectively. The values of these aforementioned indices were in a declining trend with increase in infestation of *C. medinalis*. A gradual increase in the value of Photochemical Senescence Reflectance Index (PSRI) was observed with subsequent rise in infestation level of *C. medinalis*. Severely infested rice plants recorded highest value of PSRI (0.18) whereas it was lowest (0.03) for the healthy vegetation. A gradual shifting of the red edge position towards the shorter wavelength (REPI) was observed with increase in infestation level of *C. medinalis*. Three new indices based on two spectral combinations {(R515/R732), (R732-R515) and (R732-R582/R732+R582)} as well as three other indices based on three spectral band combination {R732/(R515+R673), R815/(R568xR732), and R815/(R673+R582)} were derived which may be used for depicting the presence of *C. medinalis* using satellite imagery. Results on the spectral signature obtained from the differential infestation by *C. medinalis* in rice variety Naveen at farmer’s field (located at Aruha, Pipili block) and under controlled conditions at ICAR-NRRI, revealed that seven spectral bands *i.e.*, 510, 583, 674, 762, 815, 897 and 1126 nm were confirmed as the pest sensitive spectral bands for infestation of *C. medinalis*. The ground truth spectral data were validated using Sentinel 2A image analysis with the satellite imagery. The analytical processing of both the ground truth data and data from satellite indicated the hotspots where infestation by *C. medinalis* were detected through the false colour composite map with the help of various colour codes.

CHAPTER - I

INTRODUCTION

Rice, *Oryza sativa* L. (Family: Graminae), the world's second most important cereal crop next to corn is mostly grown in hot and humid to subhumid regions of the globe under tropical and subtropical climate (Hosseini *et al.*, 2012). This major species of rice is believed to have been originated in South India (Vavilov, 1951). In actuality, it provides more than a fifth of the calories that people consume globally. More than 90 per cent of the world's rice is produced and consumed in the Asia-Pacific region. More over half of the world's rice is produced by the top two producers, China and India.

Rice is being cultivated in India for decades with significant influence on social life and economic growth of the millions of rural households. Its cultivation in our country extends from 8 to 35⁰ N latitude and from sea level to as high as 3000 metres. This crop is grown under diverse ecological conditions in an area of approximately 40.35 million hectares in *Kharif* season with a production of 105.2 million tons and productivity of 2607 kg per hectare. Similarly in Rabi season it is grown in 5.4 million hectares with a production of 19.16 million tons and productivity of 3541 kg per hectare during 2020-21 (Annon, 2021). With a yield of 9.63 million tonnes and a productivity of 2453 kg per hectare, rice cultivation in Odisha accounts for around 47.8% of the state's total cultivated land for food grains (Annon, 2020). A production of 140 MT rice would be needed to meet the needs of the 1.6 billion Indians who will be living within the constraints of the natural environment by 2050 (Annon, 2015). This can be accomplished by the development of different abiotic stress tolerant rice varieties with climate resilience, the biotic and abiotic stress management, farmer-friendly farm mechanization and the improvement of environmental quality.

In recent times insect pests and disease problem are frequently threatening the rice production both qualitatively and quantitatively under the fluctuating climate change. Although more than 800 insect species have been reported in rice crop worldwide, but only 20 insect species inflict significant damage in tropical Asia (Dale, 1994). The average losses in rice yield due to insect pest attack in India is estimated to the tune of 27.9 percent (Pathak and Dhaliwal, 1981; Mondal *et al.*, 2017). The leaf folder or leaf roller, *Cnaphalocrocis medinalis* (Guenee) (Lepidoptera: Crambidae), an

important leaf eating pest of rice is observed in the rice-growing regions of Asia, Australia and Africa, between 48⁰N and 24⁰S latitude and 0⁰E to 172⁰W longitude (Khan *et al.*, 1988; Mohapatra *et al.*, 2021; Mohapatra *et al.*, 2019). Out of the eight species of leaf folder, the most widespread one is *C. medinalis* in rice ecosystem (Bhatti, 1995). It is a migratory pest with 1 to 11 generations per year (An *et al.* 2014). Rice is the most favourable host plants for *C. medinalis* among several other alternate hosts viz., corn, sugarcane, wheat, sorghum, and several graminaceous weeds (Khan *et al.*, 1996). In many Asian nations, it was once regarded as a minor pest. However, there have been major outbreaks of the pest in various nations that cultivate rice, including India, China, Japan, Malaysia, Vietnam, Korea and Sri Lanka (Wada *et al.*, 1980; Heong and Escalada 1997). Since the 1980s, it has become a major pest affecting rice production in various regions of India, including Odisha.

The adoption of modern rice technologies, such as continuous and overlapping cropping, the cultivation of high yielding varieties, the introduction of broad leaf dwarf, and high tillering, are largely responsible for the change in pest status (Tanwar *et al.*, 2019). Greater plant density, planting either too early or too late, the use of more N fertiliser, and increased pesticide treatments for pest management have a negative impact on the leaf folder's natural enemies. This pest is prevalent from the nursery stage through the harvest stage, although the reproductive and ripening stages indicate the highest levels of infestation (Litsinger *et al.*, 2006). The abundance of grassy weeds from rice fields and the borders around the field, high humidity, and shaded places all favour the pest's rapid development. The yellowish green larvae of *C. medinalis* roll a rice leaf around themselves and attach the leaf margins together with silken strands. They scrape the leaf tissues inside the folded leaf causing longitudinal white and transparent streaks which becomes white and dry due to significant reduction in photosynthesis. During a severe infestation, the entire field seems burnt and the production of rice may decrease by up to 30 per cent, depending on population densities and environmental factors (Litsinger *et al.* 2006; Rani *et al.* 2007). Its severe infestation resulted yield losses up to 63-80 percent (Murugesan and Chelliah, 1986; Karim and Riazuddin, 1999). Leaf folder infested rice plants are also vulnerable to infection by bacteria and fungi (Bashir *et al.*, 2004).

To cope with the leaf folder menace in rice, farmers mostly rely on synthetic insecticides which in long run results in pest resurgence, development of insecticide resistance, residual perseverance, health and environmental hazards (Natarajan and Ramaraju, 1997). Due to rapid development and spread of *C. medinalis* in rice ecosystem, an accurate and quick assessment of the extent and severity of damage caused by the pest is of prime importance. In view of several drawbacks of field visual inspection method of monitoring of insect pest, recently remote sensing, the most advanced and cost-effective method of pest monitoring technique is gaining importance in which crop loss due to insect pest is assessed instantaneously over a wide area (De Jong and Van de Meer, 2006). In monitoring agricultural changes, hyperspectral remote sensing techniques are rapid, non-destructive and precise (Tan *et al.*, 2019; Mohapatra *et al.*, 2019). Hyperspectral remote sensing technique provide information on qualitative and quantitative vegetation spectrum so as to determine the crop condition parameters (Blackburn, 1998). It is often possible to identify pests via remote sensing because herbivory-induced plant biotic stress causes plants to go into defensive physiological response, which typically results in changes of leaf reflectance. The emphasis of current research has intensified as a result of India's recent launch of new hyperspectral sensing satellites, with the goal of making the best possible use of this technology for the agricultural community. Rapid use of remote sensed information in modern agricultural production system enables the farmers to detect and discriminate insect pest infestations in several crops (Riley, 1989; Hatfield and Pinter, 1993; Reisig and Godfrey, 2006; Fraulo *et al.*, 2009; Hillnhütter *et al.*, 2011).

Considering the fact that stress factors interfere with photosynthesis or the physical structure of plants and impact the absorption of light energy, which in turn affects the reflectance spectrum of plants, remote sensing (usually from satellite or aircraft) is used to detect crop stress (Riley, 1989; Moran *et al.*, 1997). As a result, distinctive reflectance properties may be found by comparing the leaf reflectance profiles of healthy (non-stressed) and stressed plants. The reflected and emitting radiation from the leaf surface is measured with the use of a digital sensor. Each surface is processed with a "spectral signature" characteristic because the amplitude and wavelengths of this radiation reflected or emitted are a surface attribute (Lillesand and Kiefer, 1987). Among different sensors, hyperspectral remote sensors (spectroradiometer) capture the subtle plant stress responses through acquiring images

over hundreds of spectral bands, thereby enabling the extraction of spectral signatures. The severity of pest damage is detected by the high spectral resolution offered by hyperspectral remote sensing in the visible spectrum (VIS) and the near infrared area (NIR) (Shibayama *et al.* 1993; Zhang *et al.*, 2006). For a disease or insect that has damaged the leaves, a reduced average reflectance in the NIR region is anticipated. Furthermore, using algorithms for insect damage detection can provide automated detection. To measure the degree of crop pest damage, spectral vegetation indices and estimated damage severity from digital image analysis can be integrated (Nigam *et al.*, 2019). Numerous pest-crop systems have employed hyperspectral remote sensing with success, including: tarnished plant bugs in cotton (Willers *et al.*, 1999), beat armyworm (Sudbrink *et al.*, 2003), small cabbage white butterfly larvae *Pieris rapae* L. (Lepidoptera: Pieridae)(Wu *et al.*, 2016) and aphid *Myzus persicae* Sulzer (Hemiptera: Aphididae)(Zhao *et al.*, 2017), in cabbage; tomato leaf miner *Tuta absoluta* Meyrick (Lepidoptera: Gelechiidae) in tomato (Mireei *et al.*, 2017) and two-spotted spider mites in glasshouse pepper (Hermann *et al.*, 2012) and bean (Hermann *et al.*, 2017). However, information on discrimination of the normal and stressed rice leaves caused by rice leaf folder is meagre (Shi *et al.*, 2009 and Huang *et al.*, 2012). It was therefore, considered proper to focus the present study on discriminating the infestation of *C. medinalis* in rice through hyperspectral signature at different damage level.

Hyperspectral remote sensing in large continuous narrow wavebands provides significant advancement in understanding the subtle changes in biochemical and biophysical attributes of the crop plants and their different physiological processes. The reflectance pattern from plant foliage is determined by chemical composition and physical properties of the plant tissue and the spectral properties of the remote sensing equipment (Bauer, 1985; Myneni and Ross, 1991). Additionally, the amount of electromagnetic radiation that is reflected, absorbed or transmitted by plants is influenced by metabolic modifications that occur during plant development, such as changes in water and chlorophyll content. Another component of the current study was the establishment of a relationship between the hyperspectral reflectance of a rice crop infested with leaf folders and the biochemical composition of rice.

The relationships between spectral characteristics and infestation symptoms must be thoroughly investigated through field studies for successful pest management

in crop (Yang *et al.*, 2007). Therefore, it is crucial that algorithms for classifying objects based on hyperspectral remote sensing data are thoroughly validated and put through comprehensive performance evaluations. The identification of pest sensitive spectral bands, the development of numerous vegetative indices and the validation of ground truth data with satellite data are all the major goals of hyperspectral remote sensing techniques for insect pest detection. Adoption of hyperspectral remote sensing, an important component of variable rate application technology (VRT) paves the better way for site-specific pest management.

In consideration of the foregoing points the present investigation on “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques” was carried out with the following objectives:

1. To discriminate the leaf folder infestation through hyperspectral signature at different damage level
2. To establish the relationship between hyperspectral reflectance data, leaf chlorophyll, soil nutrient and leaf folder damage in rice
3. To establish the specific relationship of field measurement of spectral signature with the leaf folder damage

CHAPTER – II

REVIEW OF LITERATURE

The relevant literature pertaining to “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques” has been reviewed here under the following headings.

1. Occurrence of leaf folder *Cnaphalocrosis medinalis* (Guenee) in rice
2. Nature and extent of damage by *C. medinalis* in rice
3. Discrimination of insect pests’ infestation in various crops through hyperspectral signature
4. Discrimination of insect pests’ infestation in rice through hyperspectral signature
5. Change in biochemical components in rice leaves due to insect infestation
6. Impact of plant biochemical parameters on hyperspectral reflectance.
7. Detection and discrimination of healthy and insect infested vegetation through ‘Sentinel 2A’ analysis

2.1 Occurrence of leaf folder *Cnaphalocrosis medinalis* (Guenee) in rice

Bautista *et al.*, (1984) reported that *C. medinalis* was the most common and major leaf folder species among the eight species inflicting significant losses to rice crop.

Paddy leaf folder is an important leaf feeding insect among about 500 insect pests of rice (Gunathilagaraj and Gopalan, 1986).

The leaf folders *C. medinalis*, *C. patnalis*, *C. ruralis* and *C. exigua* have pestiferous capacity and reported to be the important pests of rice (Pandya *et al.*, 1987).

Shrivastava, (1989) stated that rice leaf folder was one of the most important insect pests in tropical and subtropical Asia hampering the rice production.

Large-scale high yielding variety farming, fertilizer use and ongoing insecticide use had all been linked to an expansion in the population of *C. medinalis*, which had spread to various nations, including India (Kaushik, 2010).

Luo (2010) regarded the rice leaf folder as a predominant foliage feeder at the booting stage of the crop and the most destructive pests in all the rice ecosystems in Asia.

The predominant species of three rice leaf folders, *i.e.*, *C. medinalis* (Genée), *Marasmia exigua* (Bradley) and *Brachimea arotraea* (Meyrick) were observed in north eastern coastal plains of Odisha. Among the Leaf folder species, higher population (83.34%) of *C. medinalis* (Genée) was found, followed by the smaller *M. exigua* (12.22%) and *B. arotraea* (4.43%) and all three species were prevalent in all the seasons (Rautaray *et al.*, 2019).

Although moths are observed throughout the years in the warm tropic region, they are usually more frequent during the rainy season. The moth is active between May and October in cool areas, which complete four to five generations throughout these periods; later generations usually overlap (Dash *et al.*, 2020).

2.2 Nature and extent of damage by *Cnaphalocrosis medinalis* in rice

A yield loss of 16.5 and 21.3 per cent was resulted due to 17.5 per cent leaf infestation and 26.6 per cent leaf infestation by *C. medinalis*, respectively (Bautista *et al.*, 1984).

Rajendran *et al.*, (1986) reported that a single *C. medinalis* larva can defoliate or remove the chlorophyll from several rice leaves, which will disrupt photosynthesis. Feeding often results in stunting, curling or yellowing of plant green foliage.

Depending on the agro-ecological conditions, the grain yield loss ranged from 63 to 80 percent. The larvae fold leaves and scrape off the green mesophyll tissue, causing extensive damage (Heong *et al.*, 1994).

Baby Rani *et al.*, (2007) observed that one unit increase in *C. medinalis* infestation resulted 14 per cent and 1.46 per cent yield loss in summer and wet conditions, respectively.

A yield loss of 30 to 80 per cent was recorded due to leaf folder in rice under epidemic situation (Shah *et al.*, 2008).

Krishnaiah and Varma (2011) opined that at national level, leaf folder accounted for 10 per cent yield loss in rice.

The larval density of leaf folder affects the effective rice crop surface of the leaf differently. The larval densities of over 3 larvae per hill resulted in up to 20 per cent unfilled grains. In tillering phase, the PS II activity was decreased by 28-57 per cent and the relative amount of water was decreased by 23 per cent as compared with control. At the flowering stage, the damage caused by flag leaf area above 25 per cent led to the unfilled grain up to more than 50 per cent which indicated a direct decline in the yields (Padmavathi *et al.*, 2013).

According to Dash *et al.*, (2020), rice leaf folder larvae chewed inside the fold by scraping the green materials. The scraped leaves developed longitudinal white streaks which inhibited photosynthesis and plant vigour. The scraped leaves turned pale and withered. In general, the crop recovered from leaf folder damage during the vegetative stage but during the reproductive stage, feeding damage to the flag leaf severely reduced grain filling which resulted in yield loss.

2.3 Discrimination of insect pests' infestation in various crops through hyperspectral signature

Cabbage crop infested by *Spodoptera exigua* (Hubner) was monitored using remote sensing techniques as well as visual measurements of damage. When compared to uninfested leaves, beet armyworm-infested leaves had a different percent reflectance. Individual leaf readings using spectroradiometry showed that the percentage reflectance patterns of damaged leaves were different from those of healthy leaves. The near infrared readings of damaged leaves were lower than those of healthy leaves (Sudbrink *et al.*, 2003).

Yang *et al.*, (2005) reported that a hand-held radiometer can detect greenbug-induced stress in wheat through analysis of the 16 bands of the radiometer's reflectance data vegetation indices were derived. The vegetation indices derived from bands centred at 800 and 694 nm, as well as the band centred at 694 nm, were found to be the most sensitive to damage caused by greenbug infestation.

As a result of greenbug feeding, the reflectance of wheat canopies in the NIR region was substantially reduced compared to the visible spectrum. Utilizing spectral reflectance measures such as the damage sensitive spectral indices (DSSI1 and DSSI2), the normalised difference vegetation index (NDVI), damage to wheat caused by greenbugs was quantified. In the wavelength range from 400 nm to the red edge

shoulder at 720 nm, the uninfested wheat canopies consistently caught more or reflected less light than the greenbug-infested wheat canopies. The majority of compiled vegetation indices showed a negative correlation to the greenbug damage percentage (Mirik *et al.*, 2006 a).

Mirik *et al.*, (2006 b) investigated the possible use of spectral data to estimate aphid density in three winter wheat field experiments and one greenhouse experiment. The relationship between reflectance data and aphid density was quantified through use of two spectral indices in regression. The coefficients of determination (r^2) ranged from 0.48 to 0.76 for the hyperspectral-derived index and from 0.43 to 0.67 for the multispectral-derived index. Monitoring aphid population density in winter wheat fields with multispectral and hyperspectral remote sensing appeared to be effective.

When compared to noninfested canopies, Russian wheat aphid-infested wheat canopies had significantly lower reflectance in the near infrared region and significantly higher reflectance in the visible range. Linear regression analysis revealed that the density of Russian wheat aphids and spectral vegetation indices had varying relationships, with the coefficients of determination (r^2) varied between 0.91 and 0.01 (Mirik *et al.*, 2007).

Reisig and Godfrey (2007) found that, compared to uninfested leaves, cotton (*Gossypium hirsutum* L.) leaves infested by spider mite (*Tetranychus spp.*) and aphid (*Aphis gossypii* Glover) had significantly higher reflectance in the near infrared wavelength centred at 850 nm.

At the short wavelengths of near infrared 800–1100 nm, spectral reflectance decreased significantly with increasing severity level of tomato leaves affected by leaf miners, but this was not the case for individual bands of 1450 and 1900 nm, where spectral reflectance increased with increasing severity level (Xu *et al.*, 2007).

Genc *et al.*, (2008) assessed the different stage of pest damage along with the sunn pest *Eurygaster integriceps* Puton population density in wheat utilizing various indices viz., Normalized difference vegetation index (NDVI) based indices; NDVI_g, NDVI_d, NDVI_r and structure insensitive pigment index (SIPI). Overall, the 3rd instar's anticipated indices had lower r^2 values than the 4th and adult stages did. When r^2 was taken into account independently, the expected SIPI index value in the third instar was lowest (80.7) and predicted NDVI_r index value was highest (87.4).

Luedeling *et al.*, (2009) assessed the feasibility of spotting spider mite damage in peach orchards. With its maximum absolute PLS model coefficient at 365 nm, the blue and near ultraviolet region of the spectrum had one significant region. The green (497 nm) and red (687 nm) regions also had one significant region each and the top of the red edge (744 nm), in the closest infrared, had another. The water absorption bands were presented in three additional major locations (1405, 1888 and 2500 nm). In the study of the canopy level reflectance data, only two significant locations could be found. These regions were located in the blue, near-ultraviolet (390 nm) and red portions of the spectrum (651 nm).

Feasibility of using remote sensing techniques to detect stress in wheat caused by aphid infestation was assessed. Reflectance data and derived vegetation indices from the 16 bands of the radiometer were analyzed using SAS PROC MIXED statistical analysis procedure. The practicability of ratio-based vegetation indices (based on 800/450 nm and 950/450 nm) was confirmed in differentiating the two stresses in wheat (Yang *et al.*, 2009)

Kumar *et al.*, (2010), found that there was a noticeable difference between the spectral reflectance of a mustard canopy that had been infected with aphids and a healthy canopy that was measured in a laboratory. The most significant spectral bands for the aphid infestation in mustard were in visible (550-560nm) and near infrared regions (700-1250 nm and 1950-2450 nm). Different mustard varieties' spectral reflectance in the NIR (720-1360 nm) region displayed appreciable variations in reflectance at various phenological stages. When compared to vegetative, flowering and pod-forming stages, the peak at 550-560 nm was also lower during maturity stages in the visible area.

The findings of field spectroscopy for bag worm infestation in oil palm derived and confirmed spectral bands of 570 nm, 680 nm, 734 nm, 787 nm, 996 nm and 1047 nm as pest sensitive wavelengths (Nordiana *et al.*, 2012).

There were significant variations in the spectral reflectance and derived variables employed in the research at various degrees of thrips (*Fulmekiola serrata* Kobus) damage in sugarcane. Reflectance difference maxima and minima at 407 and 700 nm for N19 and 514, 636 and 700 nm for N12, as well as reflectance sensitivity maxima and minima at 400, 635, 680 and 697 nm for N19 and 465, 502, 675, 693 and

1955 nm for N12, were found to be the most strongly affected by thrips damage (Abdel-Rahman *et al.*, 2010).

Prabhakar *et al.*, (2013 b) discovered that the percent reflectance varied significantly between the green, NIR and SWIR band regions when the cotton plants were in the early stages of bug infestation. For higher pest infestation, the difference was significant in four band regions *viz.*, green, red, NIR and SWIR. Between different infestation grades, the percentage of reflectance in the blue zone was not significantly different (P values ranged from 0.1816 to 0.7441). The hyperspectral reflectance sensitivity analysis identified the most sensitive mealybug sensitive wavelengths as being those centred at 492, 550, 674, 768 and 1454 nm.

Ranjitha *et al.*, (2014) reported that in comparison to undamaged plants, near infrared (770-860 nm) reflectance decreased, while blue (450-520 nm), green (520-590 nm) and red (620-680 nm) reflectance increased in cotton (cv- *Surabi*) affected by thrips, *Thrips tabaci* (Lind). It was shown that the green red vegetative index (GRVI) and the red band (at wavelengths of 691 and 710 nm) were more susceptible to thrips damage. The sensitivity curve contained a single peak in the blue area, which was indicative of thrips damage (about 496 nm). A correlation between pest damage and VIs was found using linear regression equations based on spectral indices and insect damage.

In comparison to undamaged plants, near infrared (770-860nm) reflectance decreased, but blue (450-520nm), green (520-590nm) and red (620-680nm) reflectance increased in cotton (cv. *Surabi*) infested by sucking pests. Among the spectral bands, the red band was shown to be the most sensitive to thrips and leafhopper damage, while the NIR band was discovered to be more sensitive to aphid damage. It was discovered that the green red vegetation index (GRVI) responds to the differentiation between sucking pest damage (Ranjitha and Srinivasan, 2014).

The successive projections algorithm (SPA) was used to select relevant wavelengths (EWs) following the acquisition of hyperspectral images. To distinguish between leaves and larvae, 13 selected EWs were used to create models for partial least squares discriminant analysis (PLS-DA) and back-propagation neural network (BPNN), both of which produced acceptable results with correlation coefficient in the calibration

set (RC) above 0.98 and classification accuracy in the prediction set above 96 percent (Wu *et al.*, 2016).

Nigam *et al.*, (2016) found that the mean reflectance spectra of a healthy cotton crop and a cotton crop infested with white flies showed drastically different spectral responses. The white fly-infested cotton crop had a low reflectance value between 350 nm and 1335 nm, 1526 nm and 1769 nm. The spectral response over healthy and white fly-infested crops, however, displayed the opposite behaviour between 2004 nm and 2317 nm. Distinct spectral intervals of 10 nm, 20 nm, 30 nm and 40 nm were discovered to be relevant for separating pest-free and pest-affected cotton crops from 410 nm to 790 nm.

Hyperspectral images of Chinese cabbage plants, including 31 healthy plants and 32 plants infested by aphid (*Myzus persicae*), were captured in the region of 380 to 1030 nm with a hyperspectral system. From the hyperspectral images of plants, 160 spectra in total were chosen. By x-loadings of PC-1 and PC-2 in principal components analysis, six significant wavelengths (IW_s) at 550, 671, 694, 742, 911 and 968 nm were discovered. The results demonstrated that at 694 and 742 nm the reflectivity and textural characteristics gave excellent differentiation between aphid-infested samples and healthy samples (Zhao *et al.*, 2017).

The sensitivity of the spectral bands of 839 nm, 918 nm and 995 nm were more than other wavelengths to detect and discriminate the two classes of healthy and wheat plants infested by *Eurygaster integriceps* Puton (Basati *et al.*, 2018).

According to Chen *et al.*, (2018), cotton leaves' visible and near-infrared spectral reflectance reduced as the degree of aphid damage increased. The NIR and SWIR spectral bands were the regions where the sensitive bands were found. RSI (R1975, R1904) and NDSI (R678, R1471), two new and straightforward spectral indices were developed.

A hyperspectral insect damage detection algorithm (HIDDA) was developed to identify and detect the insect damage in green coffee beans by using only a few bands and one spectral signature. From the several bands 850–950 nm, an important wavelength range was detected in beans infested with insect (Chen *et al.*, 2020).

Yan *et al.*, (2021) confirmed the reflectance of healthy cotton leaves was somewhat higher than that of leaves infested by *Aphis gossypii* Glovers. The only difference between healthy leaves and infected leaves for the first derivative spectra of average spectra was about 720 nm.

The outcomes of the discriminant analysis performed on the hyperspectral data showed a definite separation between the various levels of whitefly infestation in soybean. Two of the eight discriminant models revealed that some bands in the visible (461, 469, 510, 520 and 673 nm), near-infrared (NIR) (703, 722 and 732 nm), and shortwave infrared (SWIR) (1360, 1426, 1713, 1819 and 1842 nm) regions were seen. The individual band 1831 nm was observed in three of the eight models (Barros *et al.*, 2021).

2.4 Discrimination of insect pest infestation in rice through hyperspectral signature

2.4.1 Striped stem borer, *Chilo suppressalis* Walker

In a study for identifying early infestation of *C. suppressalis* in rice, significant changes in reflectance were found in the ranges of 530-700 nm and 750-940 nm. The reflectance increased with the degree of the infestation in the visible range of 570–700 nm. The reflectance of DI0 was greater than that of the infected samples in the 750–1000 nm region of the near infrared spectrum. The reflectance decreased with the severity of the insect infestation (Fan *et al.*, 2017).

2.4.2 Brown plant hopper, *Nilaparvata lugens* (Stal)

The spectral properties of rice plants at different stages *N. lugens* infestation were measured. Reflectance was in the order of severity, especially between 737 and 925 nm. Reflectance among infections varied significantly, especially at wavelengths of 755 and 890 nm. To distinguish between different levels of infestation, spectral measures like the normalised difference vegetation index (NDVI) and cumulative reflectance may also be used (Yang and Cheng, 2001).

Rice panicle hyperspectral reflectance was measured in the visible and near-infrared regions. Healthy panicles, empty panicles affected by *N. lugens* and panicles contaminated with *Ustilaginoidea virens* were divided into three classes based on their health conditions. The red edge of the healthy panicle was 696 nm, while that of the

empty panicle was 692 nm. There were two maxima for the contaminated panicle, one at 696 and the other at 735 nm. Second-order derivative reflectance (SDR) of healthy panicles was 5 and 7 times larger than that of empty and contaminated panicles, respectively. The peak wavebands in the far-red region for the empty, healthy and sick panicles were 682, 685 and 686 nm, respectively (Liu *et al.*, 2010).

Prasannakumar *et al.*, (2013 a) found that damage by *N. lugens* influenced reflectance of rice plants compared to uninfested plants in the visible and near-infrared regions of the electromagnetic spectrum. Four wavelengths were found particularly susceptible to BPH stress on rice plants: 1986, 665, 1792 and 500 nm. These wavelengths were determined by the correlations between plant reflectance and BPH damage when plotted against wavelengths. Three hyperspectral indices were created using the reflectance of rice plants at the sensitive wavelengths. The normalized pigment chlorophyll index and soil adjusted vegetation index both exhibited a positive correlation with the damage by *N. lugens* and a negative correlation with both of those indices.

Hyperspectral remote sensing was utilized to detect the stress on rice plant due to *N. lugens* under glasshouse as well as field conditions. Four sensitive wavelengths, namely 1986 nm ($r = 0.63$), 665 nm ($r = 0.58$), 1792 nm ($r = 0.53$) and 500 nm ($r = 0.52$) were shown in a plot of correlation coefficients (r) between plant reflectance and BPH damage levels, against wavelengths. In the field, it was discovered that the sensitive wave lengths were 961 nm ($r = -0.706$), 1201 nm ($r = -0.705$), 764 nm ($r = -0.676$) and 1664 nm ($r = -0.609$). Infrared (NIR) (740-925 nm) and mid-infrared (MIR) (926-1800 nm) wavelength variations in plant reflectance caused by BPH damage were reduced at shorter wavelengths (350-730 nm) and bigger at longer wavelengths, indicating the feasibility of detecting BPH stress on rice (Prasannakumar *et al.*, 2013 b).

Prabhakar *et al.*, (2013 a) conducted a comparative study among simple ratio (SR), normalized difference vegetation index (NDVI), normalized total pigment to chlorophyll index (NPCl), disease water stress index (DWSI) and water index (WI) to discriminate healthy and infested rice plants by *N. lugens*. All the indices were found to perform better at differentiating increasing degrees of BPH damage (moderate and severe), but only DWSI worked well at differentiating early damage (3.07 for healthy, 2.88 for low severity).

Prasannakumar *et al.*, (2014) observed that spectral reflectance of uninfested plants was lower than that of crops infested by *N. lugens* in the VIS region (400–700nm). The damage was shown to be directly correlated with the reflectance of infested plants in the VIS, with reflectance rising with increasing damage from the red edge shoulder at 400 nm to 668 nm. However, an uninfested crop had a larger peak of spectral reflectance in the VIS region about 550–560nm than an infested crop. An uninfested crop had a higher reflectance in the NIR (740–925nm) spectrum than an infested crop, with reflectance declining as infestation increased. Four sensitive wavelengths i.e., 764, 961, 1201 and 1664 nm were identified in correlations between plant reflectance and BPH damage in relation to stress due to *N. lugens* on the rice crop.

Sun and Liu (2010) found that the spectral reflectance in the visible light and near infrared areas drastically decreased with increase in number and instar of *N. lugens*. The reflectance was inversely linked with the number of insects at wavelengths of 520–570 nm and 700–1000 nm, with substantial correlation coefficients. The peak waveband of a healthy panicle in the blue-green zone was 518 nm, but those of empty and contaminated panicles migrated toward shorter wavebands at 17 and 10 nm, respectively. The red edge was between 680 and 750 nm as a plant stress indicator in first order derivative spectra. The red edge of the healthy panicle was 696 nm, while that of the empty panicles was 692 nm. There were two maxima for the contaminated panicle, one at 696 and the other at 735 nm. Second-order derivative reflectance (SDR) of healthy panicles was 5 and 7 times larger than that of empty and contaminated panicles, respectively. The peak wavebands in the far-red region were 682, 685 and 686 nm for the empty, healthy, and sick panicles, respectively.

2.4.3 Rice leaf folder, *Cnaphalocrocis medinalis* (Guenee)

Spectral reflectance from rice at the tillering and heading stage was negatively correlated to infestation scale of *C. medinalis*. The heading had a lower negative value of the correlation coefficient 'r' than the active tillering in the linear association between spectral reflectance from the canopy and infestation scale. In the active tillering stage, the maximum absolute value of r was placed at 757 nm; however, in the heading stage, it moved to 445 nm. At the booting stage of this study, the maximum absolute value of r was found to be at 938 nm. When rice infested by *C. medinalis*, the

sensitive spectral region was different during the tillering, booting, and heading stages (Yang *et al.* 2007).

Shi *et al.*, (2009) designed a support vector classifier for the recognition of leaves damaged by *C. medinalis* and the band depth and slope were extracted in the 430–530 nm and 560–730 nm ranges.

Huang *et al.*, (2010) reported that when the degree of damage to *C. medinalis* increased, the spectral reflectance of rice leaf decreased in the green (530-570 nm) and near-infrared (700-1050 nm) wave-length regions while increasing in the red wave-length region (610-700 nm). The regions of the yellow-edge (SDy), the difference of the areas of the red-edge and blue-edge (SDr-SDb), and the vegetation index (Rnir-Rred) of the spectral indices could considerably identify the six categories of leaf roll rates (0%, 10 %, 30 %, 50 %, 70 % and 90 %). The leaf roll rate could be identified using the area of yellow edge (SDy) index and up to 86 per cent of diagnoses were correct. The spectral reflectance could be used to track rice leaf damage caused by *C. medinalis*.

The hyperspectral response characteristic analysis of rice leaves indicated that the damaged leaves by *C. medinalis* presented a higher reflectance in the visible and one shortwave infrared (2080~2350 nm) region and a lower reflectance in the near infrared (780~890 nm) and the other shortwave infrared (1580~1750 nm) region than the normal leaves. In the visible blue, green, near-red and red-light regions, the hyperspectral reflectance of stressed leaves increased by 2.9, 1.9 and 3.3 times more than the normal ones, respectively. However, in the NIR and one SWIR (2.08–2.35 μ m) region, stressed leaves' hyperspectral reflectance fell by 20.7 and 9.7 per cent, respectively, compared to unstressed leaves. However, compared to the normal ones, the hyperspectral reflectance increased by 28.9 per cent in the other SWIR zone. The peak wavebands from healthy and stressed canopy spectra in the blue light region were both found to be at 521 nm (Liu *et al.*, 2011).

Huang *et al.*, (2012) found that the leaf-roll rate increased during the rice booting stage, the reflectance from rice leaves reduced greatly in the green (530-570 nm) and near infrared (700-1000 nm) regions, but increased significantly in the blue (450-520 nm) and red (580-700 nm). For all levels of the infestation scales, the reflectance was negligible between 400 and 737 nm. As the leaf-roll rate grew, the first-

derivative value of reflectance at the peaks dramatically fell, but it significantly increased at the valley. The reflectance from rice leaves displayed two clear peaks at 520 nm (the blue edge peak) and 710 nm (the red edge peak), as well as a visible valley at 575 nm in the first-derivative values. The second-derivative values of reflectance from rice leaves increased significantly at 720–770 nm but dramatically reduced at 680–720 nm when the leaf-roll rate increased. 503-521, 526-545, 550-568, 581-606, 688-699, 703-715 and 722-770 nm were the sensitive bands for leaves, and 747-754 nm were the sensitive bands for the canopy. When rice was damaged by *C. medinalis*, the red edge's position in the rice spectra significantly shifted.

With increasing levels of *C. medinalis* damage in the same wavelength range, the reflectance in the visible range progressively declined, whereas it gradually increased in the NIR region. Particularly in the SWIR band, the curves obtained appeared to have been flattened (2000-2350 nm). Spectral curves' overall patterns were flattened, particularly in the visible and near-infrared spectrum (350-1350 nm). Particularly in the NIR and SWIR spectral bands, the curves of a healthy rice canopy were clearly distinguished from other levels. Three bands located at 424 nm ($r=-0.802$), 758 nm ($r=-0.916$) and 1141 nm ($r=-0.895$) were found as sensitive bands for leaf folder damage in a study on identification and characterization of rice leaf folder damage using the ground-based hyperspectral data (Zhao *et al.*, 2013).

According to the examination of the hyperspectral response characteristics, the leaves infested by *C. medinalis* had greater reflectance in the visible (430–470 nm, 490–610 nm, and 610–680 nm) and short-wave infrared (2080–2350 nm) regions. As compared to healthy leaves, the impacted leaves had a reduced reflectance in the near infrared (780–890 nm) and short-wave infrared (1580–1750 nm) regions. The near infrared (NIR) area indices were more closely connected than the indices in the visible region. Simple Ratio and Red Edge in the NIR region were the most sensitive indices and had the best correlation with RLF infestation levels (F-values 33.10 and 19.9) as compared to the transformed chlorophyll absorption ratio index in the visible region, having the least correlation with infestation levels (F-value 2.10). The higher differences in the NIR regions suggested that this region was more efficient than the visible spectral range for detecting insect pest infestation (Singh *et al.*, 2013).

Wang *et al.*, (2018) reported that reflectance from the rice canopy infested by *C. medinalis* significantly decreased in the green (530-570 nm) and near infrared (700-1000 nm) regions and significantly increased in the blue (450-520 nm) and red (580-700 nm) regions with the increase in pest population. The reflectance dramatically decreased in the spectral areas from 737 to 1000 nm, with the strongest association at 941 nm. A highly significant association ($P < 0.01$) was found between the indices NDVI, EVI, EVI2, SAVI, OSAVI, and leaf folding population. SAVI exhibited a higher correlation of 0.94 in addition.

The spectral reflectance of rice leaves (healthy, 50 % folded and 100 % folded) was recorded by the ASD FieldSpec hyperspectral spectroradiometer and the spectral curves were obtained by standard procedures. From the spectral curves obtained mean curves of reflectance spectra from different scales of insect infestation were clearly differentiated. There was a slight change in magnitude in the visible range for both healthy and affected samples but the change is quite obvious in the Near Infrared (NIR) region. The maximum value was at 815nm for both healthy and affected samples on the original spectra. The existence of red edge area caused the graph to incline at about 700 nm. The red edge, which was characterised as the wavelength range between 690 and 750 nm, was also sensitive to chlorophyll material and the movement of the red edge towards shorter wavelengths during senescence or stress-induced chlorosis was due to a reduction in the depth and breadth of the chlorophyll absorption feature. As a result, the *C. medinalis* was sensitive to the bands 716, 720, 733, 762 and 766 nm (Adhikari *et al.*, 2020).

During the booting stage, the reflectance in the near-infrared spectral band dropped as leaf-roll rates increased. Chlorophyll was responsible for the reflection peak at about 550 nm, while pigments' high absorption was responsible for the absorption peak at about 480 nm. Around 730 nm, or the so-called red-edge position, the canopy spectral curve abruptly shifted upward. As the leaf-roll rate increased, a "blue shift" was visible at the red-edge point. For calculating leaf-roll rates by leaf folder during the booting stage, the newly created two-band spectral index (R490R470) and three-band spectral index (R400R470)/(R400R490) demonstrated good applicability. When used to estimate leaf-roll rates, the published vegetation indices (R550R531)/(R550+R531) performed well. For the detection of infestation by *C. medinalis*, spectral bands of 410, 470, 490, 570, 625, 665 and 720 nm were sensitive regions (Liu *et al.*, 2020).

2.4.4 Yellow stem borer, *Scirpophaga incertulas* (Walker)

Studies were carried out by Mageshwaran *et al.*, (2014) on detection and estimation of damage caused by *S. incertulas* using hyperspectral radiometry. It was found that the wavelength most sensitive to YSB damage fell between 673 and 678 nm. The NIR band, which has wavelengths between 757 and 769 nm, was where the sensitivity analysis curve's greatest negative value was located. On the majority of the observation days, there was a strong inverse relationship between YSB damage and the normalized difference index (NDVI), simple ratio (SR) and green red vegetation index (GRVI) values.

2.5 Change in biochemical components in crop plants due to insect pest infestation

Mustard leaves with aphid infestations had lower reflectivity despite having 50 per cent less chlorophyll content than uninfested plants (Kumar *et al.*, 2010).

Usha Rani and Jyothisna (2010) found that due to the infestation of *C. medinalis* in rice plants, proteins, phenols and carbohydrates were increased. It was shown that the higher amounts of biochemicals may be a significant factor in plant resistance.

Reflectance from healthy and infested cotton plants by leaf hopper displayed a significant difference in VIS and NIR regions. In plants with leaf hopper infestations, *Chl a* pigment reduction was more noticeable than *Chl b* and the ratio of *Chl a/b* decreased as leafhopper severity increased. LH severity and *Chl* showed a significant linear relationship through regression analysis ($R^2 = 0.505$) and relative water content showed a comparable match ($R^2 = 0.402$) (Prabhakar *et al.*, 2011).

Zhao *et al.*, (2013) found that the chlorophyll content decreased substantially as the extent of leaf folder damage increased in rice. Particularly, the curve features for the spectral response qualities were extremely similar for various levels.

Subsequent to infestation of *C. medinalis* in TN 1 rice variety the total phenol content was increased by 23.85 per cent (3.48 mg/g in healthy and 4.31 mg/g in leaf folder infested plants) due to a significant increase in defensive mechanisms based on antibiosis, which persistently prevented oviposition, population growth, survival and adult emergence in insect (Punithavalli *et al.*, 2013).

Prabhakar *et al.*, (2013 b) opined that in healthy and mealybug-infested cotton plants, spectrophotometric measurement of chlorophyll revealed a considerable reduction in *Chl a* with increasing damage severity. Additionally, *Chl b* displayed a decreasing trend as the severity of the damage increased. The per cent reduction in the total chlorophyll content (*Chl a + b*) due to mealybug infestation was between 12.83 and 35.83 per cent for grades-1 to 4 and it was significant only in the plants with infestation grade-2 and higher. The decline in *Chl a/b* ratio between grades, however, was not statistically significant ($P = 0.0763$).

A declining trend was observed for the carotenoid level in the leaves of *Nephrolepis biserrata* infested with *Coccus hesperidum* (Golan *et al.*, 2015).

Anjali *et al.*, (2017) reported that the leaves of sorghum infested with *Raphalosipum maidis* had lower carotenoid levels as compared to untreated control. The carotenoid content considerably decreased in moderately infested plant (200 aphids/plant) and highly infested plant (300 aphids/plant) compared to lower infested crop.

Rice accessions with higher levels of total phenol and ortho-hydroxy phenol were resistant and moderately resistant but in case of TN1 rice variety all the above-mentioned biochemical parameters significantly decreased after insect infestation of *S. insertulas*. The results from the biochemical analysis of TN1 variety confirmed that there was increase of total phenol, total sugars, reducing sugars as well as non-reducing sugars by 13.11, 64.35, 64.48 and 61.17 per cent respectively after it was infested by *S. insertulas* (Amsagowri *et al.*, 2018).

Chen *et al.*, (2018) reported that cotton plants that were both healthy and aphid-infested showed a considerable reduction in *Chl a* and *Chl b* levels. For Grades 1-4, the overall decrease in chlorophyll content (*a + b*) was between 14.83 and 65.39 percent as a result of aphid infestation.

The concentration of starch in the leaves was higher in the unaffected rice plants and significantly lower in the plants infested by *C. medinalis*. The level of reduction of *chlorophyll a* was maximum for infested plant samples and there was not a significant change in *chlorophyll b* concentration due to insect feeding. Therefore, compared to the control plants the ratio of *chlorophyll a* to *chlorophyll b* increased in case of pest infestation. Also, a reduction in carotenoid concentration in infested leaves was observed (Nayak *et al.*, 2019).

2.6 Impact of plant biochemical parameters on hyperspectral reflectance

2.6.1 Relationship of chlorophyll content of the plants with the pest sensitive spectral bands

At 550–560 nm and 700–710 nm, maximum sensitivity to *chlorophyll a* concentration was discovered in maple and chestnut. For both of the examined plant species, reflections at 700 nm and 550 nm showed strong correlations across a broad range of chlorophyll content (Gitelson and Merzlyak, 1998).

Wheat plants damaged by Russian wheat aphid and greenbug with leaf reflectance 625–635 and 680–695 nm ranges were substantially correlated with total chlorophyll concentrations. Thus, this reflectance index and both of these wavelength ranges were reliable predictors of chlorophyll loss and leaf senescence brought on by aphid damage. The value of NPCI was always significantly higher in greenbug damaged leaves than other treatments. The value of normalized pigment chlorophyll index (NPCI) was also greater in case of Russian wheat aphid infestation than the younger healthy leaves (Riedell and Blackmer, 1999).

Carter and Spiering (2000) estimated the chlorophyll absorption in broadleaved vegetation using regression analysis. Overall, regressions were substantial in the 550–625 nm wavelength range as well as at wavelengths near 700 nm, where reflectance, transmittance and absorptance most closely matched with chlorophyll content.

In general, chlorophyll concentrations were most closely correlated with reflectance, transmittance and absorptance at wavelengths about 700 nm. When data from the planar-leaved species were combined, the chlorophyll *a* + *b* values were best-fit to wavelengths of 707 to 709 nm (Carter and Spiering, 2002).

Gitelson *et al.*, (2003) analysed the reflectance of maple, chestnut, wild vine and beech leaves in a variety of pigment richness and composition. In the spectral regions from 520 to 550 nm and 695 to 705 nm, it was shown that the total chlorophyll content of leaves from all species was substantially linked with reciprocal reflectance.

Studies on influence of spectral bandwidth and position on chlorophyll content retrieval at leaf and canopy levels revealed that the ideal bands at the leaf level were

748–786 nm and 713–732 nm, respectively. The best bands at canopy level were in the ranges 770–750 and 765–738 nm, respectively (Dian *et al.*, 2016).

Sowmya and Giridhar (2017) analysed the spectral reflectance of crop *Capsicum annum* at different stages of growth using the continuum removal in the software ENVI. In the continuum removed graph, at 410 nm the chlorophyll reflection was observed. A peak of reflection was observed at 550 nm due to Beta carotenoid whereas at 760–940 nm dip was observed due to the presence of anthocyanins. Thus, using the reflectance library, the stage of the species could be explored.

2.6.2 Relationship of phenol with the pest sensitive spectral bands

The phenol was found in three absorption bands near 880nm, 1130nm and 1660nm with the highest absorptivity at 1130nm and the lowest at 1660nm (Kokaly and Skidmore, 2015).

Zhang *et al.*, (2017) reported that the total phenols having a high relevance in grape seeds were predicted at the spectral bands of 1200 and 1450 nm.

The extractability of total phenols (ETP), extractability of flavanols (EF), extractable flavanolic content (EFC), total phenolic content (TPC), total flavanolic content (TFC), extractable total phenolic content (EPC) and extractable flavanolic content (EFC) were measured for the selected grape seed samples and used as reference parameters in the subsequent chemometric approaches. The experimental findings confirmed the existence of important characteristics in the spectrum regions at 1200 and 1400 nm, proving the presence of phenolics (Baca-Bocanegra *et al.*, 2018).

Yan *et al.*, (2021) reported that phenolics were detected at 1131.7nm and 1657.3nm, respectively in the phenol absorption curve in barley malt.

2.6.3 Relationship of carotenoid content in plant with the pest sensitive spectral bands

Chappelle *et al.*, (1992) located spectral bands responsive to pigment concentration by ratio analysis of reflectance spectra. A small peak at 500 nm was attributed to carotenoid (Car) absorption in spectrum. The result recommended using the ratio R_{760}/R_{500} , where R_{760} and R_{500} were suggested the reflectance at 760 and 500 nm, respectively, as a quantitative measurement of carotenoid.

Blackburn (1998) found that the ideal individual waveband for estimation of carotenoid was 470 nm for which the carotenoid content was assessed using the pigment-specific ratio $R800/R470$ and a pigment-specific normalised difference $(R800 - R470)/(R800 + R470)$.

The maximum sensitivity of reflectance to variation in pigment content was found in the green band region at 550 nm and the red-edge region at 708 nm. A reflectance band ratio index $(R672/(R550 \times R708))$ was then proposed for pigment content estimation and it had a good correlation with carotenoid content (Datt, 1998).

Merzlyak *et al.*, (1999) discovered that the index $(R680 - R500)/R750$ was demonstrated to be sensitive to carotenoid/chlorophyll and was used to quantify leaf senescence and fruit ripening. The difference $R680 - R500$ was dependant on pigment composition.

Standardization of the leaf absorbance spectra (A) was done to the red Chl absorbance at 678 nm in order to locate spectral regions that were most sensitive to concentration of carotenoid in green leaves (A678). As a consequence, the contribution of Chl was greatly decreased and a strong peak was observed at 510 to 520 nm in the spectra of the standard deviation of $A/A678$ for leaves with a wide range of chlorophyll and carotenoid content (Zur *et al.*, 2000).

The spectral reflectance of maple, chestnut and beech leaves was studied across a wide range of pigment concentration and composition in order to develop a non-destructive method for estimating total carotenoid (Car) content in higher plant leaves. Reflectance near three spectral bands, 510 nm, 550 nm, or 700 nm, as well as the near infrared region above 750 nm were sufficient for non-destructively estimating total Car content in plant leaves (Gitelson *et al.*, 2003).

Hernández-Clemente *et al.*, (2012) devised a simple ratio index (SRcar, $R515/R570$) at both the leaf and canopy levels, which demonstrated a high connection with carotenoid content.

2.7 Detection and discrimination of healthy and insect infested vegetation through ‘sentinel’ analysis

For validating the locations of the healthy and Fall Army Worm (FAW)-damaged maize crop hyperspectral data sets, the sentinel bands (Bands 2, 3, 4, 5, 6, 7

and 8) were utilised in the experiment. The sentinel analysis, which identified and distinguished between healthy and infested places based on several colour codes, was the source of the false colour composite (Champagne, 2019).

Moso *et al.*, (2021) investigated the application to GPS recordings of combine harvesters and crop damage detection in crop dataset. The outcomes supported the validity of the receiver operating characteristic (ROC) curve discovered by Sentinel data analysis. The study of the crop dataset revealed that 30 per cent of the anomalies were directly related to crop damage. Anomaly detection might therefore be incorporated into the decision-making process of farm operators to enhance crop health and harvesting effectiveness.

On the basis of pictures of the crop in the field, deep learning models were employed to diagnose lesions on cotton leaves. Support vector machines (SVM), Closest k-neighbors (KNN), artificial neural networks (ANN) and neuro-fuzzy (NFC) were used to process images with convolutional neural networks proving to be up to 25 per cent more accurate (Calderia *et al.*, 2021).

Ali *et al.*, (2021) reported that the entire summer season was covered by the multitemporal Normalized Difference Vegetation Index (NDVI) that was taken from nine different Sentinel-2 images. The classification map produced by the supervised closest neighbourhood object-based technique had a kappa coefficient of 0.93 and a 95 percent overall accuracy.

CHAPTER - III

MATERIALS AND METHODS

Field and laboratory experiments on “Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques” were carried out at ICAR- National Rice Research Institute, Cuttack during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19. Various materials used and the methodologies followed in conducting the present investigation has been presented in the following paragraphs.

3.1 Experimental location and seasons

Field experiments were conducted at the research plot of ICAR- National Rice Research Institute, Cuttack located at 28°36'36" North latitude, 77°13'48" East longitude and at an elevation of 25.9 m above mean sea level (Fig 1). The experiment was carried out in a medium land with assured irrigation facility. Cuttack comes under the sub-tropical climate and is placed under East and South Eastern Coastal Plain of Odisha with an average annual rainfall of 1500 mm. Soil of the experimental plot was sandy loam with an average pH of 6.5. The detailed meteorological data of ICAR- National Rice Research Institute, Cuttack during the period of study has been presented in Annexure I.

3.2 Discrimination of the leaf folder infestation through hyperspectral signature at different damage level

To discriminate the damage by rice leaf folder to rice canopy and leaf with the help of hyperspectral remote sensing techniques, the detailed flow chart of various steps has been represented in Fig 2.

3.2.1 Simulation of differential damage level of rice leaf folder in the microplots

In order to create the differential damage level of *C. medinalis* in the microplots, field experiments were carried out during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 and the details of the experiments are given below.

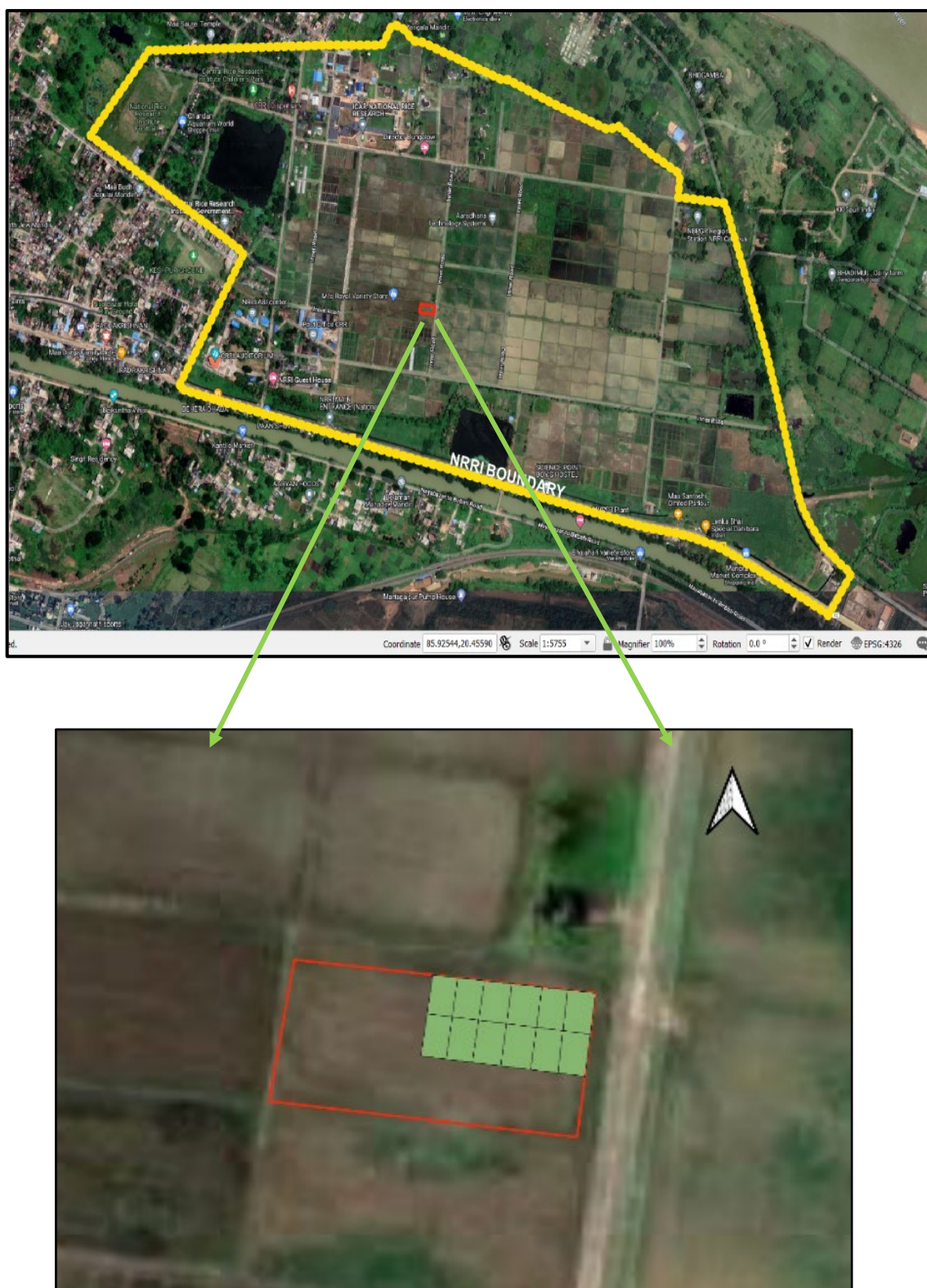


Fig 1: Location of experimental field at ICAR-NRRI, Cuttack, Odisha

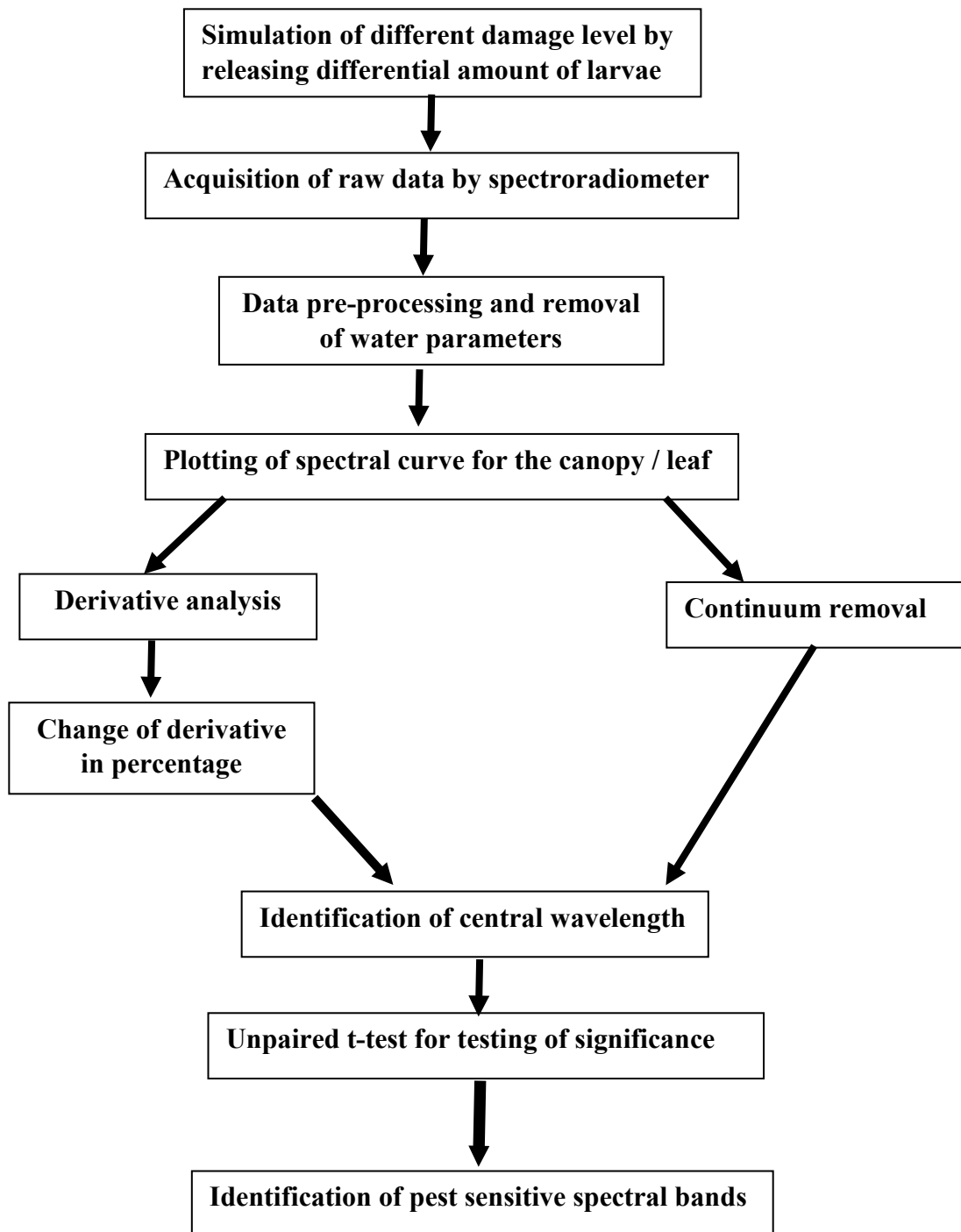


Fig 2: Flow chart of damage discrimination of *C. medinalis* by hyperspectral remote sensing techniques

Design	: Randomized Block Design
Crop	: Rice
Variety	: TN 1
Duration	: 120-125 days
Date of transplanting	: 10/01/2018, 08/08/2018 and 13/01/2019
Plot size	: Each micro-plot measured 1m ² (1m.x1m.)
Spacing	: 20cm X 15cm
FYM	: 5 tonnes /ha
Fertilizers	: 100:50:50 kg of N: P ₂ O ₅ : K ₂ O per hectare
Date of harvest	: 12/04/2018, 21/12/2018 and 15/04/2019
Replication	: Four
Treatments	: Six

Table 1. Treatments for the experiment at ICAR-NRRI, Cuttack:

Sl No	Treatments	Number of larvae of <i>C. medinalis</i> released per microplot	Damage by larvae
1	T ₁	0	No damage (Untreated control)
2	T ₂	10	Slight
3	T ₃	20	Slight to moderate
4	T ₄	40	Moderate
5	T ₅	60	Moderate to severe
6	T ₆	100	Severe

The micro-plots measuring 1m² (1m.x1m.) were separated from each other by 0.5m for intercultural operations as well as various experimental works. Drainage and irrigation facilities were adequately provided to the plots as per the requirement. Recommended agronomic packages of practices were followed for raising the crop during various seasons. The layout of the experiment is presented in Fig 3. Each micro-plot (1m X 1m) of rice plants was covered with small mosquito nets of approximately similar size (1.3 m X 1.3 m) (Fig 4) to avoid infestation of other pests and to maintain the damage level by *C. medinalis*.

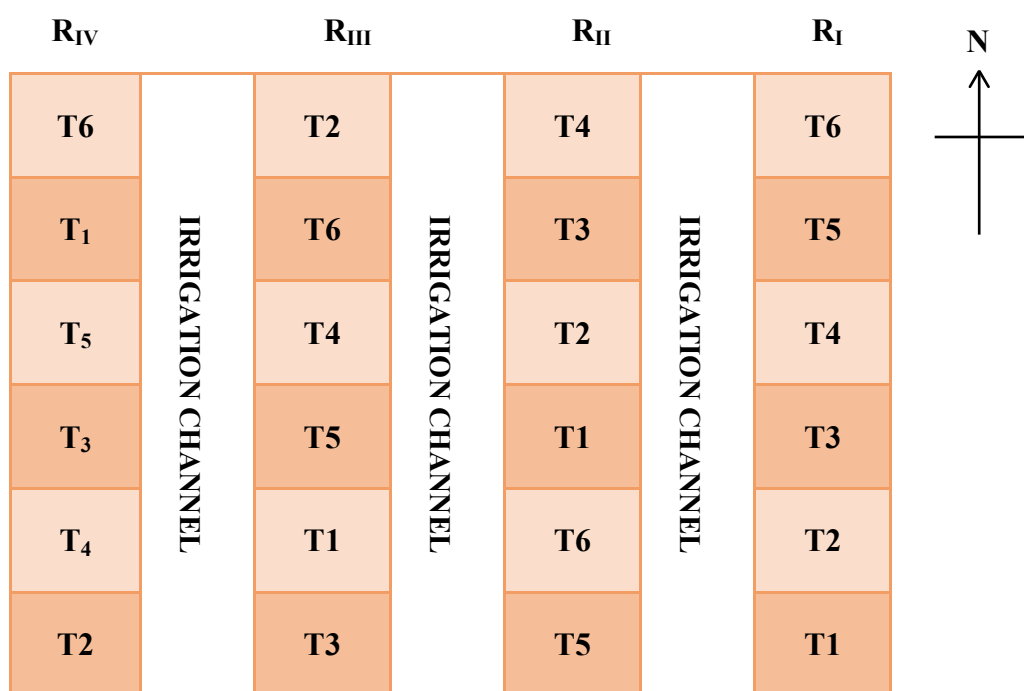


Fig. 3: Layout plan of experimental field



Fig. 4: Experimental microplots covered with nylon nets

3.2.1.1 Rearing and multiplication of *C. medinalis*:

Adults of *C. medinalis* comprising of both males and females were collected from nearby rice field with the help of sweep net and insect collecting tubes. Equal numbers of male and female adult moths were then released into potted rice plants which were covered with mylar cages for avoiding the escape of the moths (Fig 5). A small cotton piece soaked in ten per cent honey solution was hanged in each mylar cage for feeding the adults. This piece of cotton in each mylar cage was resoaked with 10 per cent honey solution whenever it was dried. The rice plants in pots were maintained by regular watering and intercultural operations. The female moths laid minute eggs on the leaves after copulation. After seven to ten days some leaves were found folded by the hatched first instar larvae. The potted plants were observed regularly until the emergence of second and third instars which were used for the experiment.

Some larvae were further reared in the laboratory to maintain the population. Each larva was reared separately in the glass tube of 10 cm height and 1 cm width with fresh piece of rice leaf which was replaced daily (Fig 6). The leaf folder larvae after completing their larval stage became pupa inside the tubes and subsequently turned into adult moths. The adult moths (both males and females) were collected and again released into potted rice plants covered with mylar cages. Then similar rearing methodology was followed to maintain the population of the insect.

3.2.1.2 Release of *C. medinalis* in microplots

Different numbers of 2nd–4th instar of *C. medinalis* were released into the plot at the rice jointing stage which resulted differential damage severity at the booting stage. During the time of releasing larvae, adequate precaution was taken to prevent the escape of larvae from the microplot so as to protect the crop from attack of other insect pests.

3.2.1.3 Determination of leaf roll rate of canopy by *C. medinalis*

The leaf-roll rate by *C. medinalis* was worked out by counting the number of healthy and infested leaves and thereby the percentage of leaves infested was computed (Huang *et al.*, 2012). Six infestation scales (0–5) were defined in Table 2 according to the leaf-roll rate as per description of INGER (1996) with some modifications. Thus, in each micro plot the desired level of infestation scale was maintained. The control plot was sprayed with pesticides on a regular basis to ensure insect pest or disease-free conditions.

Table 2. Infestation scales of *C. medinalis* as per INGER, 1996

Treatments (Incidence)	Insect level (Grade)	Leaf rolling ratio per unit area (Rolling leaves /total leaves) (%)
No damage	0	0
Slight	1	<5.0
Slight to moderate	2	5.0 - 20.0
Moderate	3	20.1 - 35.0
Moderate to severe	4	35.1 - 50.0
Severe	5	> 50.0

3.2.2 Acquisition of raw data by spectroradiometer

After creating the differential damage level of *C. medinalis* in the micro plots the reflectance was recorded by ASD Field spec Hyper spectral spectroradiometer from the infested crop canopy as well as from the differentially infested individual leaves. The principle behind the reflectance data by hyper spectral spectroradiometer was to record continuous bands which help to create or form the spectral library and draw the spectral curves for both healthy and infested vegetation. The reflectance from a healthy plant differed from the reflectance from the infested one. So, in this way the spectral signatures were recorded by this instrument from the vegetation.

3.2.2.1 White referencing:

To calculate the reflectance of the sample, an independent measurement of the light source illumination on a known reflectance reference is needed. Before taking the spectral signatures by the hyper spectral spectroradiometer, the instrument was optimized by taking reflectance data or spectral signatures from the white reference plate or spectralon in absolute sun light (Fig 8). For correct validation of data, the position (same distance and angle from the fore optic) of the white reference plate was set similar to the position of the target for capturing the spectral data. The measurements were collected approximately at every ten minutes. The use of white reference standard with near 100 per cent reflectance simplified this calculation.



Fig. 5: Rearing of *Cnaphalocrocis medinalis* (Guenee) in pots



Fig. 6: Rearing of *C. medinalis* by natural leaf diet

3.2.2.2 Recording of spectral reflectance from rice canopy

The canopy spectra for rice were measured by ASD Field Spec hand held spectroradiometer between 12:00 and 14:00 under clear and windless weather conditions (Fig 9a and Fig 9b), as per Salisbury (1998). Before recording reflectance, the spectroradiometer was calibrated using a white BaSO₄ calibration panel. The spectroradiometer was positioned at a height of 0.3 to 0.4 metres above the rice canopy and from each microplot 10 spectral reflectance data were collected. The reflectance from each plot was calculated using the average of these ten readings. The number of damaged and healthy leaves was counted after the reflectance measurements were made, creating and validating their damage scales as suggested by INGER (1996). The spectral reflectance data were thus collected from the rice canopy for three cropping seasons i.e., Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19.

3.2.2.3 Recording of spectral signatures from rice leaves

About sixty leaves selected from the experimental microplots were selected as the representative samples on the basis of damaged area of individual leaf by *C. medinalis*. From the visual observations the damaged leaves were categorized into six different groups and from the individual representative leaves, data was recorded by ASD FieldSpec hand held spectroradiometer. Before recording reflectance, the spectroradiometer was calibrated by white referencing. The spectroradiometer was set 0.1- 0.15 m above the representative rice leaves and spectral reflectance data were collected. All the aforesaid precautions and protocols for recording canopy spectral data were followed while taking the reflectance from individual leaves.

After collection of reflectance data from rice leaves at field scale, the damage area of leaves of rice were determined by graphical method and validated with the visual observations taken for grouping into six different categories for discriminating the reflectance from each category. A damaged leaf was placed on the transparent sheet, and the damaged area's outline was drawn. The area was measured while being held up to a graph sheet with a 1 mm square grid. The total number of grids the outline covered was counted. An outline was considered to be occupied if it took up more than half of the grid. The grid count was used to compute the leaf folder damage, which was then represented as square millimetres (Chintalapati *et al.*, 2017).

The leaf reflectance data was taken only for confirmatory studies and to compare the reflectance as well as spectral signatures with the canopy spectra. The leaf reflectance data was taken with the ASD Fieldspec spectroradiometer for one season only i.e., Rabi 2018-19.

Table 3. Categories of leaves according to percentage of infestation of *C. medinalis*

Incidence	Grades	Leaf infestation (%)
No damage	0	0
Slight	1	< 10
Slight to moderate	2	10-20
Moderate	3	20-30
Moderate to severe	4	30-50
Severe	5	> 50.0

(Huang *et al.*, 2012)

3.2.3 Data pre-processing and removal of water parameters

The data collected from the rice canopy (both healthy and infested) through hyper spectral spectroradiometer were grouped on the basis of infestation level of *C. medinalis*. The reflectance values or the spectral data were classified as per the concerned damage level. The data recorded from the vegetation (.asd format) were converted into .txt and then finally to .xls format for smooth calculation and analysis using View Spec Pro software which was borrowed by ICAR- NRRI, Cuttack from Space Application Center (SAC), ISRO.

For the ASD reflectance conversion, ASD-viewspec Pro Version 6.0 was used to export original radiance values to Excel (Surase *et al* 2018) and Eq. (1) was used to calculate the converted reflectance using the ASD spectrometer:

$$Rt = \frac{Rad_t}{Rad_r} \times Rr \times 100\% \quad (1)$$

Where Rt is the radiance values acquired by the ASD spectrometer, Radr is a reference panel' s measured radiance, Rr is the known reflection of the reference panel and Rt is the calibrated reflection of the target by means of its reference panel.

Due to atmospheric interference, low signal to noise ratios is observed naturally in certain wavelength ranges, such as water vapour at 1350-1440nm, 1790-1990nm and 2360-2500nm. The most noise in the field spectroscopy data is caused by water vapour.



Fig. 7: ASD FieldSpec hyperspectral spectroradiometer



Fig. 8: White referencing

In other words, in universe the reflectance of snow is tested to be the highest which ranges from 0 to 1. So, any object that reflects the energy in form of spectrum, the reflectance value exceeding one or negative were deleted. This is the procedure which is otherwise called as noise removal or removal of atmospheric perturbations (Fig 10). From the spectral data taken by the ASD FieldSpec hyperspectral spectroradiometer, the bands which were identified to be obsolete or noisy and they were eliminated before the spectral curve was produced.

3.2.4 Discriminating the damage of *C. medinalis* by plotting the spectral curve

The spectral signatures data taken by hyperspectral spectroradiometer were simulated for discriminating the damage at different damage levels by *C. medinalis* for each season and the spectral graphs were plotted at various spectral band viz., from 400 nm to 700 nm (visible range), 700 nm to 1100 nm (Near Infrared range) (NIR) and from 1100nm to 2500nm (Short-Wave Infrared Region) (SWIR). The spectral curves were plotted with wavelength and reflectance on the X and Y axes, respectively, after the water components were removed. From these spectral graphs various conclusions were drawn which defined many discriminating features of a damaged rice plant by *C. medinalis* than a healthy plant. This biotic stress was indicated by progressive decrease in Near-IR reflectance but a reversal in Short-Wave IR reflectance. Analysis of specific bands in a particular spectral graph which was related to biophysical and biochemical attributes was done following standard procedure.

3.2.5 Identification of central wavelengths by derivative analysis

3.2.5.1 Calculation of first order and second order derivatives

Derivative analysis is generally done to overcome or improve absorption features that are masked by interfering background absorption (Curran *et al.*, 1990; Filella and Penuelas, 1994). While high-order derivatives are used in some studies, first and second-order derivatives are the most widely used. To obtain spectral position-based variables, first- and second-order derivatives were used in this analysis following the method as per Thorp *et al.*, (2017).

The instantaneous rate of change of a dependent variable with respect to an independent variable is represented by the first order derivative.



Fig. 9 a: Recording of observations



Fig 9 b: Recording of observations from crop canopy

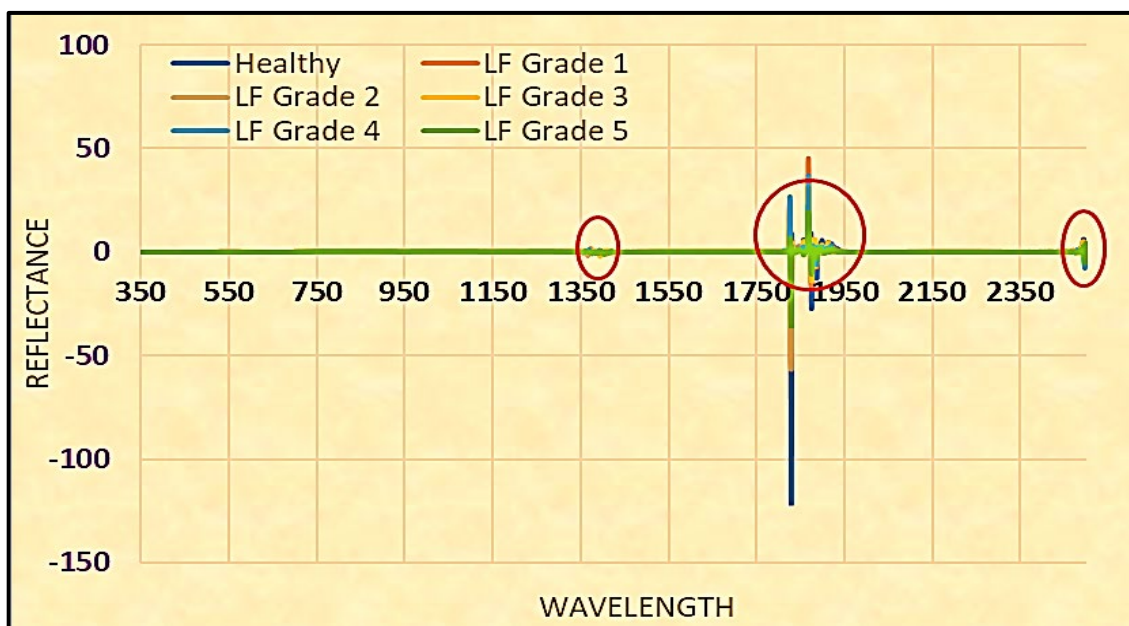


Fig 10: Removal of water parameters

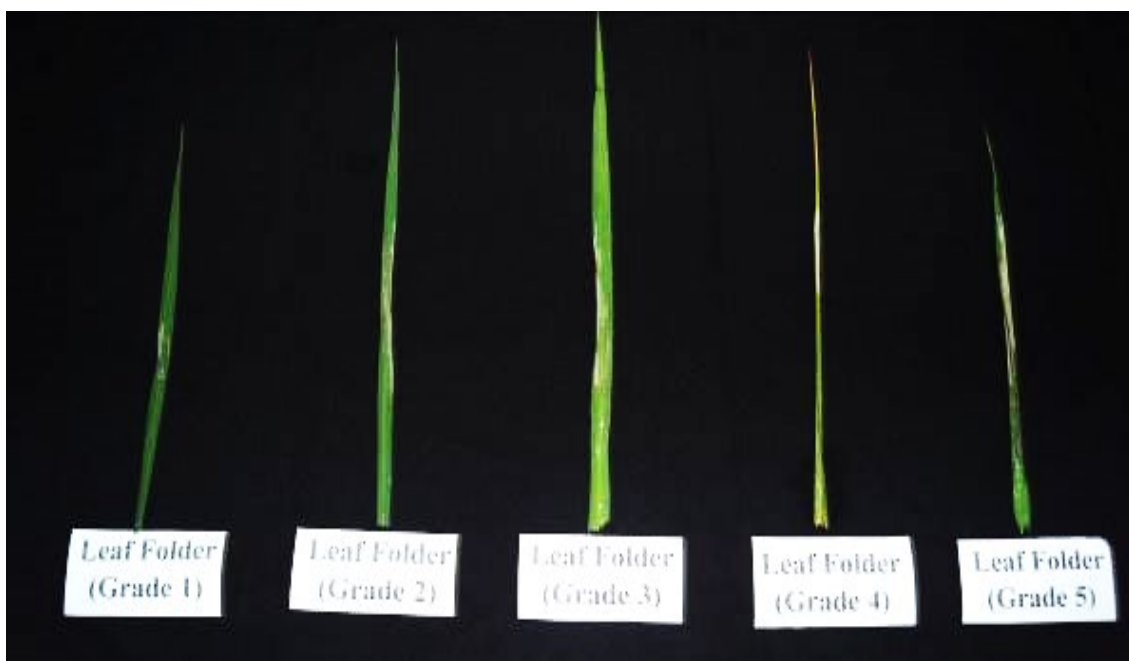


Fig 11: Rice leaves differentially infested by *C. medinalis*

The first order derivative provided the slope of the tangent line drawn at a specific point on the graph curve in terms of the graph derived from the experiments in three crop seasons. The analysis revealed significant differences between the healthy and leaf folder-infested samples, and the gaps in the results indicated that water parameters had been removed and were analysed further. The second-order derivative is the derivative of the first derivative corresponds to the curvature or concavity of the graph. The graph of a function is upward concave if the second-order derivative value is positive. The sign of the second derivative tells us whether the slope of the tangent line to f is increasing or decreasing.

The first- and second-order derivatives were calculated using the equations (2) and (3)

$$\frac{dy}{dx} = f \frac{(x+dx)-f(x)}{dx} \quad (2)$$

$$\frac{d^2y}{dx^2} = \frac{d}{dx} \left(\frac{dy}{dx} \right) \quad (3)$$

Where x indicates the reflectance and y indicates the wavelength.

3.2.5.2 Calculation of change in derivatives in percentage

For each experimental season, the percentage change in first order derivative was calculated from both the canopy and the leaf, taking into account the sensitive spectral areas. The graphs were created using the percentage change in derivative values as well as the wavelengths. The wavelengths that were chosen as the central wavelengths for insect damage because they showed the maximum percentage change in derivative values.

3.2.6 Identification of central wavelengths by continuum removal

After the generation of spectral libraries for both the healthy as well as infested plant samples from different spectral ranges, various absorption windows were identified. For each absorption window, the continuum removal was performed. The continuum removed spectral graphs were derived by using ENVI software. Since the continuum is a convex hull fitted over the top of a spectrum using straight-line segments that connect local spectra maxima, the overall concave form of a spectrum was removed in order to quantify absorption features in spectra (Sowmya and Giridhar, 2017).

The first and last spectral data values are on the hull; therefore, the first and last bands in the output continuum removed data file are equal to one. The formula representing the continuum equation is

$$S_{cr} = \frac{S}{C} \quad (4)$$

where S_{cr} is continuum removed spectra, S stands for original spectrum and C is indicating the continuum curve.

When the continuum and spectra match, the image spectrum is equal to 1.0, and when absorption features appear, it is less than 1.0. The central wavelengths were established and standard techniques were used to analyse them.

3.2.7 Identification of pest sensitive spectral bands through unpaired t-test

The spectral bands identified as central wavelengths were subjected for testing of its significance through unpaired t-test. In the derivative and continuum methods, the repeating of comparable bands or bands with mere proximity was avoided and just one band was exposed to the significance test. Unpaired t-tests were performed on these central wavelengths with increments of 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 nm on either side. The wavelengths that showing significance with increments of up to 100 nm on either side were chosen as the most significant bands or most sensitive bands for leaf folder infestation. The non-significant bands were also removed since they were unrelated to leaf folder infestation.

3.3 Establishment of relationship between hyperspectral reflectance data with reference to leaf folder damage in rice and biochemical composition of plant

The relationship between the pest sensitive spectral bands and various plant biochemical parameters i.e., chlorophyll, phenol and carotenoid were established in order to determine the exact reason of sensitivity of spectral bands. The best band combination was identified utilising the feature selection approach as well as the computation of several vegetative indices specific to leaf folder damage.

3.3.1 Relationship of hyperspectral reflectance with plant biochemical parameters

Healthy and infested leaves (infested by *C. medinalis*) at different damage level of the experimental microplots were analyzed for estimating different plant biochemical

parameters i.e., chlorophyll, phenol and carotenoid in the laboratory of ICAR- National Rice Research Institute, Cuttack during Rabi 2018-19.

3.3.1.1 Estimation of leaf chlorophyll

Total chlorophyll content was estimated by the method described by Arnon (1949). The leaf samples (2nd leaf) of 25 mg was dipped in 10 ml of 80 % acetone in a graduated glass tube. The glass tubes were incubated in dark at 4⁰C for 48 hours. The absorbance data were measured after 48 hours at 645 nm and 663 nm. Quantification of total chlorophyll, *chlorophyll a* and *chlorophyll b* content in an 80 % acetone extract was done by the following formulae.

Total chlorophyll (mg/g fresh weight) = $20.2 (A_{645}) - 8.02 (A_{663}) * \text{dilution factor}$

Chlorophyll a (mg/g fresh weight) = $12.7 (A_{663}) - 2.69 (A_{645}) * \text{dilution factor}$

Chlorophyll b (mg/g fresh weight) = $22.9 (A_{645}) - 4.68 (A_{663}) * \text{dilution factor}$

Where, A_{645} and A_{663} are the absorbance at 645 and 663 nm respectively.

3.3.1.2 Estimation of phenol

Phenol content in the leaves was determined as per the methodology suggested by Malik and Singh (1980). Each sample's homogenate was centrifuged for 20 minutes at 10,000 rpm. The residue was then extracted using five times as much 80 percent ethanol and centrifuged as before. The supernatant was then preserved. The supernatant was kept and dried in a bath of hot water. Each test tube was filled with 5ml of distillate water. Then each test tube received 0.5ml of Folin-Ciocalteu reagent. Test tubes were shaken vigorously. After 3 min. 2ml of 20% Na_2CO_3 (W/V) was added to each tube. The contents were mixed thoroughly. Then test tubes were kept in hot water bath at 100°C for 1minute. The reaction mixture was cooled and absorbance was measured at 650 nm against a reagent blank. Standard curve was prepared using different concentrations of catechol equivalents as milligram per gram of leaf tissue on fresh weight basis.

3.3.1.3 Estimation of carotenoid

The method recommended by Litchenthaler and Wellburn (1983) was used to determine the amount of carotenoid in the leaves. To keep the chosen leaf samples

fresh, they were sealed in wet polythene bags. The centre of the leaf was used to extract 100 mg of fresh leaf, which was then cut into little pieces. The leaf discs were then put in a solution of 80% v/v acetone and left in the dark for 24 hours. The filtrate was then used to measure the absorbance (OD) at 480 nm after they had been filtered by Whatman No. 1 filter paper. The respective chlorophyll content was calculated by using the following formula and expressed as mg/g FW of leaf.

$$\text{Carotenoid} = [(OD_{480} + (0.114 \times OD_{663}) - (0.638 \times OD_{645})) \times V / 1000 \times W$$

The correlation between the reflectance value at the sensitive bands identified and the various biochemical parameters at various damage levels was determined and correlation coefficients (R) were calculated using MS Excel. The value of the correlation coefficient with R values more than 0.5 were regarded to be distinct bands of absorption for that component.

3.3.2 Identifying the best band combination by feature selection

In the present research, the hyperspectral signatures of healthy and leaf samples infested by *C. medinalis* were evaluated using a non-imaging spectroradiometer. Using the RELIEFF method in MATLAB, significant and most relevant wavelengths and two band normalised changes from 400 to 900 nm describing the impact of pest were retrieved from the data-set. The optimal weighted combination of a single wavelength and a normalised wavelength difference was sought to generate hyperspectral indices.

Evaluation functions using Support Vector Machine (SVM) based upon the error rate were far superior to those based upon intrinsic properties of the data (Preet and Batra, 2015). Several combinations of a search algorithm and an evaluation function were used to determine the optimal feature subset for a particular database. The optimal set of features for an intrusion detection system was determined using random generation together with sequential selection and backward sequential selection, as well as at least two separate error rate evaluation methods. Because weaker features are not considered during subset selection, it is said that backward selection finds weaker subsets of features (Ren *et al.*, 2020).

3.3.3 Determination of vegetative indices

Spectral vegetative indices (VI) are mathematical combinations of various spectral bands, primarily in the visible and near-infrared regions of the electromagnetic

spectrum which is determined on the basis of vegetation's reflectance properties. The spectral vegetation indices are primarily intended to improve the information in spectral reflectance data by extracting variability caused by plant properties (such as leaf area index, vegetation cover) and minimising influences from soil, the atmosphere, and sun-target-sensor geometry. Each VI is intended to highlight a different aspect of the vegetation. The majority of them are referred to as broadband VIs because they combine reflectance in the red (R) and near infrared (NIR) spectral bands (Elvidge and Chen, 1995) *i.e.*, normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) to detect crop stress (Vigier *et al.*, 2004; Yang *et al.*, 2009).

3.3.3.1 Determination of predetermined vegetative indices

Normalized Difference Vegetation Index (NDVI): NDVI has been routinely utilised to diagnose agricultural stress because of its significant correlation with vegetation characteristics like biomass and green leaf area (Curran, 1980). It is the normalized difference of green leaf scattering in NIR and chlorophyll absorption in red region (Sims and Gamon, 2002; Yang *et al.*, 2009). NDVI is defined by the following equation.

$$NDVI = \frac{(RNIR - RRED)}{(RNIR + RRED)} \quad (5)$$

where, RRED and RNIR indicate reflectance in the red and near infrared (NIR) wavelength bands, respectively. This index's value lies between -1 and 1. The typical range for green vegetation is between 0.2 and 0.8. It can, however, saturate in dense vegetation conditions when LAI becomes high (Rouse *et al.*, 1973).

Leaf Area Index (LAI): This index is used to forecast crop growth and yield and to assess foliage cover. Using the empirical formula from Boegh *et al.*, (2002), ENVI calculates green LAI.

$$LAI = (3.618 * EVI - 0.118) \quad (6)$$

Where *EVI* is the Enhanced Vegetation Index value.

High LAI levels often range between 0 and 3.5. However, the LAI values can go above 3.5 when the scene include clouds and other bright features that result in saturated pixels. EVI is most useful in high LAI regions and the values of EVI values should range from 0 to 1 for vegetation pixels.

Enhanced Vegetation Index was originally developed for use with MODIS data as an improvement over NDVI by optimizing the vegetation signal in areas of high leaf area index (LAI). It is most useful in high LAI regions where NDVI may saturate.

$$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + 6 * Red - 7.5 * Blue + 1)} \quad (7)$$

Red Edge Position Index (REPI): This index measures narrowband reflectance and is responsive to variations in chlorophyll content. With more chlorophyll present, the absorption characteristic is widened and the red edge is moved to longer wavelengths. In the vegetation red edge region of the spectrum, the highest derivative of reflectance has a wavelength that ranges from 690 nm to 740 nm. The common wavelength range for greenery is 700–730 nm (Curran *et al.*, 1990).

Photochemical Reflectance Index (PRI): This index, which measures reflectance, is responsive to changes in the carotenoid pigments in live foliage. Carotenoid pigments are a good indicator of photosynthetic light use efficiency purpose or the rate of carbon dioxide uptake per unit of energy (Penuelas *et al.*, 1995 and Gamon *et al.*, 1997)

$$PRI = \frac{(R531 - R570)}{(R531 + R570)} \quad (8)$$

Where R531 and R570 are the reflectance in 531 and 570 nm. The value of this index ranges from -1 to 1. The common range for green vegetation is -0.2 to 0.2.

Plant Senescence Reflectance Index (PSRI): This index maximizes the sensitivity of the index to the ratio of bulk carotenoids to chlorophyll. An increase in PSRI indicates increased canopy stress (carotenoid pigment), the onset of canopy senescence and fruit ripening. The value of this index ranges from -1 to 1. The common range for green vegetation is -0.1 to 0.2 (Merzlyak *et al.*, 1999).

$$PSRI = \frac{\rho_{680} - \rho_{500}}{\rho_{750}} \quad (9)$$

3.3.3.2 Determination of new vegetative indices

Spectral analysis was done to evaluate all available chlorophyll indices for leaf and canopy level estimate using the experimental data. Only a few leaf scale indices were shown because they gave interesting findings or worked well at the canopy size.

Furthermore, various two-band and three band indices using two and three random available wavebands (selected from the sensitive bands found) were calculated viz., (1) a simple ratio (SR) index; (2) a normalized difference (ND) index and (3) a simple difference (SD) index to determine the best indices and the extent of the effective band combination regions for chlorophyll assessment, as shown in equations. (10) – (12).

$$SR = \frac{R1}{R2} \quad (10)$$

$$ND = \frac{R1-R2}{R1+R2} \quad (11)$$

$$SD = R1 - R2 \quad (12)$$

For rice total chlorophyll, the simple ratio, simple difference and normalized differences indices from any two and three random sensitive bands were compared. The best performing SR, SD and ND indices were found in the visible and near infrared (NIR) waveband ranges. The relation of two band and three band combinations with the leaf chlorophyll was evaluated by estimating the linear regression and computing the value of goodness of fit (R^2) for each damage level.

The equations for the linear regression were also noted as per the reference. The particular band combination which had R^2 value more than 0.5 or the value nearer to 1, the combination was selected as a new and best fit indices for estimating leaf chlorophyll for damage due to *C. medinalis*.

3.4 Relationship of field measurement of spectral signature with the leaf folder damage

After discriminating the damage by leaf folder through hyperspectral remote sensing techniques and identifying the pest sensitive bands or significant spectral bands, the information was validated by recording and analysing the reflectance data from farmer's field which was without any controlled condition and the damage caused by the insect was not induced by releasing different numbers of larvae. For comparing the particular spectral conclusions, along with the farmers field data similar rice variety was again transplanted and in controlled condition and the damage was simulated by releasing differential leaf folder larvae. Further the ground truth hyperspectral data including the healthy and damaged vegetation was validated with satellite imagery using sentinel analysis.

3.4.1 Identification of pest sensitive bands (farmers field and controlled conditions)

3.4.1.1 Acquisition of spectral data of rice variety Naveen from farmer's field

The observations were taken from farmer's field located in village Aruha of block Pipili, Puri located at 20°08'39" North latitude, 85°50'68" East longitude and at an elevation of 25.9 m above mean sea level during Rabi, 2018-19. The farmer's fields were located in a medium land with assured irrigation facility. Soil of the experimental plot was sandy loam with an average pH of 6.7. The variety cultivated by the farmers was *Naveen*, a high yielding rice variety evolved by ICAR- National Rice Research Institute, Cuttack, Odisha. The particular variety was duration of 115- 118 days with optimum yield of 5-6 tonnes per hectare. All the recommended agronomic practices were followed by the farmers for raising the crop. Observation on infestation of *C. medinalis* in the farmer's field was recorded and the level of infestations was categorized into five broad classes as per Huang *et al.*, 2012 (Table 4).

Table 4. Categorization of leaf folder infestation in farmer's field

Category of infestation	Leaf infestation (%)	Damage
Category 1	0	No damage (Healthy)
Category 2	< 10	Slight damage
Category 3	10-30	Slight to moderate
Category 4	30-50	Moderate to severe
Category 5	> 50.0	Severe

3.4.1.2 Determination of spectral signature in the mimicking rice variety

The rice variety Naveen cultivated in farmer's field was chosen as mimic variety to determine the spectral signature. The mimicking process was adopted to nullify the varietal spectral variation and to make the comparative spectral study smoother in both the field (natural conditions) as well as conditions controlled by human interference. The microplots of size 0.5m x 0.5 m were selected for transplanting the mimicking variety.



Fig 12: Observation from farmer's field at Aruha, Pipili



Fig 13: Rice variety 'Naveen' in experimental subplots as mimicking variety

Design	: Randomized Block Design
Crop	: Rice
Variety	: Naveen
Duration	: 110-120 days
Date of transplanting	: 22/11/2018
Plot size	: Each micro-plot measured 2.25 m ² (0.5m.x 0.5m.)
Spacing	: 20cm X 15cm
FYM	: 5 tonnes /ha
Fertilizers	: 100:50:50 kg of N: P ₂ O ₅ : K ₂ O per hectare
Date of harvest	: 10/03/2019
Replication	: Four
Treatments	: Six

To avoid the intrusion of other insect pests, the microplots were covered with nylon nets measuring 0.6m x 0.6m. Rice leaf folders, the target insect, were captured from the field and reared in the laboratory. To achieve differential damage levels, the second to fourth instar larvae were released in the microplots at varied counts. Differential damage levels by leaf folder infestation were established in separate microplots with mimicking variety (Naveen) after a week of larval release. Spectral data collection and its subsequent processing technique were followed from these microplots to determine the sensitive bands based on differential damage levels according to INGER, 1996 (Table 2).

Table 5. Treatments of the experiment to find out the reflectance rice variety ‘Naveen’ at ICAR-NRRI, Cuttack at differential damage level

Sl No	Treatments	Number of larvae of <i>C. medinalis</i> released per microplot
1	T ₁	0
2	T ₂	5
3	T ₃	10
4	T ₄	20
5	T ₅	30
6	T ₆	50

3.4.1.3 Data acquisition and pre-processing

Spectral reflectance of the rice leaves, having differential leaf folder damage were measured at 1-nm intervals over wavelengths ranging from 400 to 2500nm with a FieldSpec3 portable spectroradiometer (Analytical Spectral Devices (ASD), Boulder, CO, USA). The measurement was carried out under absolute sun light (12.00 – 14.00) recommended by Salisbury (1998). Before collecting spectral reflectance, the instrument was standardized with respect to solar radiation by using a white reference plate. The raw data of rice leaves having differential leaf folder damage from each microplot was taken. The spectroradiometer was placed approximately 10-15cm above the rice canopy and 10 spectral reflectance readings were taken from each plot. The spectral observations were carried out both from farmer's field as well as the experimental plots which had the same variety as farmer's field.

The data generated using a hyper spectral spectroradiometer from the rice canopy (both healthy and infested) was classified by infestation scales. The reflectance readings were categorized according to the damage level in concern. The data were pre-processed with View Spec Pro software. The water parameters or the atmospheric perturbations were removed from the spectral data and the spectral curves for the vegetations from farmer's field as well as the experimental plots were plotted. From the spectral curves, the vegetations were discriminated on the basis of the infestation and various conclusions were drawn.

3.4.1.4 Identification of pest sensitive bands for reflectance from farmers field and mimicking variety in experimental plot

The first and second order derivatives were computed from the spectral data. The change in slope was described by the first order derivative, while the change in curvature was explained by the second order derivative. The change in derivative (percentage) were also calculated and represented by the spectral graphs. The particular spectral bands with maximum change in derivatives were considered as the central wavelengths. The ENVI software package was used to create the continuum removed spectral signatures. From the continuum removed curves derived, the central wavelengths were also selected having maximum dip in the continuum removed graph. The central wave bands selected and at 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 nm

interval the unpaired t-test was performed. The bands found significant at each interval were chosen as the significant bands for detection of rice leaf folder infestation.

A comparison was done between the sensitive bands found after rice leaf folder infestation at different damage level earlier for the susceptible rice variety TN1 and the bands which were identified for the farmer's cultivated and adopted variety (*Naveen*). The common bands from above study were marked and concluded as the sensitive bands for rice leaf folder infestation. The bands found for rice leaf folder infestation were confirmed as insect specific bands irrespective of variety.

3.4.2 Validation of the ground truth data with satellite imagery using sentinel analysis

The ground truth hyperspectral data taken from the field by the ASD Fieldspec spectroradiometer was validated with the satellite data by sentinel analysis following various technical protocols. Sentinel 2 is part of the Copernicus earth observation program developed by the European Space Agency (ESA) to study the earth's surface. In the present research the sentinel 2A imagery was used for the validation purpose. Sentinel 2A satellite completes the Sentinel-2 mission with a global coverage of images with spatial resolutions of 10m, 20m, and 60m. It has 13 bands available in VNIR (Visible and Near-Infra-Red) and SWIR (Short Wave Infra-Red) with a 290 km swath width. These are the two focal plane assemblies within the passive multi-spectral instrument (MSI).

The validation work was carried out using Sentinel 2A satellite multispectral imagery shown in Fig 14. The procedure was started with downloading of Sentinel 2A cloud free satellite imagery of the particular location (Aruha, Pipili) from where the ground truth data was taken. The downloaded cloud free image of the location was the image of very near date to the experimental date. Four bands of Sentinel-2A with 10 m resolution (Band 2, 3, 4 and 8) and three bands from 20 m resolution (Band 5, 6 and 7) were used for the analysis. the bands from 20 m resolution were resampled to 10 m as well as five common VIs (NDVI, LAI, REPI, PRI and PSRI) were chosen for its ability to estimate leaf chlorophyll as well as carotenoid content. The ground truth data was recorded on 7th September, 2019 when the vegetation was in the booting stage.

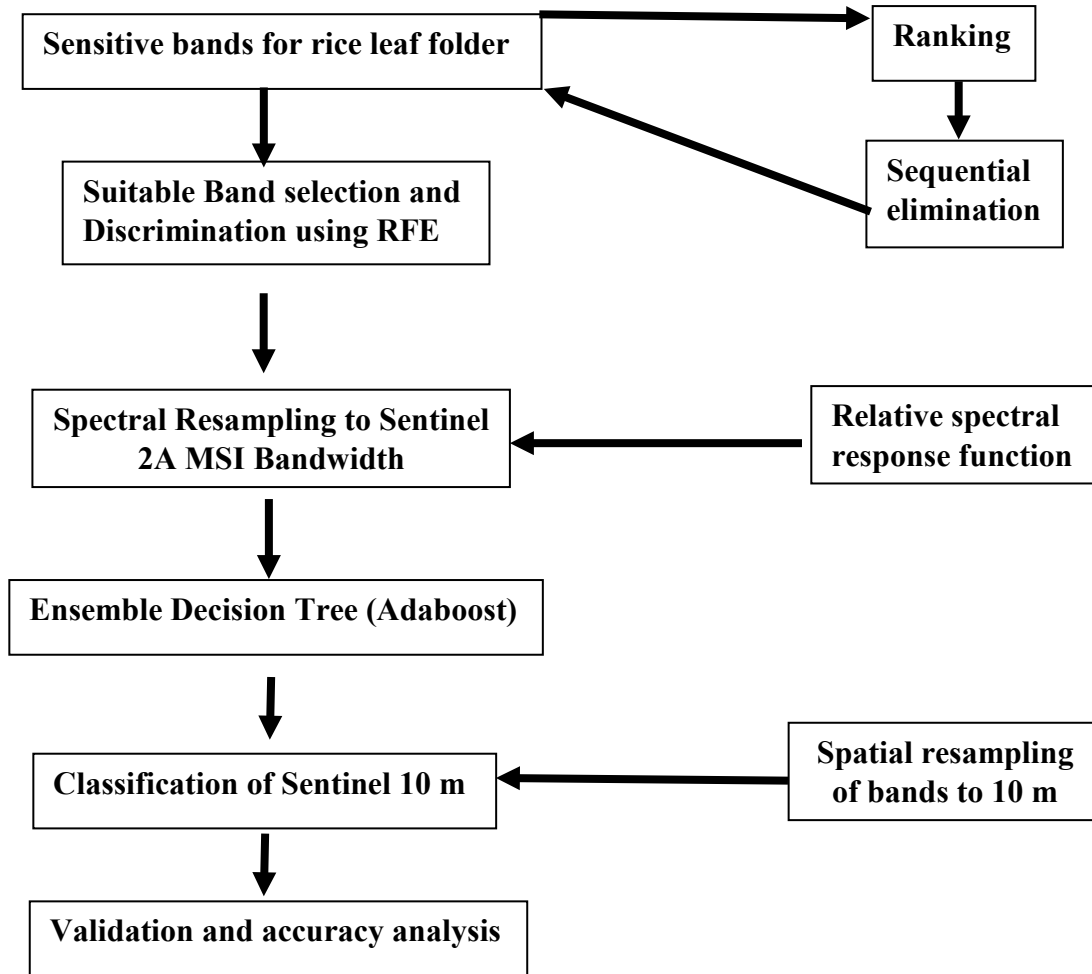


Fig 14: Sentinel 2A spectral data validation flowchart

Table 6. Sentinel 2A spectral bands

Sentinel Bands		Centre (λ) in nm	Spectral width ($\Delta\lambda$) in nm
B	1	443	20
B	2	490	65
B	3	560	35
B	4	665	30
B	5	705	15
B	6	740	15
B	7	783	20
B	8	842	115
B	8a	865	20
B	9	945	20
B	10	1375	30
B	11	1610	90
B	12	2190	180

After superimposing the image and finding out the composite imagery using sentinel 2 to 8 bands, the false colour composite (FCC) imagery was derived in the ENVI software with plotting the Receiver Operating Characteristics (ROC) curve and estimating the accuracy percentage. The FCC indicated the exact spots of the healthy and infested vegetation by different colour codes.

3.5 Softwares and statistical analysis

3.5.1 Softwares

Different software tools were used for hyperspectral image analysis. The ViewSpec Pro was used for preprocessing the hyperspectral reflectance data. The continuum removal procedure as well as the sentinel analysis were aided by ENVI software. MATLAB provided tools for data exploration, visualization, and algorithm development that support hyperspectral imaging workflows. A supervised learning algorithm called a support vector machine (SVM) is one of the important methods in MATLAB software utilised for feature selection and data redundancy. ArcGIS and QGIS were also helpful in the research for obtaining the spatial maps and image analysis.

3.5.2 Statistical analysis

The data generated on leaf roll rates of differentially infested canopy were suitably transformed following Gomez and Gomez (1984) and analysed statistically to arrive at meaningful conclusion. Treatment variations were tested for their significance for which F-test standard error and mean standard error i.e., $SE(m) \pm$ and critical difference (CD) at 5 per cent level of significance were calculated following standard procedure for RBD. The unpaired t-test of independent variables with equal variances was performed for each central wavelengths up to 100 nm interval according to method suggested by Rangaswamy (2014) to test its significance.

CHAPTER- IV

RESULTS

Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenee) damage in rice using ground based hyperspectral remote sensing techniques was carried out during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19. The salient findings on various aspects of the study are presented in this chapter.

4.1 Discrimination of rice leaf folder damage by hyperspectral remote sensing techniques through identification of sensitive spectral bands

4.1.1 Extent of leaf roll in response to various population level of *C. medinalis* in rice

Differential damage levels of *C. medinalis* in the crop canopy of rice (var TN1) were created artificially through manual release of larva in microplots during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19. All the treatments involving various levels of larval release showed significant difference in leaf roll rate by *C. medinalis* over untreated control (T_1) during various years of experimentation. Significantly highest leaf roll rate of 73.87 per cent, 60.37 per cent and 66.87 per cent was observed in T_6 (100 larva/m²) during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19, respectively. The untreated microplot (unreleased plot) recorded no leaf roll in rice canopy (Table 7).

Table 7. Intensity of leaf roll at different population level of *C. medinalis* during Rabi 2017 18, *Kharif* 2018-19 and Rabi 2018-19.

Treatments	Leaf roll rate in cropping seasons (%)		
	Rabi 2017-18	<i>Kharif</i> 2018-19	Rabi 2018-19
T_1 (0 larvae / m ²)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
T_2 (10 larvae / m ²)	3.42 (10.62)	2.73 (9.40)	2.45 (8.96)
T_3 (20 larvae / m ²)	11.17 (19.49)	10.47 (18.85)	10.2 (18.51)
T_4 (40 larvae / m ²)	23.62 (29.04)	21.4 (27.55)	28.4 (32.17)
T_5 (60 larvae / m ²)	37.36 (37.64)	37.87 (37.97)	42.6 (40.74)
T_6 (100 larvae / m ²)	73.87 (59.36)	60.37 (51.02)	66.87 (55.13)
SE(m) $\pm$	1.274	0.943	1.717
CD (P=0.05)	3.84	2.84	5.17
CV %	9.79	7.82	13.25

- Figures in parentheses are the transformed (Arc sine $\sqrt{\%}$) values

4.1.2 Discrimination of damage by *C. medinalis* in rice through plotting of spectral curve

In general, the graph derived from rice spectral data (Fig 15, Fig 16, Fig 17 and Fig 18) at differential damage level of *C. medinalis* revealed that uninfested plants (healthy) had higher reflectance in the visible region than infested plants with peak reflectance at around 520-540 nm. Though the reflectance data was available from 350 to 2500 nm, the data from 350 to 399 nm was excluded since this range of reflectance was not in the visible (VIS) range of light. They had increased reflectance in the near infrared (NIR) range. The peak reflectance of infested plant was recorded at 520-540 nm.

Reflectance in the VIS (400-700 nm) was found to be directly related to leaf folder damage, with reflectance increasing from 400 nm to the red edge shoulder at 684, 685 and 690 nm, respectively, corresponding to reflectance from differentially infested and folded leaves at 695 nm during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19, respectively.

However, in the NIR band, reflectance value was reduced with corresponding increase in damage of *C. medinalis*. Highest variation in plant reflectance occurred between leaf folder damage level 5 and damage level 0 in the NIR region. Each graph had a small dip at 760-765 nm which was resulted due to oxygen absorption. The blank space in the spectral curves indicated that the spectral reflectance data had been stripped of water factors and atmospheric disturbances.

The atmospheric disturbances were mostly seen between 1350 and 1450 nm and 1780 and 2000 nm. The elimination of water bands occurred due to a higher reflectance value of more than one. Symptoms of damage of *C. medinalis* included leaf curling and loss in chlorophyll pigments in the form of white patches, which represented feeding injuries caused by the larvae. Uninfested plants were greener as they absorbed blue (450 nm) and red (680 nm) radiation better than the infested plants.

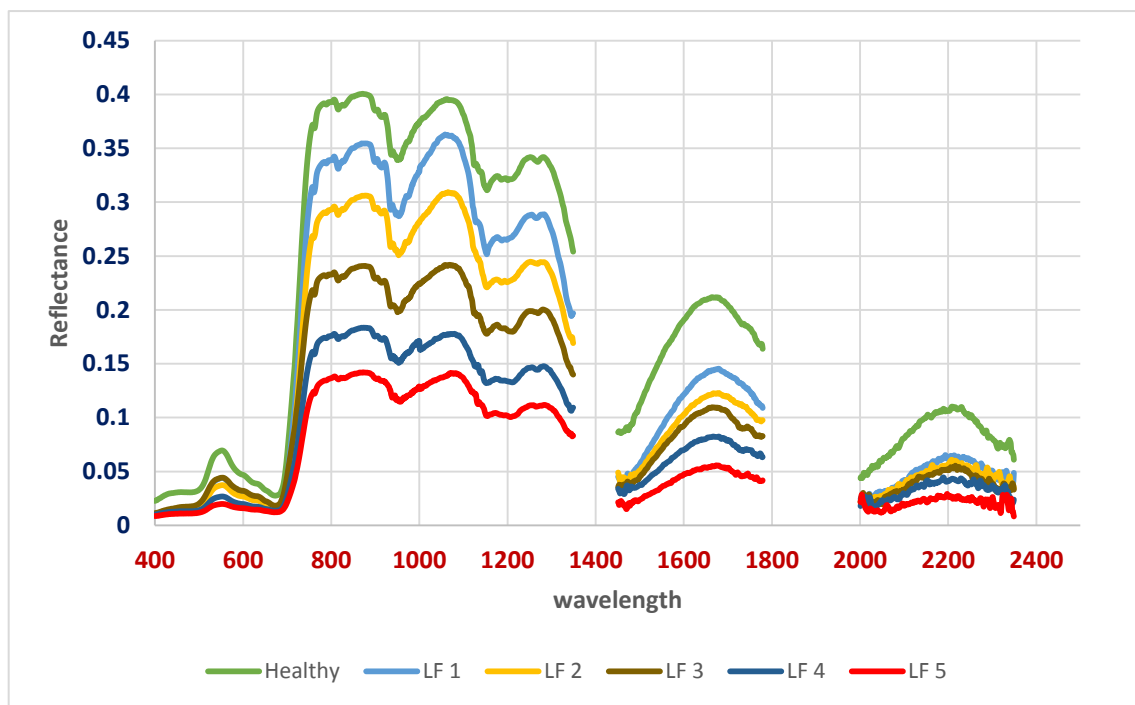


Fig 15. Canopy reflectance graph for Rabi 2017-18

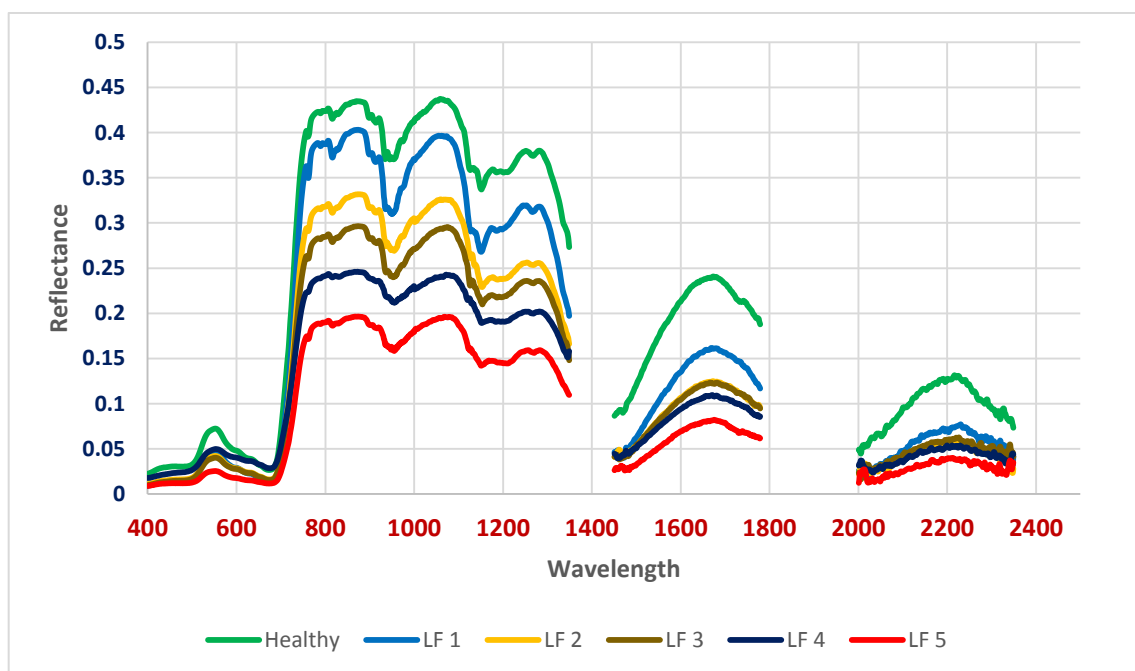


Fig 16. Canopy reflectance graph for *Kharif* 2018-19

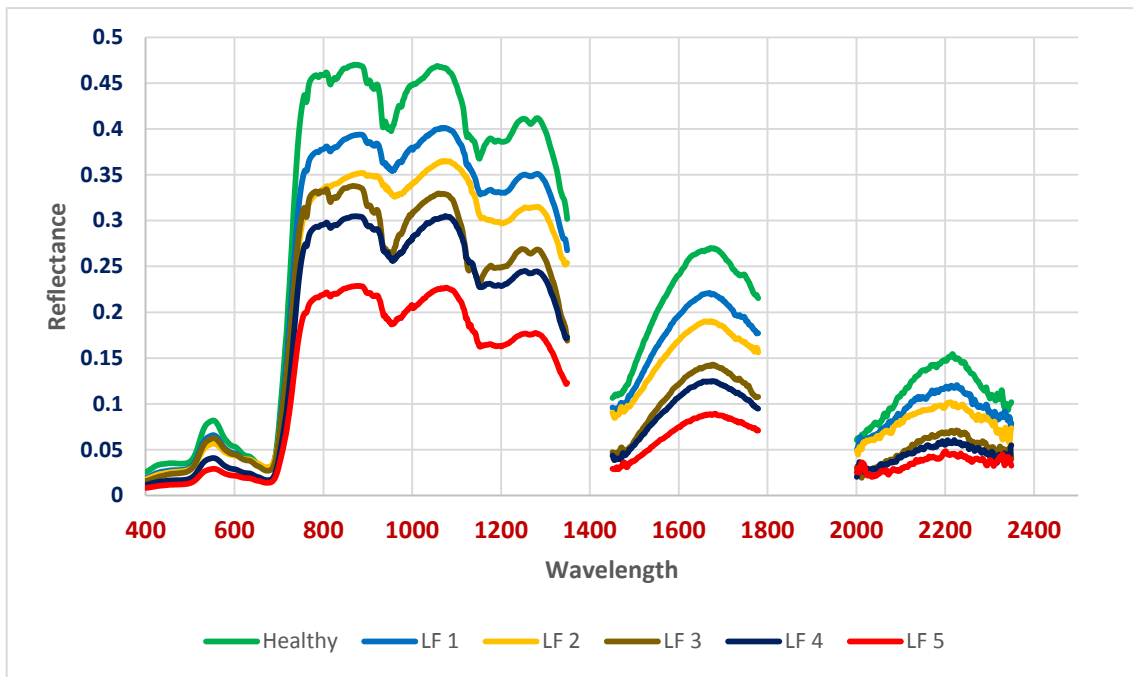


Fig 17. Canopy reflectance graph for Rabi 2018-19

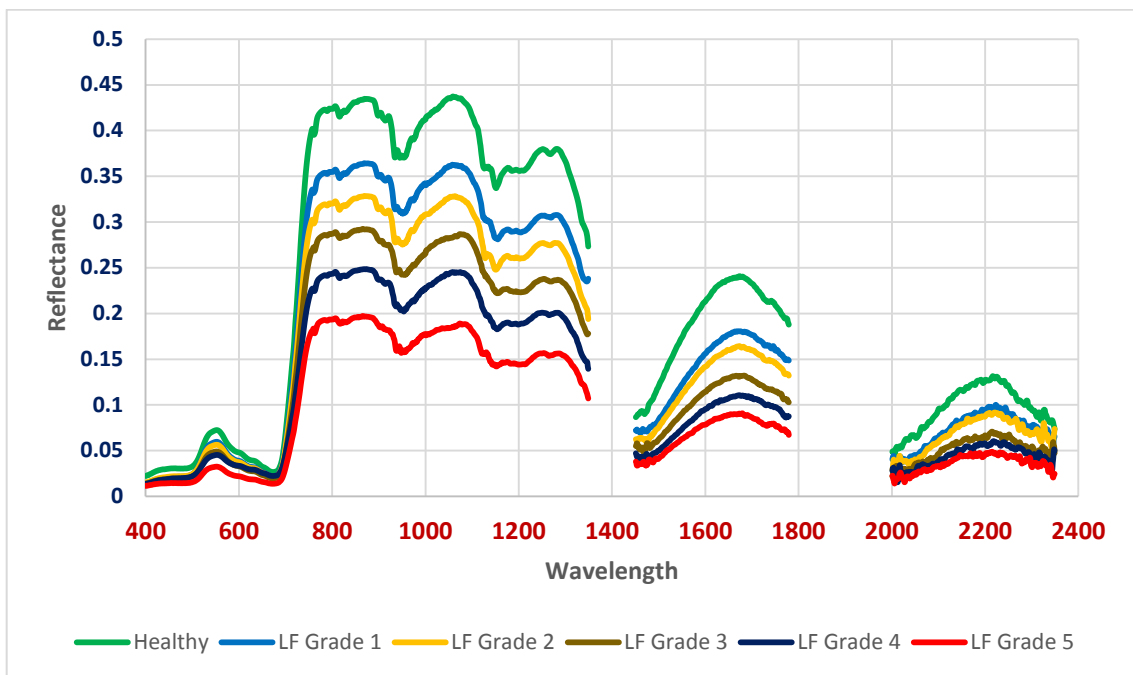


Fig 18. Leaf reflectance graph for Rabi 2018-19

4.1.3 Assessment of change in slope and curvature of spectral bands through derivative analysis

The first and second order derivatives were generated for healthy and leaf folder infested samples at different damage levels so as to assess the change in slope and curvature of the spectral curve after obtaining the pre-processed spectral curve during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 (Fig 19 a to Fig 19 h). Different spectral areas' derivatives were computed and peaks and troughs for different samples in different spectral regions were identified. The change in derivatives (%) was computed to identify the particular spectral band where percentage change was maximum. The specific wavelengths at which the dips and peaks with significant differences found were considered as central wavelengths and they were subjected to t-test for testing of significance.

a) Canopy reflectance:

Results on derivative analysis of canopy spectra for Rabi 2017-18 revealed that at 597, 672, 732, 806, 900 and 1131 nm the percentage change was maximum as shown in the graphs (Fig 20a to Fig 20 f). It was observed that at spectral bands of 411, 597, 672, 733, 806, 898 and 1130 nm the per cent change in derivative was maximum for *Kharif*, 2018-19 (Fig 21 a to Fig 21 g). In a similar manner comparable outcomes were observed for Rabi 2018-19. After calculating the percentage change in derivative for several spectral areas as shown in Fig 22 a to Fig 22 f, it was found that some of the spectral bands in the visible, near infrared (NIR) and short-wave infrared (SWIR) regions had the highest percentage change in derivative. The results were nearly identical to the aforementioned findings from prior seasons. The spectral bands *viz.*, 596, 673, 757, 783, 806 and 1137 nm were identified as designated spectral bands for Rabi 2018-19.

a) Leaf reflectance:

Results on the derivative analysis of leaf reflectance for Rabi 2018-19 indicated that the percentage change in derivative was maximum at spectral bands *viz.*, 411, 597, 672, 733, 806, 898 as well as 1130 nm which discriminated these bands from other (fig 23 a to Fig 23 g).

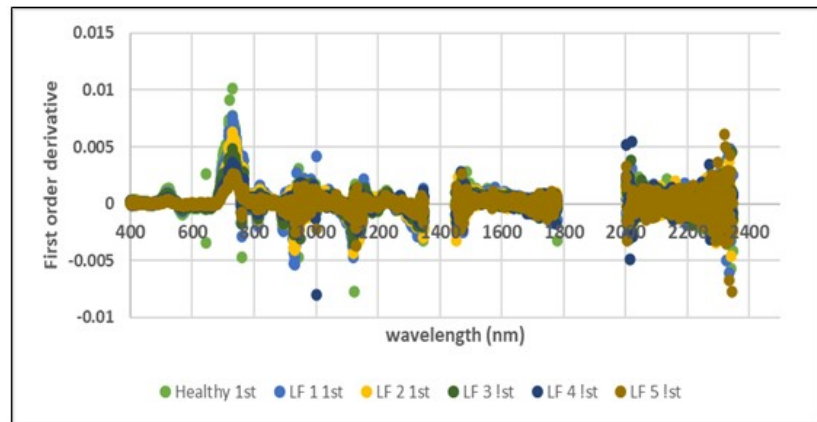


Fig 19 a: First order derivative of Canopy for Rabi 2017-18

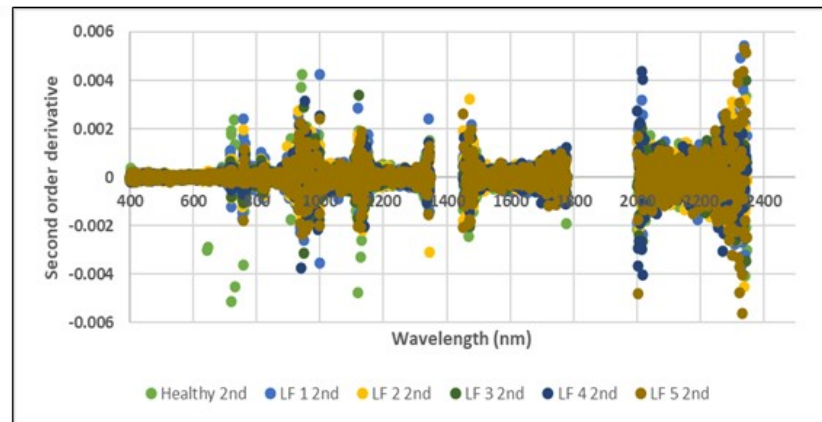


Fig 19 b: Second order derivative of Canopy for Rabi 2017-18

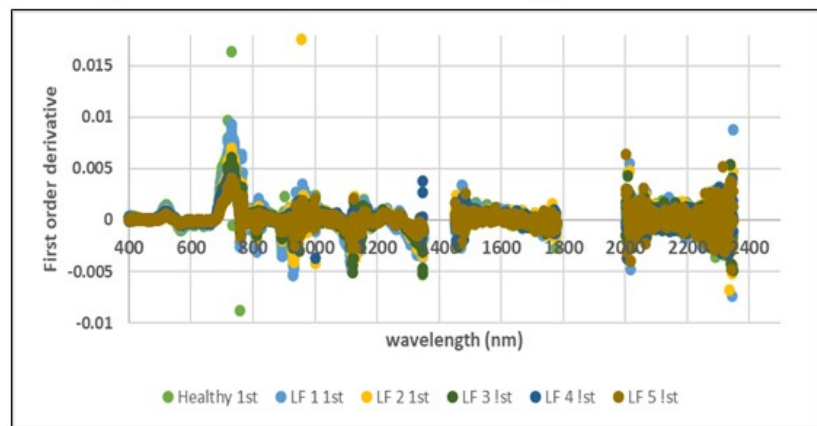


Fig 19 c: First order derivative of Canopy for *Kharif* 2018-19

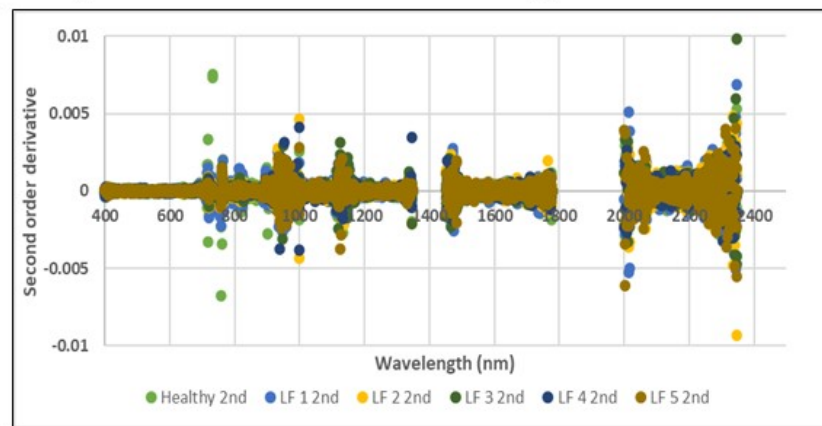


Fig 19 d: Second order derivative of Canopy for *Kharif* 2018-19

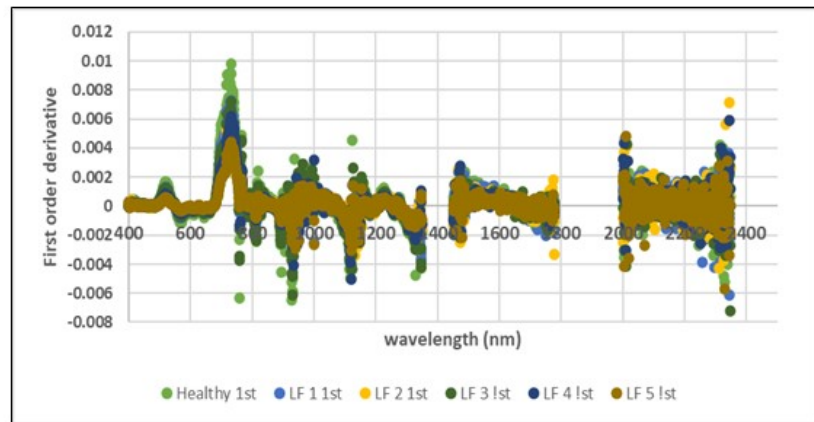


Fig 19 e: First order derivative of Canopy for Rabi 2018-19

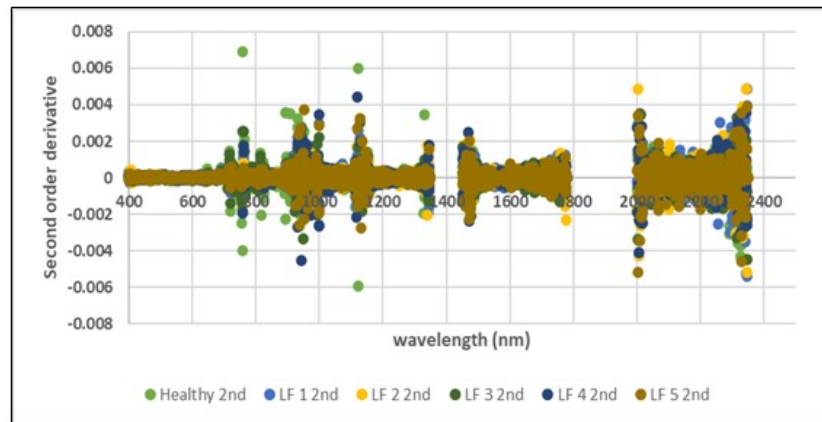


Fig 19 f: Second order derivative of Canopy for Rabi 2018-19

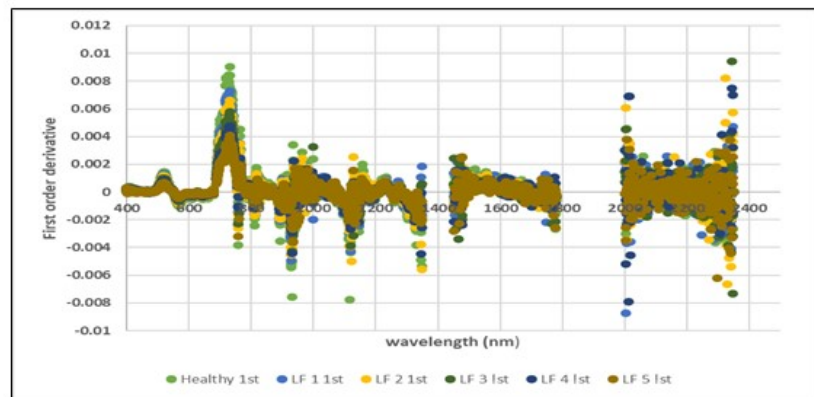


Fig 19 g: First order derivative of leaf for Rabi 2018-19

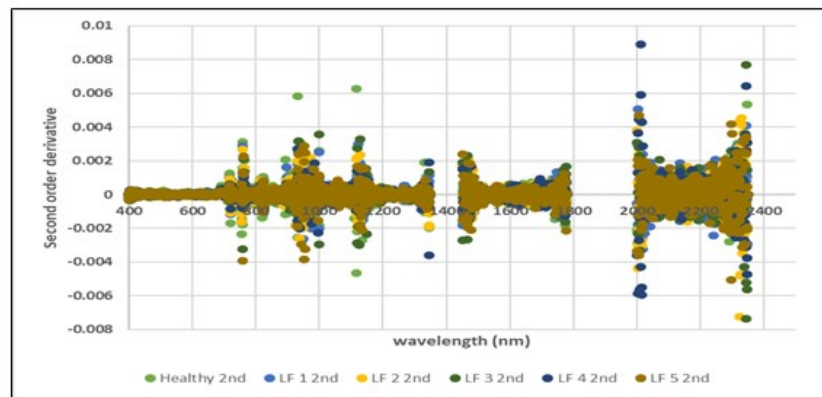


Fig 19 h: Second order derivative of leaf for Rabi 2018-19

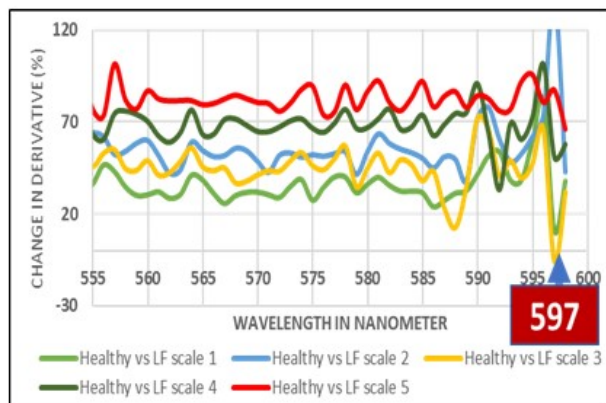


Fig 20 a. Change in derivative 555-600 nm for Rabi 2017-18(canopy)

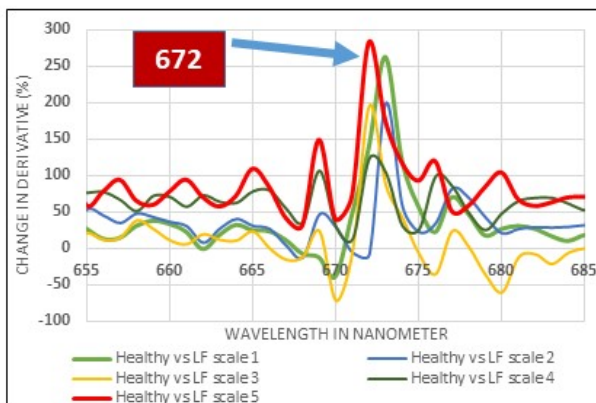


Fig 20 b. Change in derivative 655-685 nm for Rabi 2017-18(canopy)

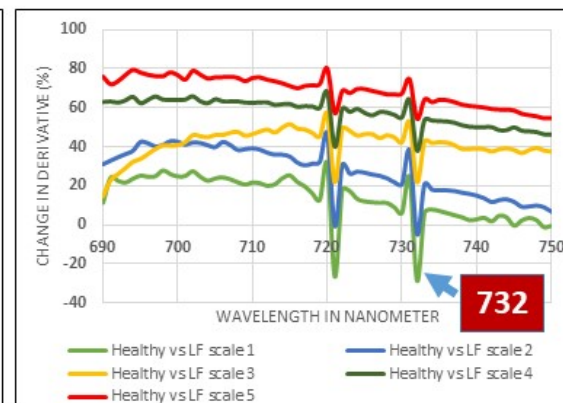


Fig 20 c. Change in derivative 690-750 nm for Rabi 2017-18(canopy)

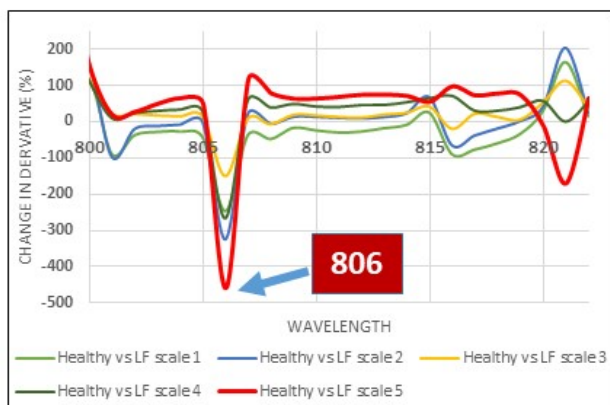


Fig 20 d. Change in derivative 800-825 nm for Rabi 2017-18(canopy)

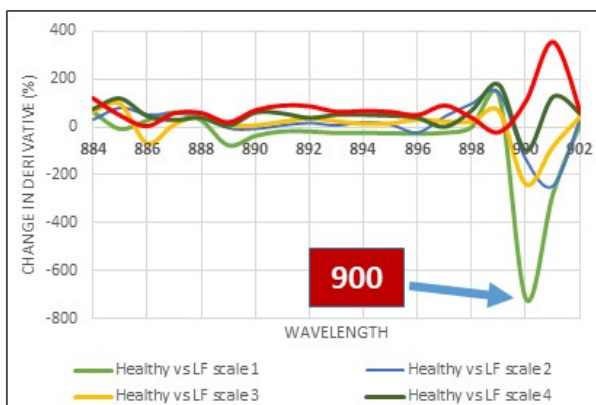


Fig 20 e. Change in derivative 884-902 nm for Rabi 2017-18(canopy)

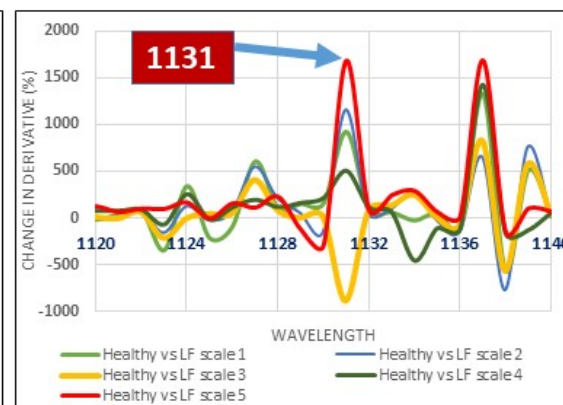


Fig 20 f. Change in derivative 1120-1140 nm for Rabi 2017-18(canopy)

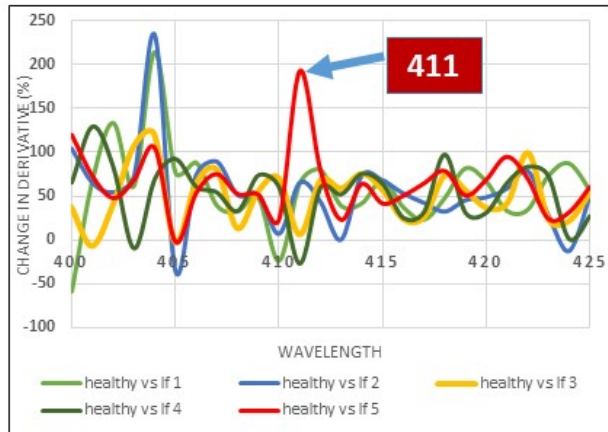


Fig 21 a. Change in derivative 400-425 nm for *Kharif 2018-19*(canopy)

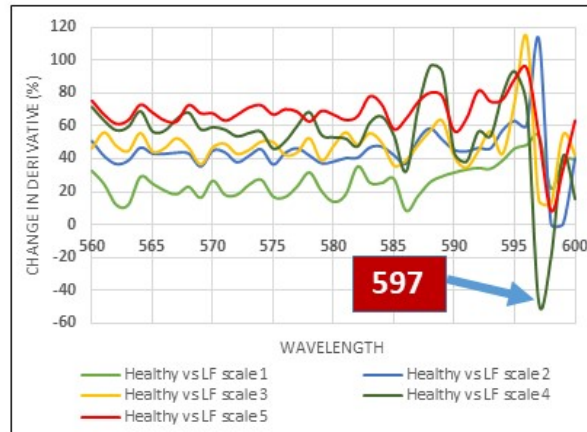


Fig 21 b. Change in derivative 560-600 nm for *Kharif 2018-19*(canopy)

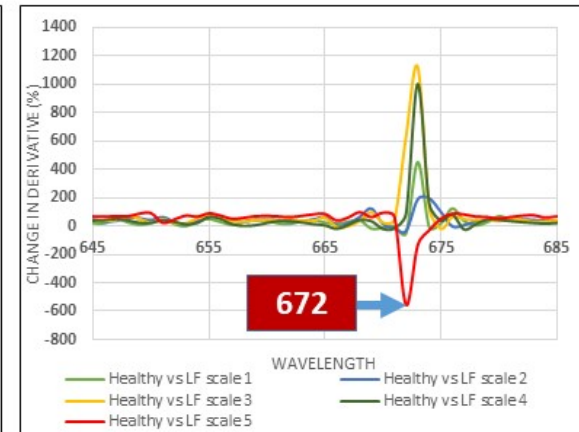


Fig 21 c. Change in derivative 645-685 nm for *Kharif 2018-19*(canopy)

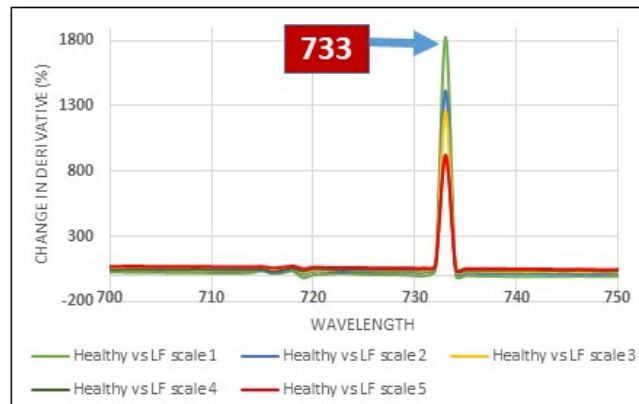


Fig 21 d. Change in derivative 700-750 nm for *Kharif 2018-19*(canopy)



Fig 21 e. Change in derivative 795-820 nm for *Kharif 2018-19*(canopy)

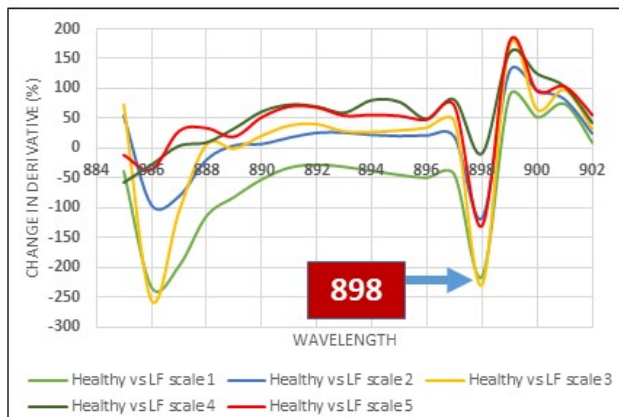


Fig 21 f. Change in derivative 884-902 nm for *Kharif* 2018-19(canopy)

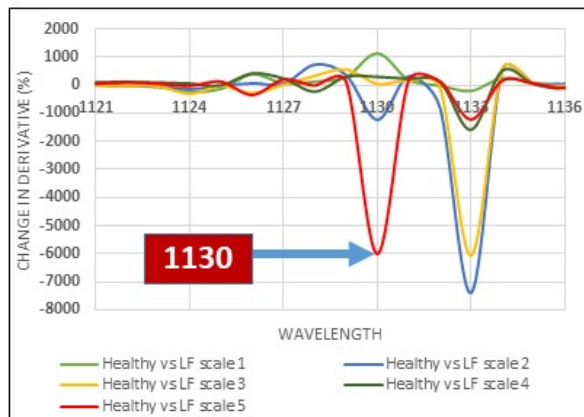


Fig 21 g. Change in derivative 1121-1136 nm for *Kharif* 2018-19(canopy)

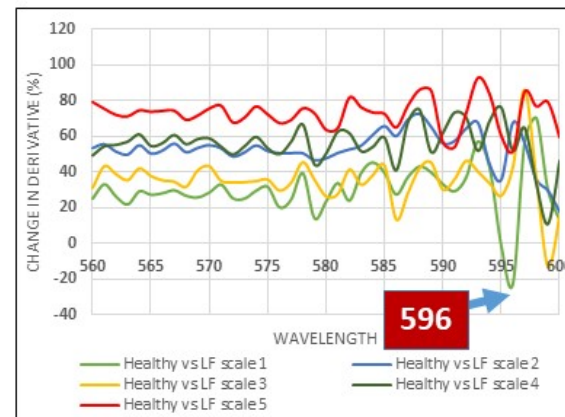


Fig 22 a. Change in derivative 560-600 nm for *Rabi* 2018-19(canopy)

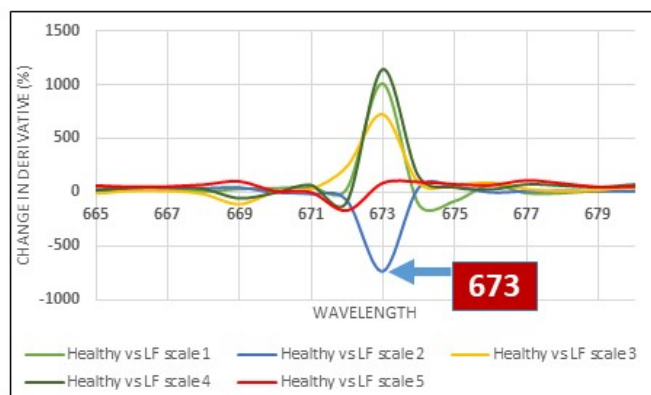


Fig 22 b. Change in derivative 665-679 nm for *Rabi* 2018-19(canopy)

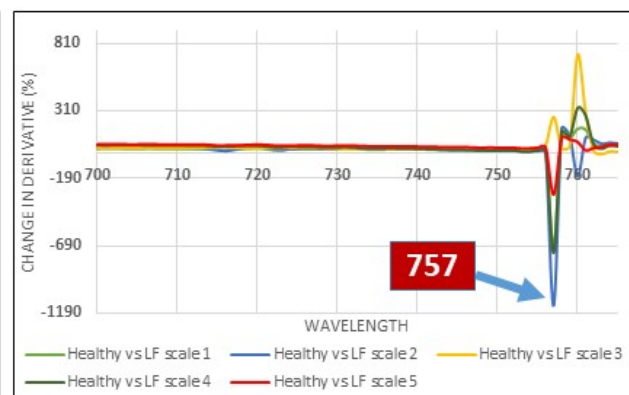


Fig 22 c. Change in derivative 700-765 nm for *Rabi* 2018-19(canopy)

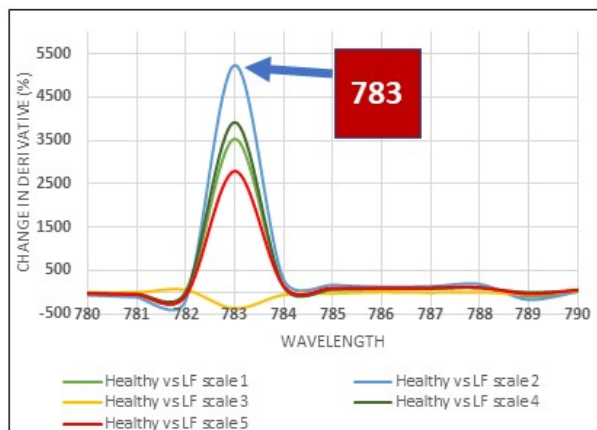


Fig 22 d. Change in derivative 780-790 nm for Rabi 2018-19(canopy)

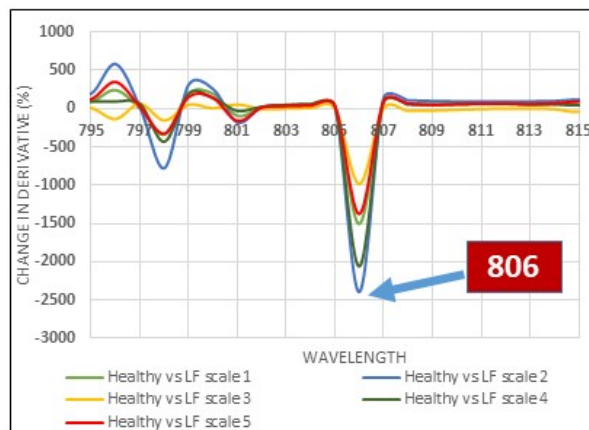


Fig 22 e. Change in derivative 795-815 nm for Rabi 2018-19(canopy)

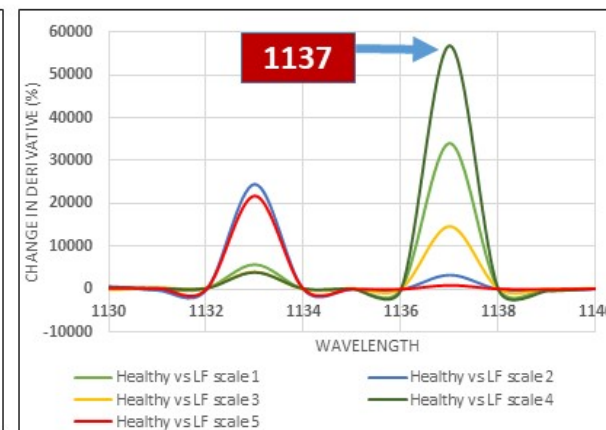


Fig 22 f. Change in derivative 1130-1140 nm for Rabi 2018-19(canopy)

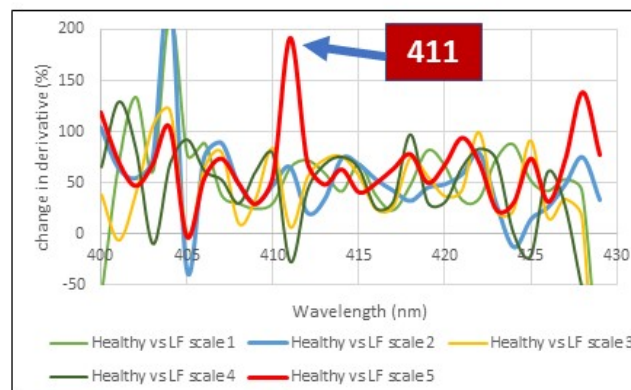


Fig 23 a. Change in derivative 400-430 nm for Rabi 2018-19(leaf)

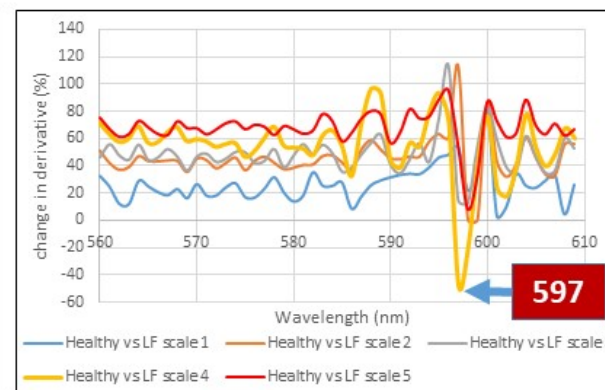


Fig 23 b. Change in derivative 560-610 nm for Rabi 2018-19(leaf)

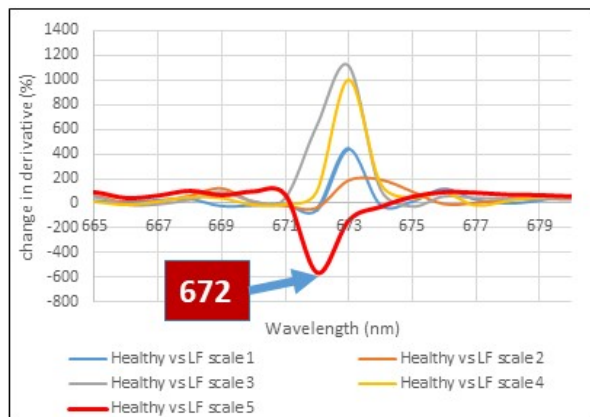


Fig 23 c. Change in derivative 665-680 nm for Rabi 2018-19(leaf)

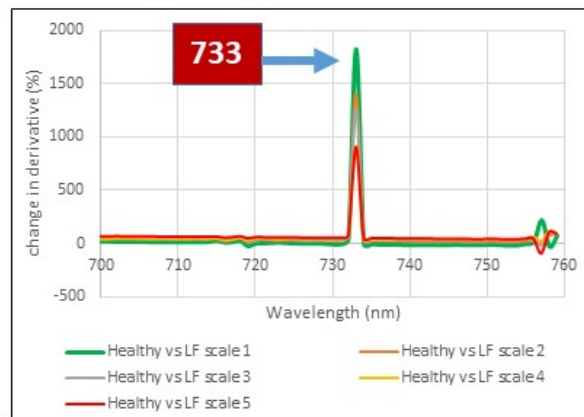


Fig 23 d. Change in derivative 700-760 nm for Rabi 2018-19(leaf)



Fig 23 e. Change in derivative 800-830 nm for Rabi 2018-19(leaf)



Fig 23 f. Change in derivative 885-905 nm for Rabi 2018-19(leaf)

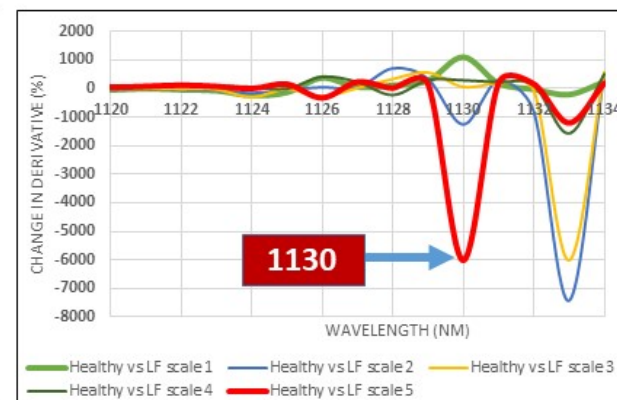


Fig 23 g. Change in derivative 1120-1134 nm for Rabi 2018-19(leaf)

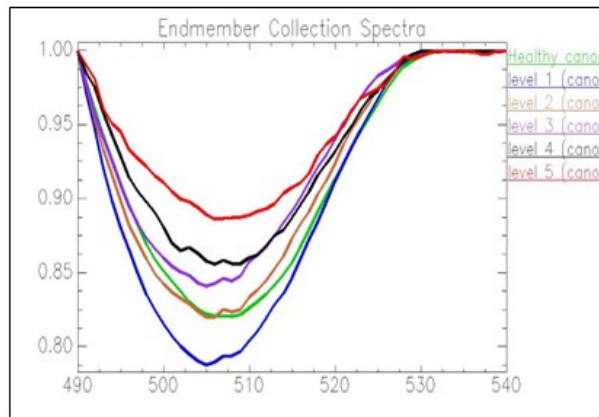


Fig 24 a. Continuum removal of 490-540 (Canopy, Rabi 2017-18)

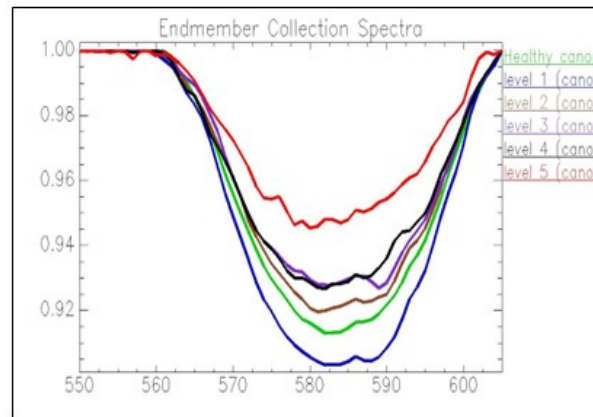


Fig 24 b. Continuum removal of 550-605 (Canopy, Rabi 2017-18)

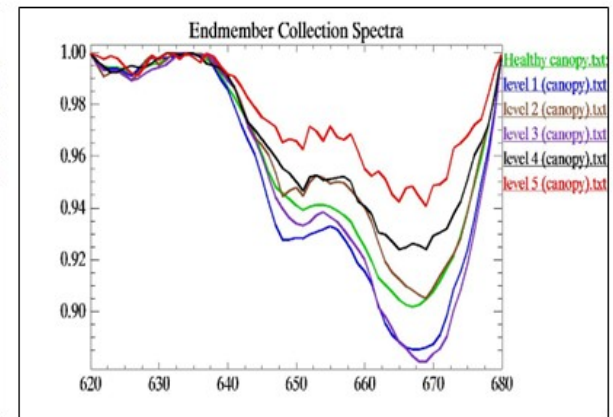


Fig 24 c. Continuum removal of 620-680 (Canopy, Rabi 2017-18)

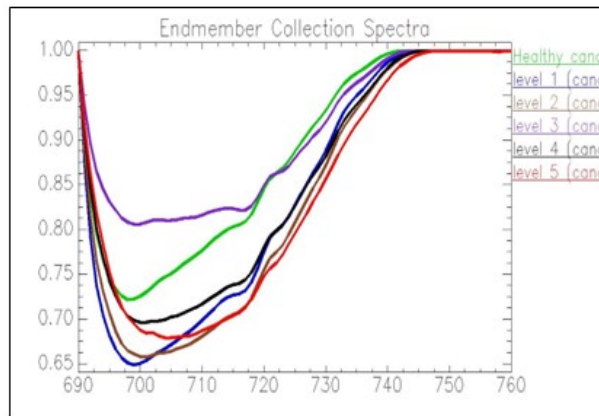


Fig 24 d. Continuum removal of 690-760 (Canopy, Rabi 2017-18)

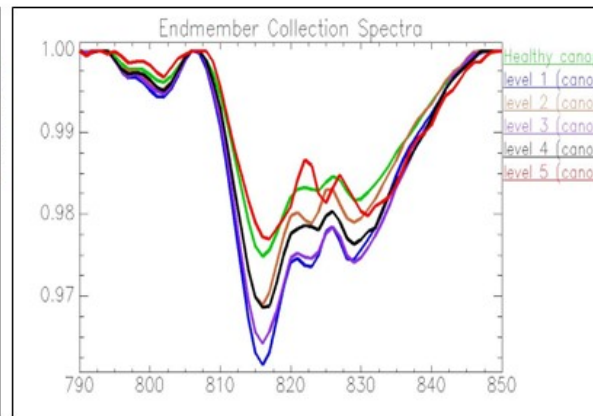


Fig 24 e. Continuum removal of 790-850 (Canopy, Rabi 2017-18)

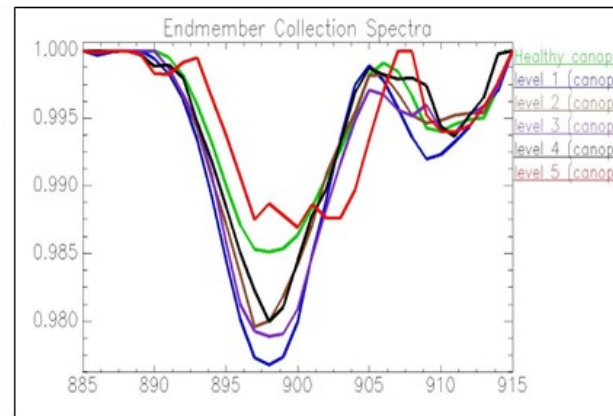


Fig 24 f. Continuum removal of 885-915 (Canopy, Rabi 2017-18)

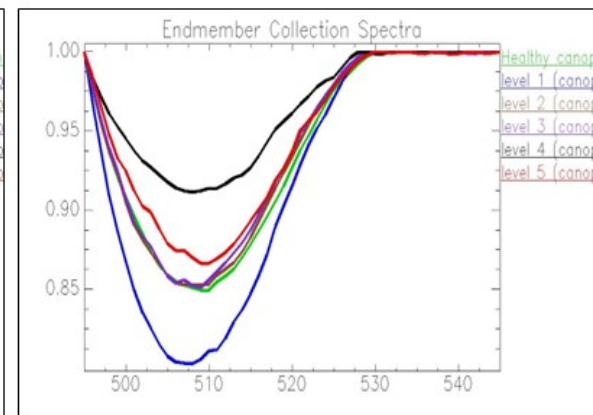
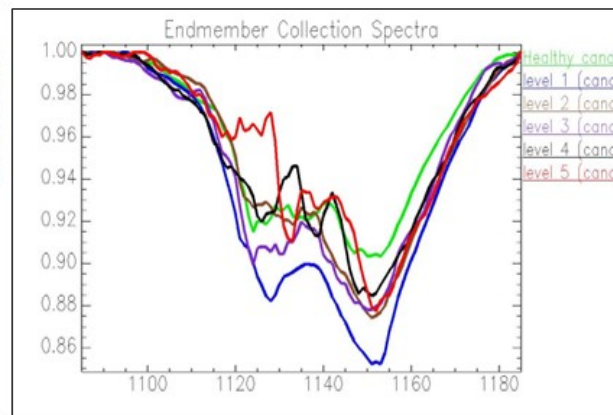
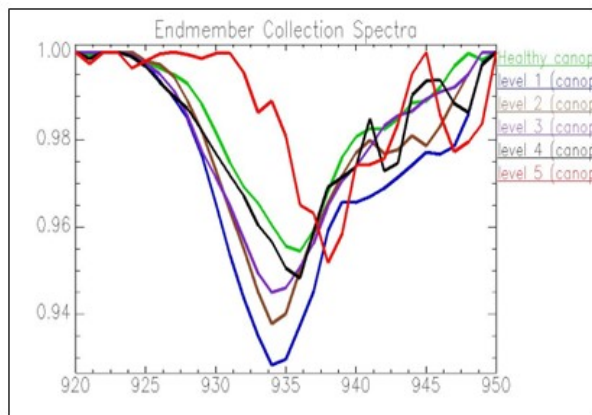


Fig 24 g. Continuum removal of 920-950 (Canopy, Rabi 2017-18) Fig 24 h. Continuum removal of 1080-1180 (Canopy, Rabi 2017-18) Fig 25 a. Continuum removal of 490-550 (Canopy, Kharif 2018-19)

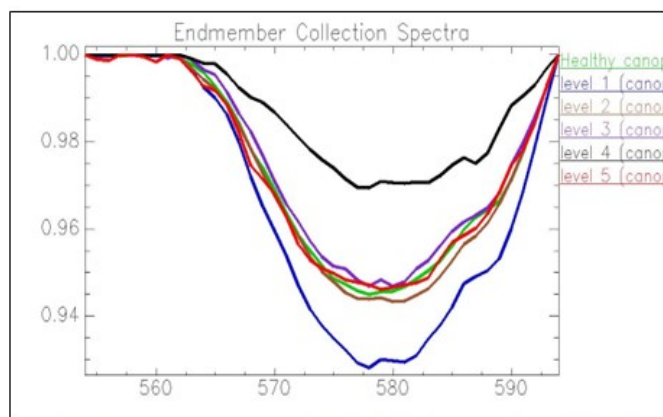


Fig 25 b. Continuum removal of 550-600 (Canopy, Kharif 2018-19)

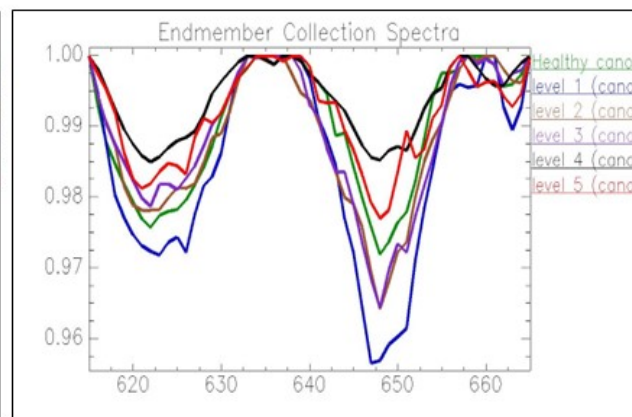


Fig 25 c. Continuum removal of 610-670 (Canopy, , Kharif 2018-19)

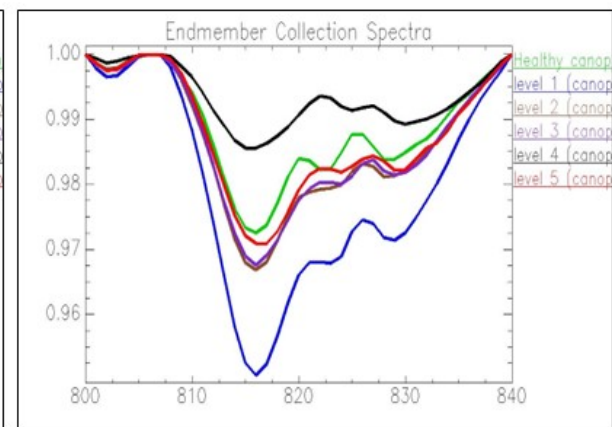
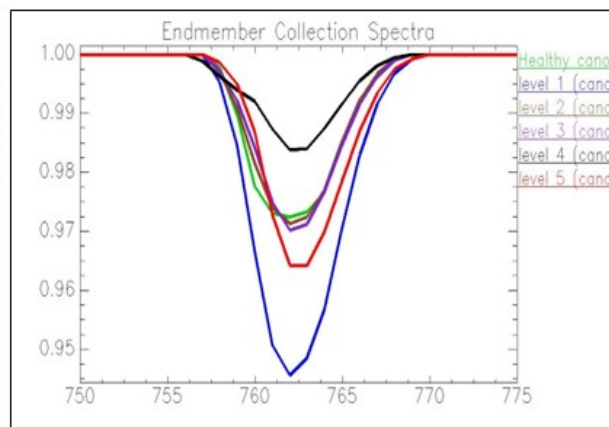
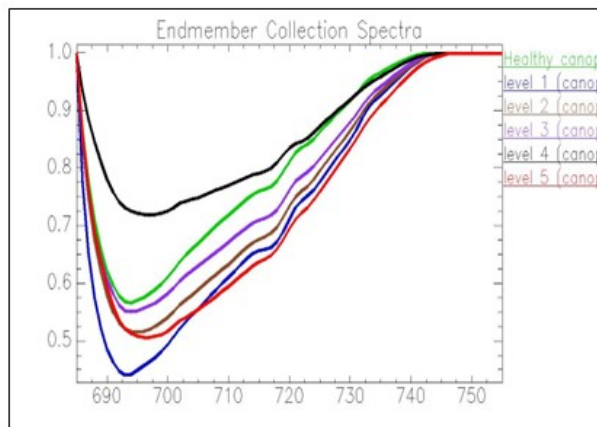


Fig 25 d. Continuum removal of 685-755 (Canopy, Kharif 2018-19) Fig 25 e. Continuum removal of 750-775 (Canopy, Kharif 2018-19) Fig 25 f. Continuum removal of 800-840 (Canopy, Kharif 2018-19)

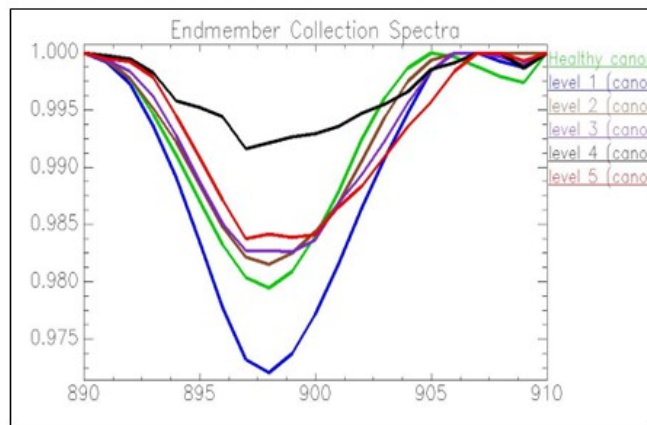


Fig 25 g. Continuum removal of 890-910 (Canopy, Kharif 2018-19)

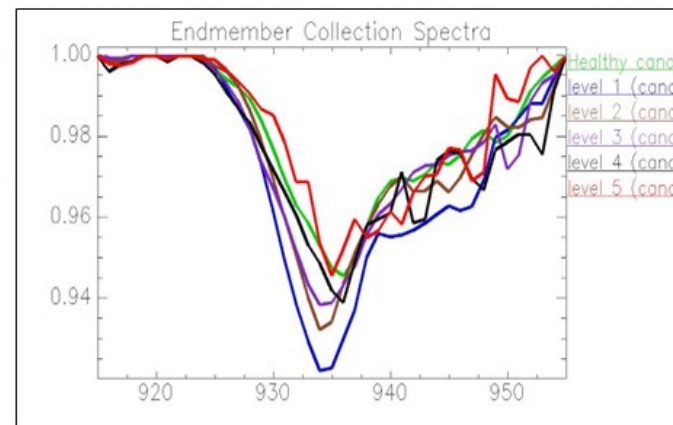


Fig 25 h. Continuum removal of 910-960 (Canopy, Kharif 2018-19)

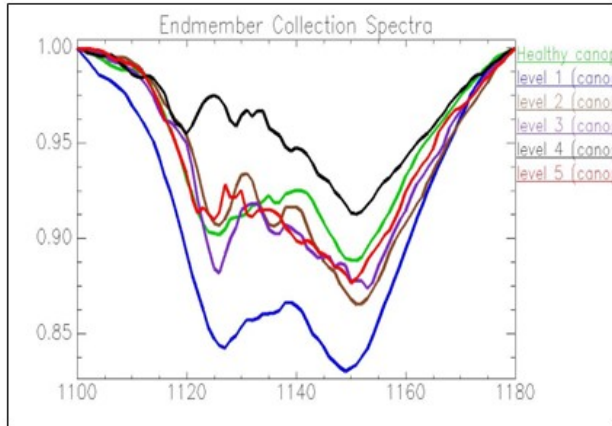


Fig 25 i. Continuum removal of 1100-1180 (Canopy, Kharif 2018-19)

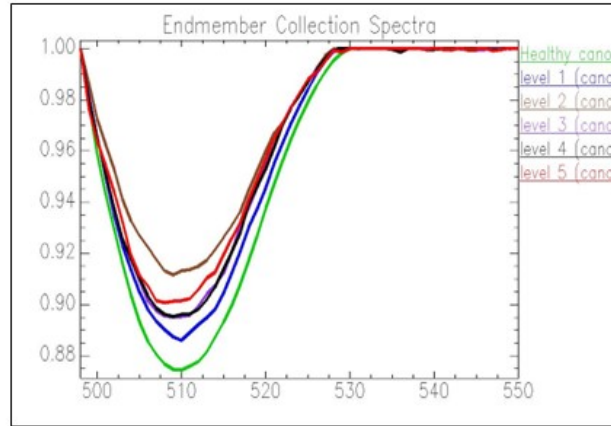


Fig 26 a. Continuum removal of 500-550 (Canopy, Rabi 2018-19)

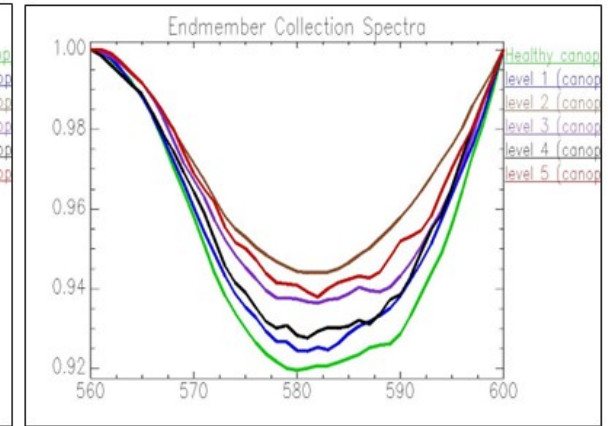


Fig 26 b. Continuum removal of 560-600 (Canopy, Rabi 2018-19)

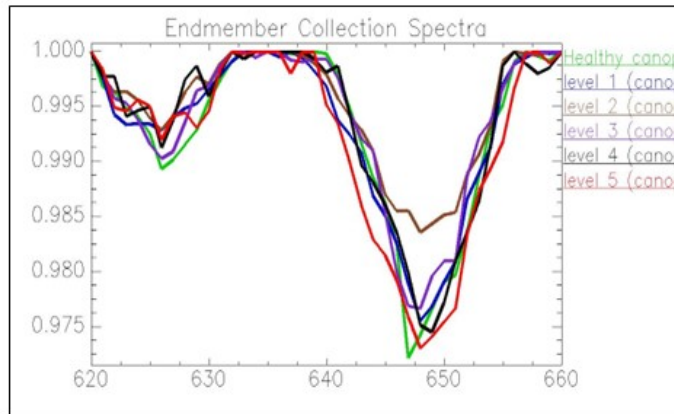


Fig 26 c. Continuum removal of 620-660 (Canopy, Rabi 2018-19)

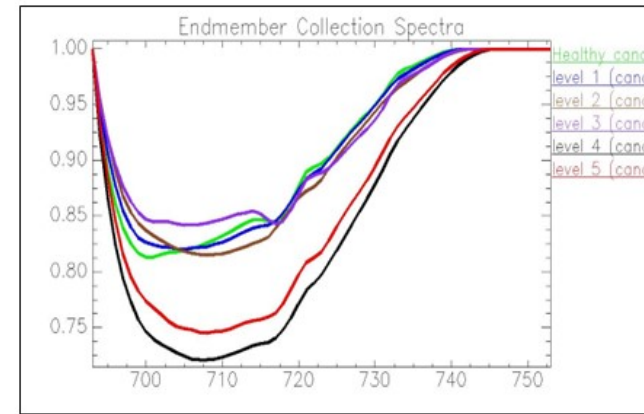


Fig 26 d. Continuum removal of 690-750 (Canopy, Rabi 2018-19)

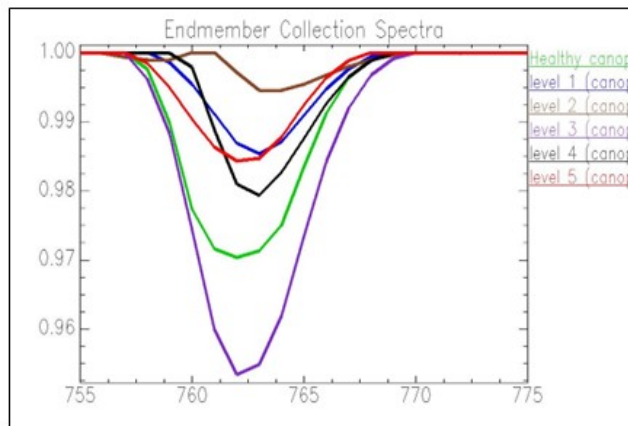


Fig 26 e. Continuum removal of 755-775 (Canopy, Rabi 2018-19)

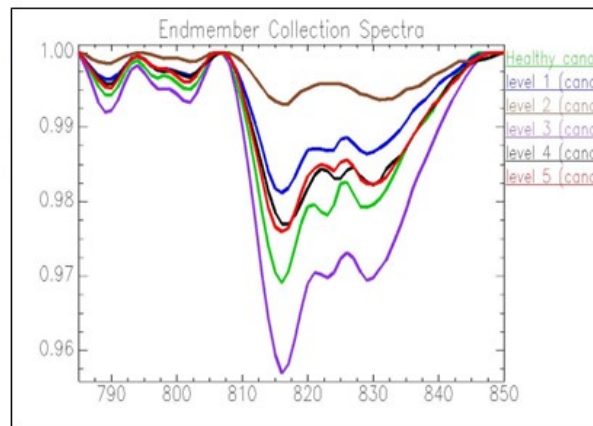


Fig 26 f. Continuum removal of 780-850 (Canopy, Rabi 2018-19)

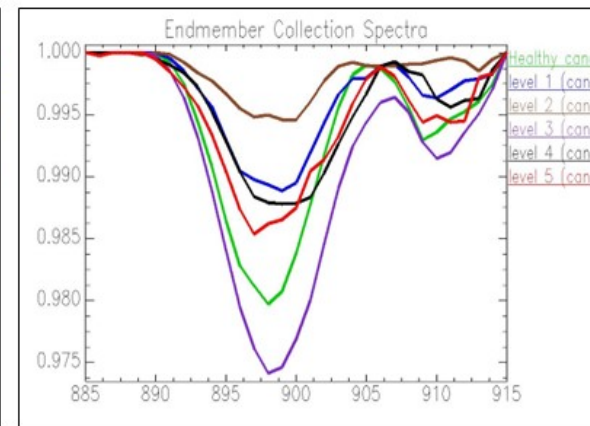


Fig 26 g. Continuum removal of 885-915 (Canopy, Rabi 2018-19)

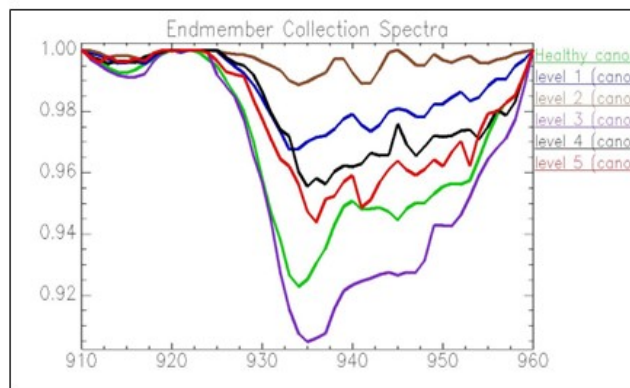


Fig 26 h. Continuum removal of 910-960 (Canopy, Rabi 2018-19)

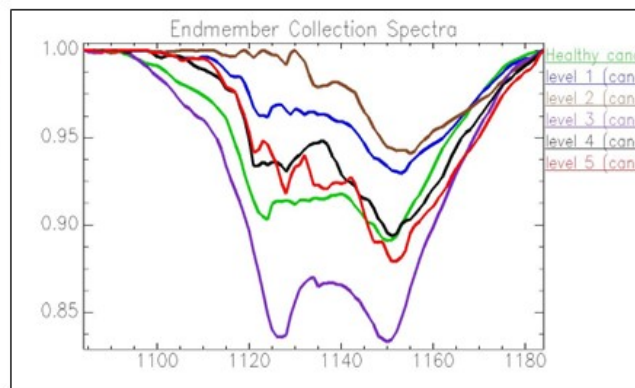


Fig 26 i. Continuum removal of 1090-1180 (Canopy, Rabi 2018-19)

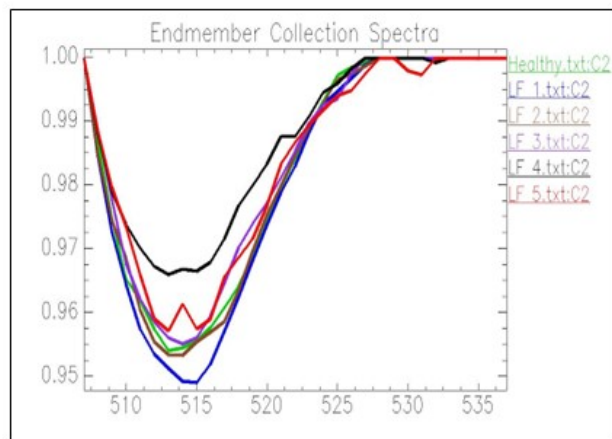


Fig 27 a. Continuum removal of 490-540 (leaf, Rabi 2018-19)

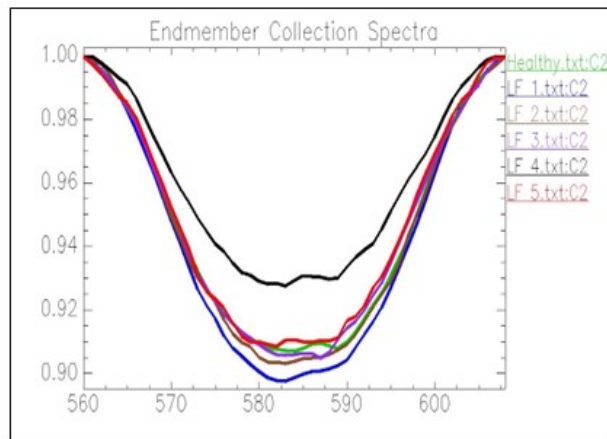


Fig 27 b. Continuum removal of 560-610 (leaf, Rabi 2018-19)

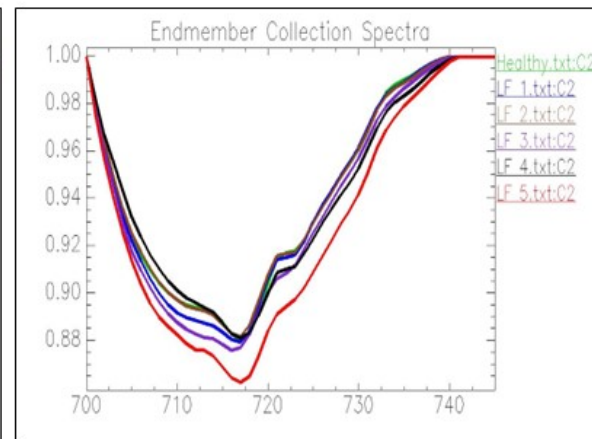


Fig 27 c. Continuum removal of 700-750 (leaf, Rabi 2018-19)

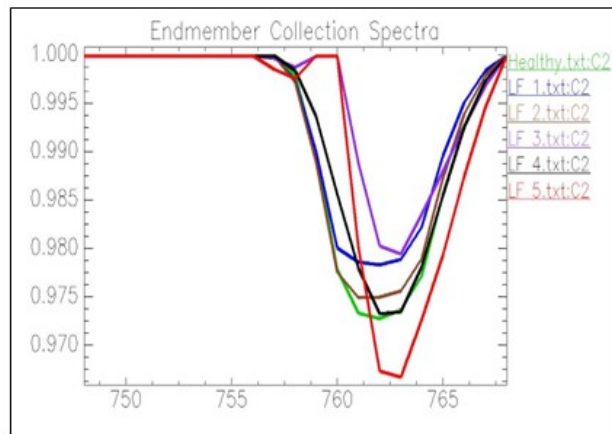


Fig 27 d. Continuum removal of 740-770 (leaf, Rabi 2018-19)

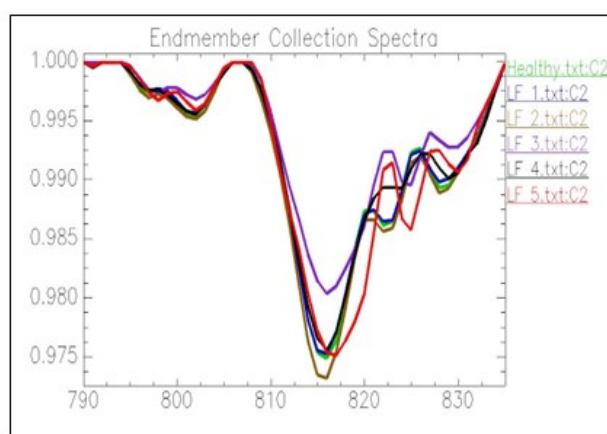


Fig 27 e. Continuum removal of 790-840 (leaf, Rabi 2018-19)

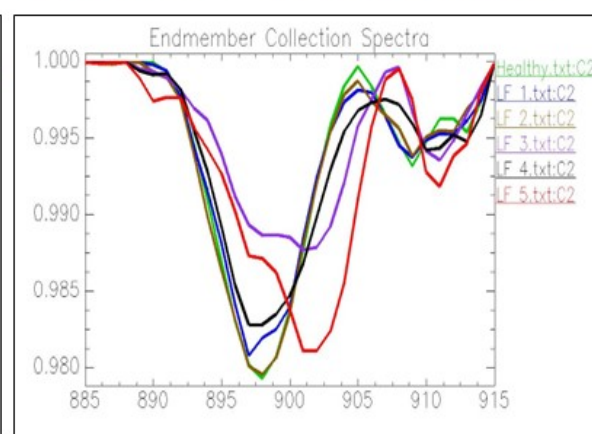


Fig 27 f. Continuum removal of 885-915 (leaf, Rabi 2018-19)

4.1.4 Discrimination of healthy and infested leaf samples by *C. medinalis* through continuum removal

For each experimental seasons the hyperspectral data was recorded and subsequently graphs were plotted. Then continuum removal was carried out by which the absorption dips with significant uniformity were obtained through ENVI software. Results on the continuum removed data for Rabi 2017-18 depicted in Fig 24 a to Fig 24 revealed that the absorption dips were located at spectral bands of 505, 583, 669, 700 nm in the visible range. In the near infrared (NIR) range the absorption dips were found at 815, 898 and 934nm. The short-wave infrared (SWIR) range had only one dip at 1152 nm after removing the continuum. Similarly, the absorption dips in the visible range were distinctly visible at spectral bands of 508, 578, 622, 646 and 694 nm for *Kharif* 2018-19 (Fig 25 a to Fig 25 i). Absorption dips were observed in the NIR region at 762, 816, 898 and 934 nm. 1125 and 1150 nm were the wavelengths of SWIR region having dips found from continuum removal. Likewise, Fig 26 a to Fig 26 i, portrayed the continuum eliminated information of canopy spectral reflectance during Rabi 2018-19. The absorption dips in the noticeable reach were observed at spectral bands of 510, 580, 646 and 706 nm. Absorption dips were recorded in the NIR range at 763, 815, 897 and 935 nm. Subsequent to removing out the continuum, two dips at 1122 and 1150 nm were also found in SWIR range. From continuum removed leaf reflectance data, six absorption dips at spectral bands of 515, 582, 718, 763, 815 and 897 nm were clearly reported after analysing with ENVI software (Fig 27 a to 27 f).

Table 8. Central wavelengths identified through derivative analysis and continuum removal

Reflectance data		Central wavelengths chosen (nm)	
		Derivative analysis	Continuum removal
Canopy Reflectance	Rabi 2017-18	597, 672, 732, 806, 900, 1131	505, 583, 669, 700, 815, 898, 934, 1152
	<i>Kharif</i> 2018-19	411, 597, 672, 733, 806, 898, 1130	508, 578, 622, 646, 694, 762, 816, 898, 934, 1125, 1150
	Rabi 2018-19	596, 673, 757, 783, 806, 1137	510, 580, 646, 706, 763, 815, 897, 935, 1122, 1150
Leaf Reflectance (Rabi 2018-19)		411, 597, 672, 733, 806, 898, 1130	515, 582, 718, 763, 815, 897

4.1.5 Identification of sensitive band through ‘t’ test

Unpaired ‘t’ test with unequal variance was carried out for choosing the spectral bands as central wavelength. This test was carried out for each central wavelength selected at 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 nm intervals. The bands found significant through unpaired ‘t’ test were considered as most significant or sensitive bands which discriminated the damage level by rice leaf folder.

Table 9.1. Determination of P value after t-test for healthy vs leaf folder damage level 1 (Rabi 2017-18)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	505	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	S	S	S
	0.005	597	S	S	S	S	S	S	S	S	S	S
600-750	0.002	672	S	S	S	S	S	S	S	S	NS	NS
	0.002	718	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	732	S	S	S	S	S	S	S	NS	NS	NS
750-950	0.005	806	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	900	S	S	S	S	S	S	S	S	S	S
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1131	S	S	S	S	S	S	S	S	S	S
	0.005	1152	S	S	S	S	S	S	S	S	S	S

Table 9.2. Determination of P value after t-test for healthy vs leaf folder damage level 2 (Rabi 2017-18)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)									
			10	20	30	40	10	60	70	80	10	100
500-600	0.005	505	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	S	S	S
	0.005	597	S	S	S	S	S	S	S	S	S	S
600-750	0.002	672	S	S	S	S	S	S	S	S	NS	NS
	0.002	718	S	S	S	S	S	NS	NS	NS	NS	NS
	0.002	732	S	S	S	S	S	S	S	S	NS	NS
750-950	0.005	806	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	900	S	S	S	S	S	S	S	S	S	S
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1131	S	S	S	S	S	S	S	S	S	S
	0.005	1152	S	S	S	S	S	S	S	S	S	S

Table 9.3. Determination of P value after t-test for healthy vs leaf folder damage level 3 (Rabi 2017-18)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
500-600	0.005	505	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	S	S	S
	0.005	597	S	S	S	S	S	S	S	S	S	S
600-750	0.002	672	S	S	S	S	S	S	S	S	NS	NS
	0.002	718	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	732	S	S	S	S	S	S	S	NS	NS	NS
750-950	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	900	S	S	S	S	S	S	S	S	S	S
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1131	S	S	S	S	S	S	S	S	S	S
	0.005	1152	S	S	S	S	S	S	S	S	S	S

Table 9.4. Determination of P value after t-test for healthy vs leaf folder damage level 4 (Rabi 2017-18)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
500-600	0.005	505	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	S	S	S
	0.005	597	S	S	S	S	S	S	S	S	S	S
600-750	0.002	672	S	S	S	S	S	S	S	S	NS	NS
	0.002	718	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	732	S	S	S	S	S	S	S	NS	NS	NS
750-950	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	900	S	S	S	S	S	S	S	S	S	S
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1131	S	S	S	S	S	S	S	S	S	S
	0.005	1152	S	S	S	S	S	S	S	S	S	S

Table 9.5. Determination of P value after t-test for healthy vs leaf folder damage level 5 (Rabi 2017-18)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 5 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
500-600	0.005	505	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	S	S	S
	0.005	597	S	S	S	S	S	S	S	S	S	S
600-750	0.002	672	S	S	S	S	S	S	S	S	NS	NS
	0.002	718	S	S	S	S	S	S	NS	NS	NS	NS
	0.002	732	S	S	S	S	S	S	S	NS	NS	NS
750-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	S	S	NS	NS	NS
	0.005	900	S	S	S	S	S	S	S	S	S	S
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1131	S	S	S	S	S	S	S	S	S	S
	0.005	1152	S	S	S	S	S	S	S	S	S	S

Table 9.6. Determination of P value after t-test for healthy vs leaf folder damage level 1 (Kharif 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
400-500	0.005	411	S	S	S	S	S	S	S	S	S	S
500-600	0.005	508	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	578	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	597	S	S	S	S	S	S	NS	NS	NS	NS
600-750	0.002	622	S	S	S	S	S	S	S	S	S	S
	0.002	646	S	S	S	S	S	S	S	S	S	S
	0.002	672	S	S	S	S	S	S	S	S	S	S
	0.002	694	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S
750-950	0.005	762	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	816	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S

Table 9.7. Determination of P value after t-test for healthy vs leaf folder damage level 2 (Kharif 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
400-500	0.005	411	S	S	S	S	S	S	S	S	S	S
500-600	0.005	508	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	578	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	597	S	S	S	S	S	S	NS	NS	NS	NS
600-750	0.002	622	S	S	S	S	S	S	S	S	S	S
	0.002	646	S	S	S	S	S	S	S	S	S	S
	0.002	672	S	S	S	S	S	S	S	S	S	S
	0.002	694	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S
750-950	0.005	762	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	816	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S

Table 9.8. Determination of P value after t-test for healthy vs leaf folder damage level 3 (Kharif 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	10	100
400-500	0.005	411	S	S	S	S	S	S	S	S	S	S
500-600	0.005	508	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	578	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	597	S	S	S	S	S	S	NS	NS	NS	NS
600-750	0.002	622	S	S	S	S	S	S	S	S	S	S
	0.002	646	S	S	S	S	S	S	S	S	S	S
	0.002	672	S	S	S	S	S	S	S	S	S	S
	0.002	694	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S
750-950	0.005	762	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	816	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	934	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S

Table 9.9. Determination of P value after t-test for healthy vs leaf folder damage level 4 (Kharif 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	10	100	
400-500	0.005	411	S	S	S	S	S	S	S	S	S	S	S
500-600	0.005	508	S	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	578	S	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS	NS
600-750	0.002	622	S	S	S	S	S	S	S	S	S	S	S
	0.002	646	S	S	S	S	S	S	S	S	S	S	S
	0.002	672	S	S	S	S	S	S	S	S	S	S	S
	0.002	694	S	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S	S
750-950	0.005	762	S	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	816	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	934	S	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S	S

Table 9.10. Determination of P value after t-test for healthy vs leaf folder damage level 5 (Kharif 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 5 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
400-500	0.005	411	S	S	S	S	S	S	S	S	S	S	S
500-600	0.005	508	S	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	578	S	S	S	S	S	S	S	NS	NS	NS	NS
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS	NS
600-750	0.002	622	S	S	S	S	S	S	S	S	S	S	S
	0.002	646	S	S	S	S	S	S	S	S	S	S	S
	0.002	672	S	S	S	S	S	S	S	S	S	S	S
	0.002	694	S	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S	S
750-950	0.005	762	S	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	816	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
	0.005	934	S	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S	S

Table 9.11. Determination of P value after t-test for healthy vs leaf folder damage level 1 (Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	580	S	S	S	S	S	S	S	S	S	S	S
	0.005	596	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
600-750	0.002	646	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	673	S	S	S	S	S	S	S	S	S	S	S
	0.002	706	S	S	S	S	S	S	S	S	S	S	S
750-950	0.005	763	S	S	S	S	S	S	S	S	S	S	S
	0.005	783	S	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	935	S	S	S	S	S	NS	NS	NS	NS	NS	NS
950-1200	0.005	1137	S	S	S	S	S	S	S	S	S	S	S

Table 9.12. Determination of P value after t-test for healthy vs leaf folder damage level 2 (Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	580	S	S	S	S	S	S	S	S	S	S
	0.005	596	S	S	S	NS	NS	NS	NS	NS	NS	NS
600-750	0.002	646	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.002	673	S	S	S	S	S	S	S	S	S	S
	0.002	706	S	S	S	S	S	S	S	S	S	S
750-950	0.005	763	S	S	S	S	S	S	S	S	S	S
	0.005	783	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	935	S	S	S	S	S	NS	NS	NS	NS	NS
950-1200	0.005	1137	S	S	S	S	S	S	S	S	S	S

Table 9.13. Determination of P value after t-test for healthy vs leaf folder damage level 3 (Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	580	S	S	S	S	S	S	S	S	S	S	S
	0.005	596	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
600-750	0.002	646	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	673	S	S	S	S	S	S	S	S	S	S	S
	0.002	706	S	S	S	S	S	S	S	S	S	S	S
750-950	0.005	763	S	S	S	S	S	S	S	S	S	S	S
	0.005	783	S	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	935	S	S	S	S	S	NS	NS	NS	NS	NS	NS
950-1200	0.005	1137	S	S	S	S	S	S	S	S	S	S	S

Table 9.14. Determination of P value after t-test for healthy vs leaf folder damage level 4 (Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	580	S	S	S	S	S	S	S	S	S	S	S
	0.005	596	S	S	S	NS	NS	NS	NS	NS	NS	NS	NS
600-750	0.002	646	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.002	673	S	S	S	S	S	S	S	S	S	S	S
	0.002	706	S	S	S	S	S	S	S	S	S	S	S
750-950	0.005	763	S	S	S	S	S	S	S	S	S	S	S
	0.005	783	S	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	935	S	S	S	S	S	NS	NS	NS	NS	NS	NS
950-1200	0.005	1137	S	S	S	S	S	S	S	S	S	S	S

Table 9.15. Determination of P value after t-test for healthy vs leaf folder damage level 5 (Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 5 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	580	S	S	S	S	S	S	S	S	S	S
	0.005	596	S	S	S	NS	NS	NS	NS	NS	NS	NS
600-750	0.002	646	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.002	673	S	S	S	S	S	S	S	S	S	S
	0.002	706	S	S	S	S	S	S	S	S	S	S
750-950	0.005	763	S	S	S	S	S	S	S	S	S	S
	0.005	783	S	S	S	S	S	S	S	S	S	S
	0.005	806	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	S	NS	NS	NS	NS	NS
	0.005	935	S	S	S	S	S	NS	NS	NS	NS	NS
950-1200	0.005	1137	S	S	S	S	S	S	S	S	S	S

Table 9.16. Determination of P value after t-test, healthy vs leaf folder damage level 1 (Leaf, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
400-500	0.005	411	S	S	S	S	S	S	S	S	NS	NS
500-600	0.005	515	S	S	S	S	S	S	S	S	S	S
	0.005	582	S	S	S	S	S	S	S	NS	NS	NS
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	672	S	S	S	S	S	S	S	S	S	S
	0.002	718	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S
	0.002	763	S	S	S	S	S	S	S	S	S	S
800-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S

Table 9.17. Determination of P value after t-test, healthy vs leaf folder damage level 2 (Leaf, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
400-500	0.005	411	S	S	S	S	S	S	S	S	NS	NS
500-600	0.005	515	S	S	S	S	S	S	S	S	S	S
	0.005	582	S	S	S	S	S	S	S	NS	NS	NS
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	672	S	S	S	S	S	S	S	S	S	S
	0.002	718	S	S	S	S	S	S	S	S	S	S
	0.002	733	S	S	S	S	S	S	S	S	S	S
	0.002	763	S	S	S	S	S	S	S	S	S	S
800-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	898	S	S	S	S	S	S	S	S	S	S
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S

Table 9.18. Determination of P value after t-test, healthy vs leaf folder damage level 3 (Leaf, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
400-500	0.005	411	S	S	S	S	S	S	S	S	NS	NS	
500-600	0.005	515	S	S	S	S	S	S	S	S	S	S	
	0.005	582	S	S	S	S	S	S	S	NS	NS	NS	
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS	
600-800	0.002	672	S	S	S	S	S	S	S	S	S	S	
	0.002	718	S	S	S	S	S	S	S	S	S	S	
	0.002	733	S	S	S	S	S	S	S	S	S	S	
	0.002	763	S	S	S	S	S	S	S	S	S	S	
800-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	898	S	S	S	S	S	S	S	S	S	S	
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S	

Table 9.19. Determination of P value after t-test, healthy vs leaf folder damage level 4 (Leaf, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
400-500	0.005	411	S	S	S	S	S	S	S	S	NS	NS	
500-600	0.005	515	S	S	S	S	S	S	S	S	S	S	
	0.005	582	S	S	S	S	S	S	S	NS	NS	NS	
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS	
600-800	0.002	672	S	S	S	S	S	S	S	S	S	S	
	0.002	718	S	S	S	S	S	S	S	S	S	S	
	0.002	733	S	S	S	S	S	S	S	S	S	S	
	0.002	763	S	S	S	S	S	S	S	S	S	S	
800-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	898	S	S	S	S	S	S	S	S	S	S	
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S	

Table 9.20. Determination of P value after t-test, healthy vs leaf folder damage level 5 (Leaf, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 5 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
400-500	0.005	411	S	S	S	S	S	S	S	S	NS	NS	
500-600	0.005	515	S	S	S	S	S	S	S	S	S	S	
	0.005	582	S	S	S	S	S	S	S	NS	NS	NS	
	0.005	597	S	S	S	S	S	S	S	NS	NS	NS	
600-800	0.002	672	S	S	S	S	S	S	S	S	S	S	
	0.002	718	S	S	S	S	S	S	S	S	S	S	
	0.002	733	S	S	S	S	S	S	S	S	S	S	
	0.002	763	S	S	S	S	S	S	S	S	S	S	
800-950	0.005	806	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	898	S	S	S	S	S	S	S	S	S	S	
950-1200	0.005	1130	S	S	S	S	S	S	S	S	S	S	

Table 10. Common spectral band range and the identified most sensitive bands

Band width (nm)	Canopy reflectance (Rabi 2017-18) (nm)	Canopy reflectance (Kharif 2018-19) (nm)	Canopy reflectance (Rabi 2018-19) (nm)	Leaf reflectance (Rabi 2018-19) (nm)	Most sensitive spectral bands identified for rice leaf folder infestation (nm)
500-600	583, 597	578, 597	510, 580, 596	515, 582, 597	515, 582, 672, 732, 815, 898, 1130
600-750	672, 732	672, 733	673,	672, 733	
750-950	806, 815, 934	762, 806, 816, 898, 934	763, 806, 815, 897, 935	763, 806, 815, 898	
950-1200	1131	1130	1137	1130	

The results from the unpaired ‘t’ test unravelled that seven spectral bands *i.e.*, 515, 582, 672, 732, 815, 898 and 1130 nm were identified as pest sensitive spectral bands for the rice variety TN1 infested with *C. medinalis* (Table 10).

4.2 Relationship between significant bands and different biochemical components

The results of the study on biochemical composition of leaves of rice infested with various population level of *C. medinalis* revealed a significant difference in the total chlorophyll, phenol and carotenoid content amongst them (Table 11.1 and Table 11.2).

4.2.1 Chlorophyll:

The *chlorophyll a* content varied from 1.11 to 2.95 mg/g fresh weight of leaves, lowest being in the leaves at infestation grade of ‘5’ (T₆) and highest in healthy leaves (T₁) (Grade 0) (Table 11.1). The *chlorophyll b* content in the rice leaves infested at various population density of *C. medinalis* ranged between 0.35 (Grade 5) and 1.00 mg/g (healthy leaves, grade 0). The total chlorophyll content of rice leaves infested at various population level of *C. medinalis* varied from 1.46 to 3.95 mg/g., the lowest being in leaves infested at Grade 5 and highest in healthy leaves (Grade 0).

4.2.2 Phenol:

The total phenol content in the rice leaves infested at various population level of *C. medinalis* ranged between 3.25 mg/g (healthy leaves) and 4.79 mg/g (leaf infestation grade 5). The phenol content was higher in the leaves with leaf folder infestation grade 5 (Table 11.2).

Table 11.1. Chlorophyll content in infested leaves in response to different population level of *C. medinalis*

Treatment	Leaf infestation (%)	Chlorophyll “a” (mg/g)	Chlorophyll “b” (mg/g)	Total chlorophyll (mg/g)
T ₁ (0 larvae / m ²)	0	2.95	1.00	3.95
T ₂ (10 larvae / m ²)	<10	2.61	0.87	3.48
T ₃ (20 larvae / m ²)	10-20	2.39	0.82	3.215
T ₄ (40 larvae / m ²)	20-30	1.88	0.65	2.535
T ₅ (60 larvae / m ²)	30-50	1.28	0.45	1.72
T ₆ (100 larvae / m ²)	>50	1.112	0.35	1.467
SE(m) ±		0.04	0.01	0.03
CD (P=0.05)		0.14	0.043	0.114
CV (%)		6.13	2.61	4.27

Table 11.2. Phenol and carotenoid content in infested leaves in response to different population level of *C. medinalis*

Treatment	Infestation in leaf (%)	Phenol (mg/g)	Carotenoid (mg/g)
T ₁ (0 larvae / m ²)	0	3.25	0.36
T ₂ (10 larvae / m ²)	<10	3.73	0.33
T ₃ (20 larvae / m ²)	10-20	3.93	0.306
T ₄ (40 larvae / m ²)	20-30	4.15	0.272
T ₅ (60 larvae / m ²)	30-50	4.32	0.243
T ₆ (100 larvae / m ²)	>50	4.79	0.207
SE(m) ±		0.02	0.009
CD (P=0.05)		0.07	0.027
CV (%)		2.41	2.04

4.2.3 Carotenoid

The carotenoid content varied from 0.20 to 0.36 mg/g in the rice leaves, the lowest (0.20 mg/g) being in leaves at infestation grade 5 and highest (0.36 mg/g) in healthy leaves.

4.2.4 Relationship between different biochemical content of rice leaves and spectral reflectance

The relationship between the spectrum reflectance data and various biochemical components of rice leaves was established using correlation coefficients (r) so as to ascertain the reason for which the bands were sensitive. It was obvious from the results that distinct spectral bands were responsible for the absorption of particular biochemical components. When the value of correlation coefficient (r) was more than 0.5, it was considered that there was a strong relationship between the spectral band and the biochemical components.

Results on the relationship between total chlorophyll content and hyperspectral remote sensing sensitive bands generated from leaf spectral data indicated that the spectral bands viz., 515nm, 582nm, 597nm and 672nm had a correlation coefficient (r) value more than 0.5 there by displayed a strong relationship with total chlorophyll content (Table 12.1). The aforementioned bands were determined to be sensitive to chlorophyll absorption. Similarly, the data on relationship between carotenoid content of rice leaves and hyperspectral remote sensing bands revealed a correlation value exceedingly more than 0.5 at spectral bands of 515 and 582 nm (Table 12.2). Results on relationship between phenol content of rice leaves and hyperspectral remote sensing spectral bands revealed correlation value more than 0.5 at spectral bands of 1130 nm (Table12.3).

Table 12.1. Correlation coefficient (r) of the sensitive bands with total chlorophyll content of rice leaves

Sensitive bands (nm)	Different damage level of <i>C. medinalis</i>					
	Healthy	LF Grade 1	LF Grade 2	LF Grade 3	LF Grade 4	LF Grade 5
411	0.234	0.348	0.443	0.456	0.487	0.42
515	0.554	0.587	0.665	0.567	0.596	0.691
582	0.667	0.702	0.612	0.538	0.665	0.631
597	0.772	0.703	0.713	0.678	0.693	0.66
672	0.534	0.548	0.543	0.567	0.587	0.52
718	0.365	0.254	0.461	0.154	0.302	0.451
733	0.331	0.316	0.382	0.012	0.141	0.246
763	0.114	0.201	0.212	0.343	0.318	0.454
806	0.125	0.113	0.102	0.210	0.221	0.132
815	0.087	0.056	0.165	0.087	0.123	0.321
898	0.034	0.065	0.431	0.098	0.092	0.123
1130	0.003	0.12	0.04	0.189	0.064	0.011

The bold and highlighted figures are significant.

Table 12.2. Correlation coefficient (r) of the sensitive bands with total carotenoid content of rice leaves

Sensitive bands (nm)	Different damage level of <i>C. medinalis</i>					
	Healthy	LF Grade 1	LF Grade 2	LF Grade 3	LF Grade 4	LF Grade 5
411	0.454	0.345	0.096	0.221	0.338	0.433
515	0.762	0.654	0.603	0.567	0.552	0.503
582	0.554	0.667	0.654	0.623	0.546	0.605
597	0.432	0.302	0.412	0.343	0.454	0.278
672	0.321	0.313	0.332	0.015	0.166	0.246
718	0.112	0.212	0.223	0.321	0.308	0.254
733	0.114	0.1	0.115	0.221	0.131	0.032
763	0.088	0.156	0.132	0.084	0.323	0.421
806	0.024	0.035	0.444	0.056	0.032	0.023
815	0.013	0.103	0.056	0.113	0.034	0.041
898	0.105	0.165	0.042	0.232	0.211	0.122
1130	0.087	0.056	0.165	0.087	0.123	0.321

The bold and highlighted figures are significant

Table 12.3. Correlation coefficient (r) of the sensitive bands with total phenol content of rice leaves

Sensitive bands (nm)	Different damage level of <i>C. medinalis</i>					
	Healthy	LF Grade 1	LF Grade 2	LF Grade 3	LF Grade 4	LF Grade 5
411	0.285	0.313	0.22	0.341	0.366	0.232
515	0.15	0.252	0.372	0.109	0.122	0.314
582	0.122	0.122	0.314	0.056	0.056	0.246
597	0.095	0.134	0.421	0.122	0.246	0.032
672	0.22	0.15	0.122	0.095	0.22	0.421
718	0.421	0.432	0.315	0.021	0.095	0.118
733	0.118	0.014	0.285	0.23	0.065	0.041
763	0.098	0.099	0.056	0.224	0.066	0.432
806	0.224	0.056	0.315	0.021	0.095	0.118
815	0.094	0.432	0.086	0.043	0.035	0.091
898	0.154	0.357	0.404	0.411	0.402	0.338
1130	0.612	0.577	0.621	0.554	0.703	0.590

The bold and highlighted figures are significant

4.2.5 Determination of best spectral pest sensitive band combination through feature selection

The seven spectral bands which were found sensitive due to leaf folder infestation were undergone through the feature selection process and the percentage accuracy of several spectral band combination were evaluated by MATLAB software through random forest elimination process.

Table 13. Feature selection table extracted from MATLAB

Bands	Accuracy (%)	Sensitive band combination (nm)										
7	78.66	515	582	673	732	815	898	1131				
6	80.66	515	582	673	732	815	898					
5	82.33	515	582	673	732	815						
4	77.33	515	582	673	732							
3	71.66	515	582	673								
2	68.33	515	582									
1	55.33	515										

Results revealed that the combination of five spectral bands (515, 582, 673, 732 and 815) was the best spectral band combination showing highest accuracy percentage (82.33) (Table 13). All the rest spectral band combinations had the lower accuracy (%) than that of the best combination. The combination of six bands (515, 582, 673, 732, 815 and 898 nm) was the second-best band combination with 80.66 per cent accuracy. The combination of all seven spectral pest sensitive bands showed the lowest accuracy percentage (78.66).

4.2.6 Determination of vegetative indices

The predetermined and published vegetative indices *viz.*, Normalized Difference Vegetation Index (NDVI), Leaf area index (LAI), Red Edge Position Index (REPI), Photochemical Reflectance Index (PRI) and Plant Senescence Reflectance Index (PSRI) were determined using the spectral reflectance data through respective formulae (Table 14).

a) NDVI: Results on the values of NDVI from the spectral reflectance of the experimental microplots revealed that the value of the index was highest (0.77) for uninfested (healthy) vegetation and it was lowest (0.51) for the rice canopy infested maximum by the leaf folder (LF grade 5). For leaf folder grade 1, 2, 3 and 4, the value of NDVI were 0.67, 0.62, 0.58 and 0.553 respectively.

b) LAI: Data on LAI indicated that the values ranged from 1.44 to 3.2 at different infestation level of *C. medinalis*. The uninfested vegetation in the microplot had highest LAI (3.2) which decreased continually and the lowest value of LAI (1.44) was observed for the highest infested rice vegetation (grade 5). Leaf area index values of leaf infestation grade of 1, 2, 3 and 4 were 3.01, 2.34, 2.15 and 1.63, respectively.

Table 14. Vegetative indices in response to various damage level of *C. medinalis*

Vegetative Indices	Healthy	LF Grade 1	LF Grade 2	LF Grade 3	LF Grade 4	LF Grade 5
Normalized Difference Vegetation Index (NDVI)	0.77	0.67	0.62	0.58	0.55	0.51
Leaf Area Index (LAI)	3.2	3.01	2.34	2.15	1.63	1.44
Red Edge Position Index (REPI)	722 nm	721 nm	719 nm	718 nm	712nm	707 nm
Photochemical Reflectance Index (PRI)	0.17	0.13	0.08	0.01	-0.09	-0.14
Plant Senescence Reflectance Index (PSRI)	0.03	0.07	0.12	0.13	0.14	0.18

c) REPI: Results on the values of REPI unravelled that with more chlorophyll content, the absorption characteristic was widened and the red edge was moved to longer wavelengths. In healthy vegetation, the red edge position was stationed at 722 nm. The position of the red edge moved to shorter wavelengths *i.e.*, at 721 nm, 719 nm, 718nm, 712 nm and 707 nm for leaf folder grade 1, 2, 3, 4 and 5, respectively.

d) PRI: Data on PRI indicated that the values varied from 0.03 to 0.18 at different infestation level of *C. medinalis*. The value of the index was 0.17 for healthy canopy and it gradually decreased. It attained a negative value of -0.09 and -0.14 at leaf folder infestation grade 4 and 5, respectively. The value of the PRI for insect grade 1, 2 and 3 were 0.13, 0.08 and 0.01, respectively.

e) PSRI: The sensitivity of the index to the ratio of bulk carotenoids to chlorophyll was maximised by Photochemical Senescence Reflectance Index (PSRI). From the reflectance data of the vegetation, the value of PSRI was highest (0.18) for leaf folder grade 5 and was lowest (0.03) for uninfested vegetation. For leaf folder grade of 1, 2, 3 and 4 the PSRI values were 0.07, 0.125, 0.129 and 0.14, respectively.

4.2.6.6 Determination of two spectral band and three spectral band vegetative

indices

The two band and three band vegetative indices in relation to chlorophyll were determined through several indices using various mathematical formula *viz.*, simple ratio (SR), simple difference (SD) and normalized difference (ND) from the best sensitive spectral bands ascertained from feature selection method. The regression graphs were plotted using the value of the vegetative indices in differentially infested

leaves (Fig 28 a to Fig 28 f). The simple ratio, simple difference and normalized differences indices from any two random spectral bands in the whole spectral range of 400–2500 nm was compared for rice total chlorophyll. In the visible and near infrared (NIR) waveband ranges (400–1000 nm), the best performing SR, SD and ND indices were determined.

By using the calibration dataset, SR (515,732), SD (732,515) and ND (732,582) performed best in the SR, SD and ND categories, respectively. An independent validation dataset was used to examine the performance of the regression models based on SR (515,732), SD (732,515) and ND (732,582). The fitted curves *viz.*, SR (515,732), SD (732,515) and ND (732,582) showed strong linear relationships with total chlorophyll. These findings revealed that all of the proposed approaches had a good relationship and usability with total chlorophyll content.

For identification of appropriate criteria for determining rice total chlorophyll, three-band ratio and normalized index indices were determined. The three-band indicators showing a strong relationship with total chlorophyll content were mostly acquired from the blue, green, and red edge wave band areas. Several three band indices such as two bands from red edge area and one from green region were combined and their simple ratio ($R_{732}/(R_{515}+R_{673})$) was calculated (Fig.28 d). Similarly other indices such as one band from green region and two bands from NIR region were combined and their simple ratio ($R_{815}/R_{568}*R_{732}$) was calculated (Fig.28 e). These three-band ratio exhibited linear relationship with total chlorophyll content. Another band combinations of two bands from visible and one band from NIR region *viz.*, $R_{815}/R_{673}+R_{582}$ (Fig.28 f) also exhibited similar kind of relationship. These ratios were confirmed as new vegetative indices.

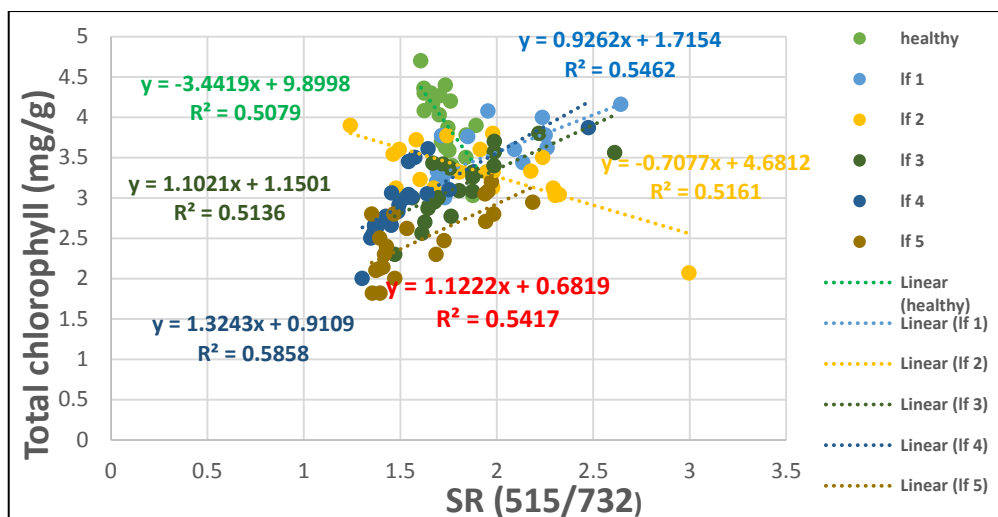


Fig 28 a. Two band vegetative index “SR (515/732)” in relation to chlorophyll

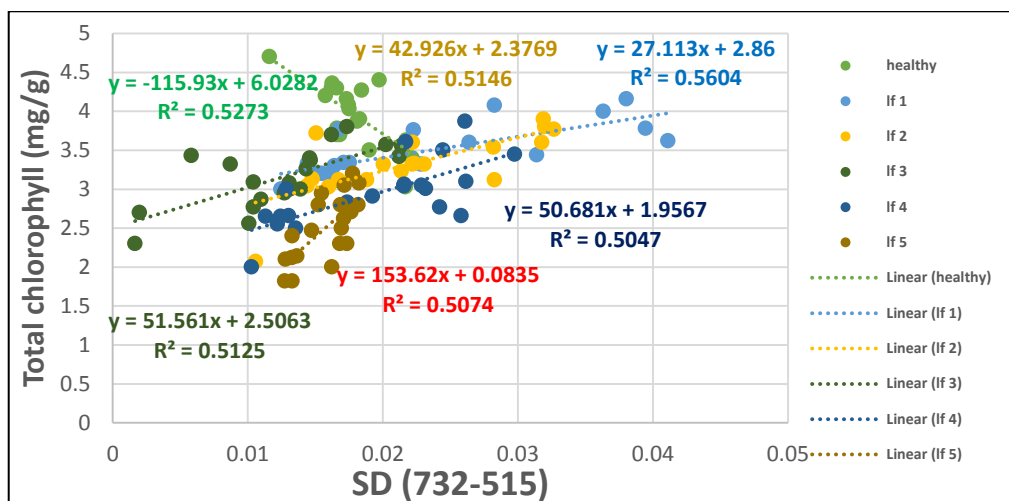


Fig 28 b. Two band vegetative index “SD (732-515)” in relation to chlorophyll

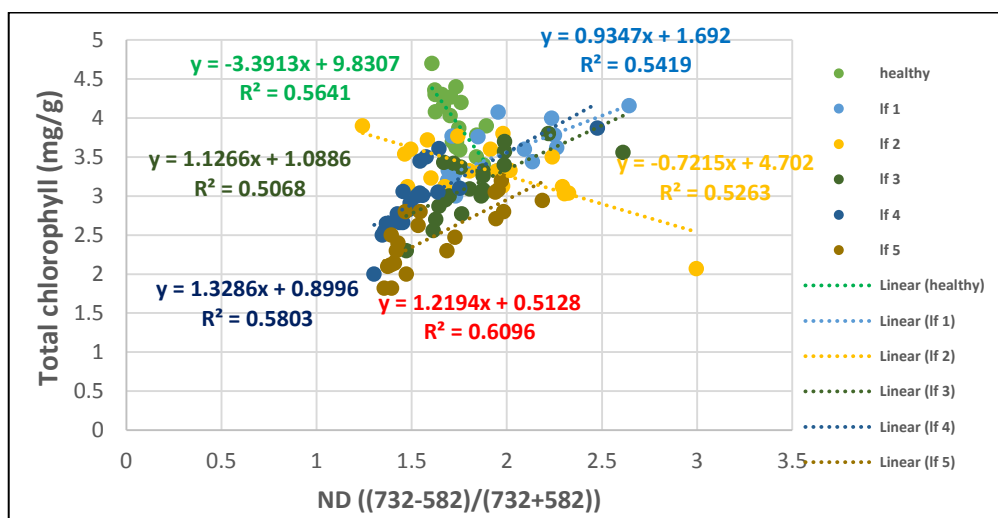


Fig 28 c. Two band vegetative index “ND {(732-582)/(732+582)}” in relation to chlorophyll

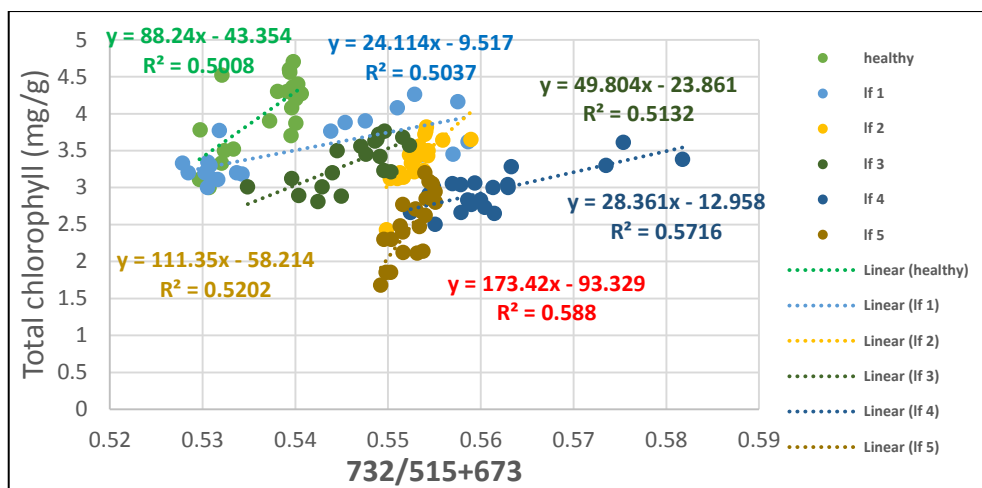


Fig 28 d. Three band vegetative index “ $732/(515+673)$ ” in relation to chlorophyll

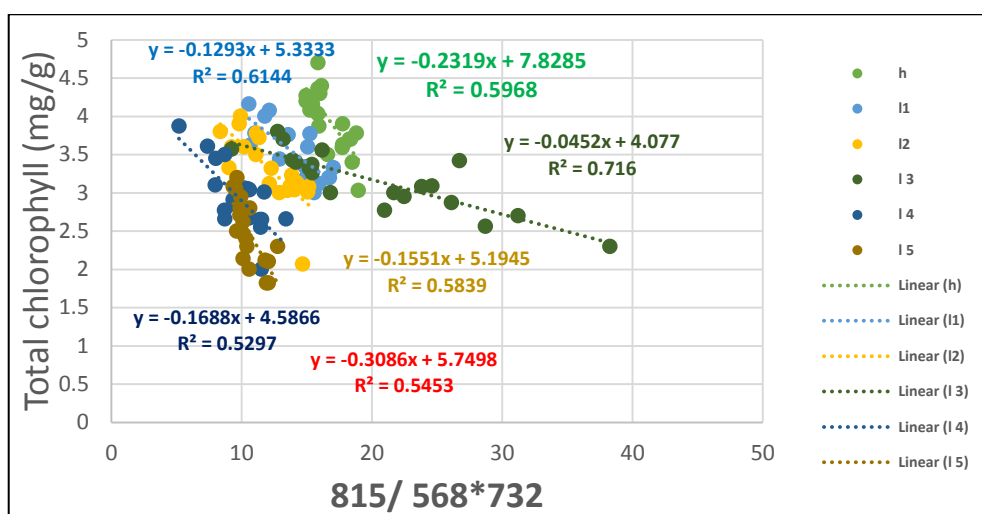


Fig 28 e. Three band vegetative index “ $815/(568*732)$ ” in relation to chlorophyll

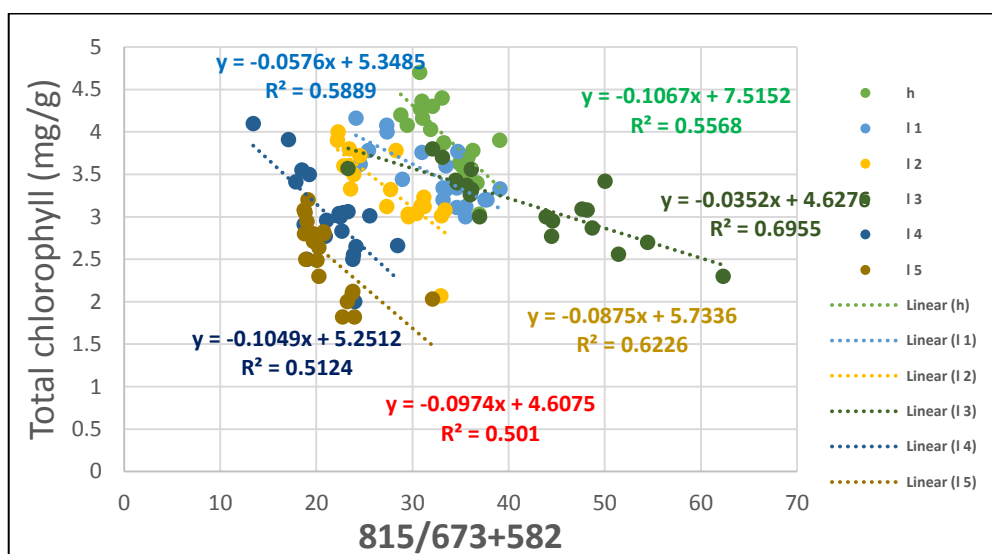


Fig 28 f. Three band vegetative index “ $815/(673+582)$ ” in relation to chlorophyll

4.3 Relationship of field measurement of spectral signature with infestation of *C. medinalis* in rice

For comparison of data generated on hyperspectral canopy reflectance through microplot experiment with spectral reflectance of rice crop from farmer's field, artificial leaf folder infestation was created through manual release of *C. medinalis* on the rice var Naveen. Additionally, utilising sentinel analysis on satellite imagery, the ground truth hyperspectral data on healthy and damaged vegetation was validated.

4.3.1 Pest sensitive spectral bands in farmers field and controlled conditions

For comparison of data generated on hyperspectral canopy reflectance through microplot experiment with spectral reflectance of rice crop from farmer's field, artificial leaf folder infestation was created through manual release of *C. medinalis* on the rice variety Naveen. Results on leaf roll rate at different infestation level of *C. medinalis* in rice variety Naveen indicated that leaf roll rate varied significantly from 0.0 to 60.37 per cent (Table 15). Highest leaf roll rate (60.37%) was recorded in T₆ (50 larvae/m²). In healthy plot no infestation of *C. medinalis* was found.

Table 15. Intensity of leaf roll rate by *C. medinalis* in rice variety (Naveen) planted as mimicking variety to farmer's field during Rabi 2018-19

Treatments	Leaf roll rate (%)
T ₁ (0 larvae / m ²)	0 (0)
T ₂ (5 larvae / m ²)	2.737 (10.286)
T ₃ (10 larvae / m ²)	10.475 (19.62)
T ₄ (20 larvae / m ²)	21.4 (29.601)
T ₅ (30 larvae / m ²)	37.86 (39.439)
T ₆ (50 larvae / m ²)	60.37 (56.655)
SE(m) ±	1.492
CD (P=0.05)	4.49
CV (%)	11.51

In both the conditions, the ASD Field Spec hyperspectral spectroradiometer was used for the spectral data acquisition and the data were analysed for the comparative study. The spectral curves were obtained for discriminating between healthy and differentially damaged rice vegetation by *C. medinalis* (Fig 29 a and Fig 29 b). Results revealed that the uninfested plants had lower canopy reflectance in the visible region than the infested plants. Peak reflectance was recorded at 520 to 540 nm as the absorption of carotenoid pigment and the fluctuation in that pigment varied under

different levels of infestation. From both the spectral curves the data from 350 to 399 nm was excluded as this range was not in the visible spectrum. It was found that the reflectance in the visible range was directly related to the leaf folder damage with the red edge shoulder at 686 and 693 nm, respectively.

It was evident from both the spectral curves that the reflectance was reduced with the increase in infestation of *C. medinalis* in the near infra-red region. Conversely the leaf folder damage had a negative correlation with the reflectance. Both the graphs had small dips recorded at 760-765 nm as a result of oxygen absorption. The gaps observed between 1350-1450 nm and 1780-2000 nm in the spectral curves confirmed that those regions as the region of atmospheric disturbances or water parameters. The eliminated water bands had a higher reflectance greater than one.

The first and second order derivatives were calculated. Further, the derivative graphs were obtained for the vegetations from farmer's field (Fig 30 a to Fig 30 b). The change in derivative (in per cent) was also calculated to ascertain the exact spectral band at which the percentage change was maximum. Results from derivative analysis unravelled that at visible region, 517, 583, 627 and 669 nm were the specific wavelengths at which the change was maximum. Likewise, at NIR 901 nm and at SWIR 1126 nm were found to be more specific to pest damage because of the maximum change in derivatives (Fig 31 a to Fig 31 f).

Similarly, derivative analysis was carried out for spectral data from the vegetation under controlled conditions and the derivative graphs were constructed (Fig 30 c and Fig 30 d). Results indicated that the particular bands 674 from the visible region and 753, 806 and 884 from the NIR region were identified as specific bands with maximum per cent change value (Fig 32 a to Fig 32 e). At short wave infrared (SWIR) region, the same band as in case of farmer's field *i.e.*, spectral bands of 1126 nm was found with maximum difference. The specific bands found from the derivative analysis for both conditions were chosen as central wavelengths and was confirmed through unpaired 't' test.

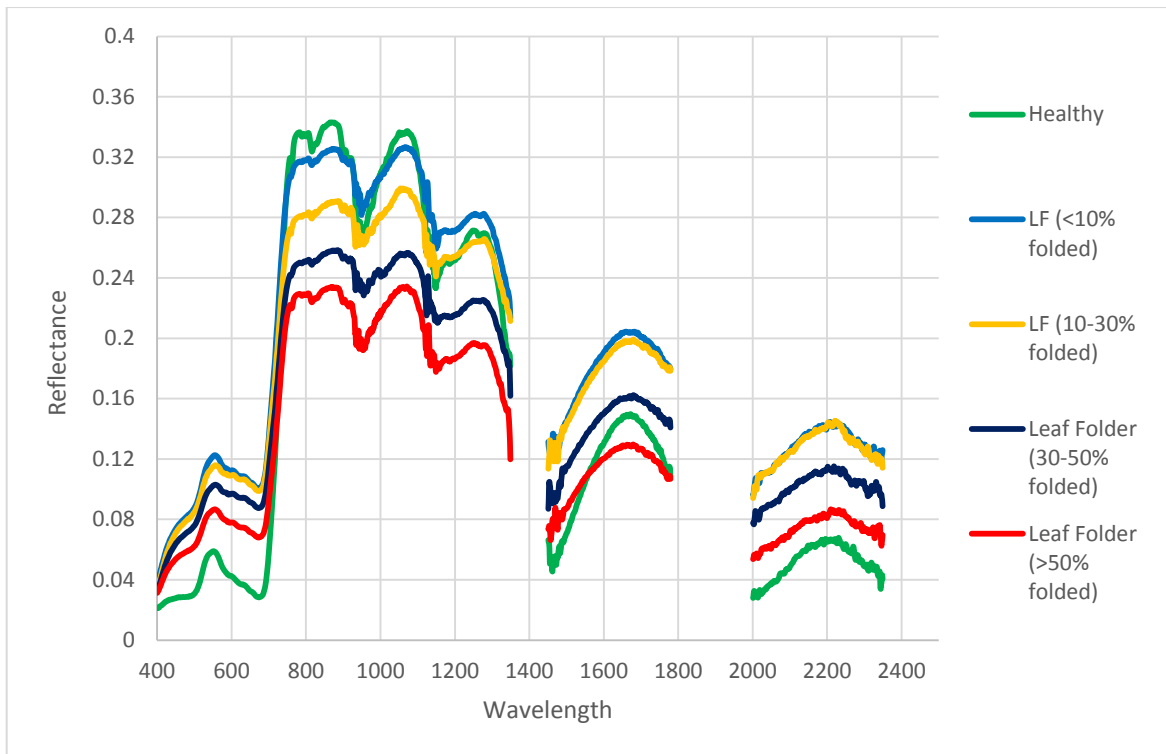


Fig 29 a. Canopy reflectance graph of farmers field during Rabi 2018-19

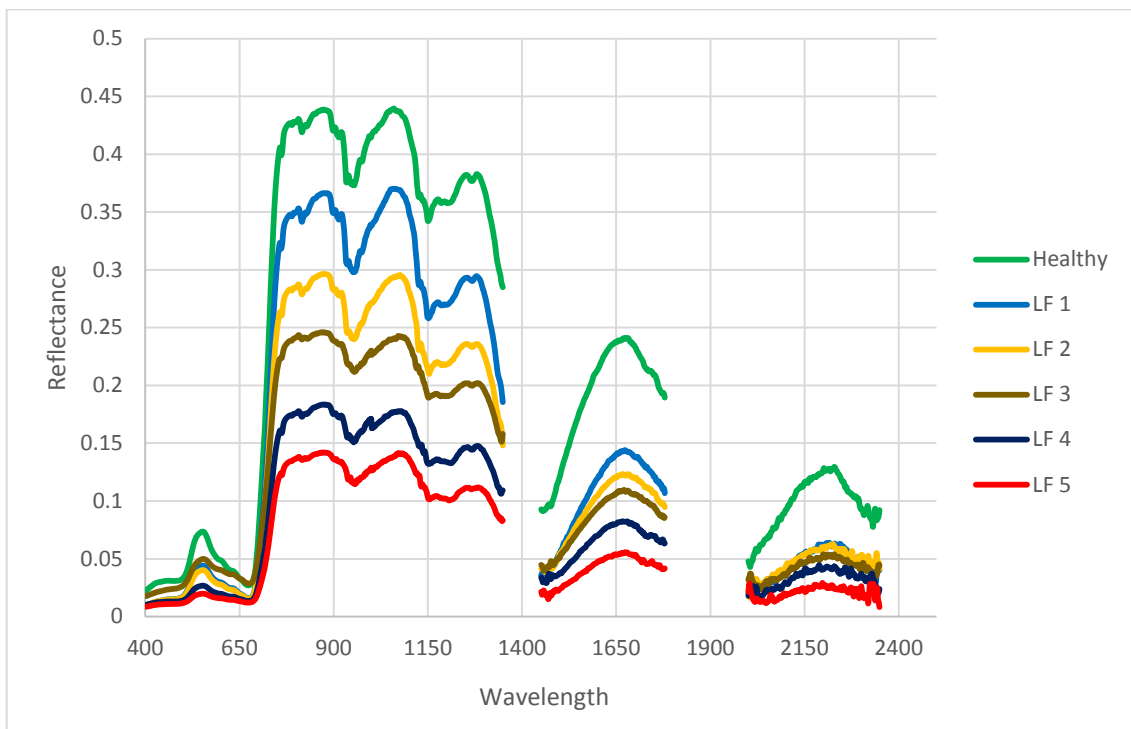


Fig 29 b. Canopy reflectance graph of rice var Naveen in controlled condition during Rabi 2018-19

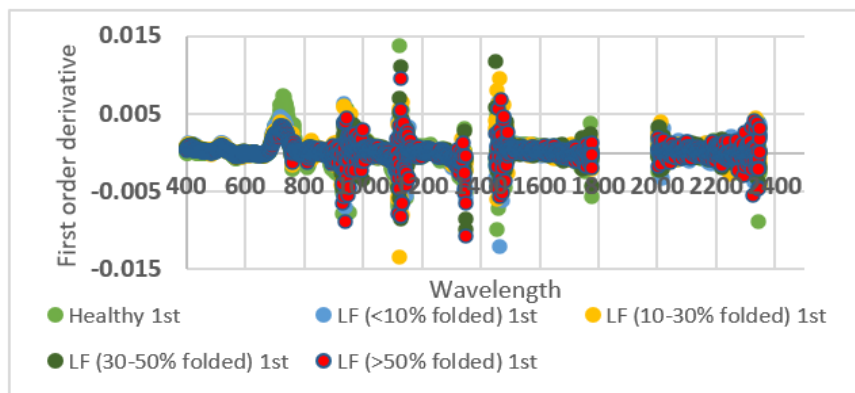


Fig 30 a. First order derivative of Canopy spectra, Farmers field

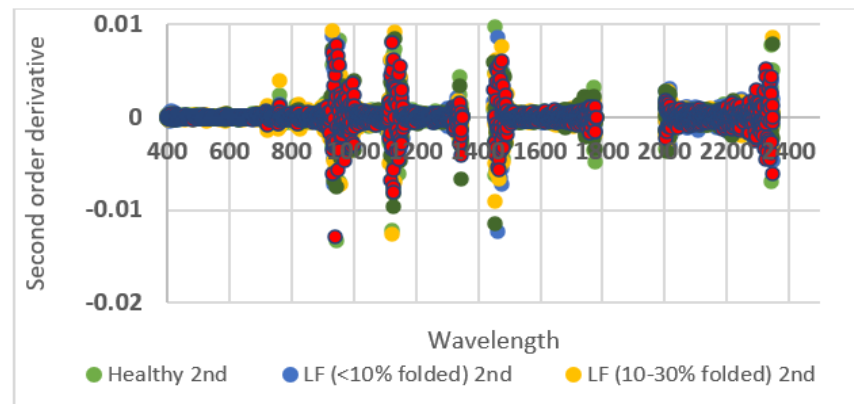


Fig 30 b. Second order derivative of Canopy spectra, Farmers field

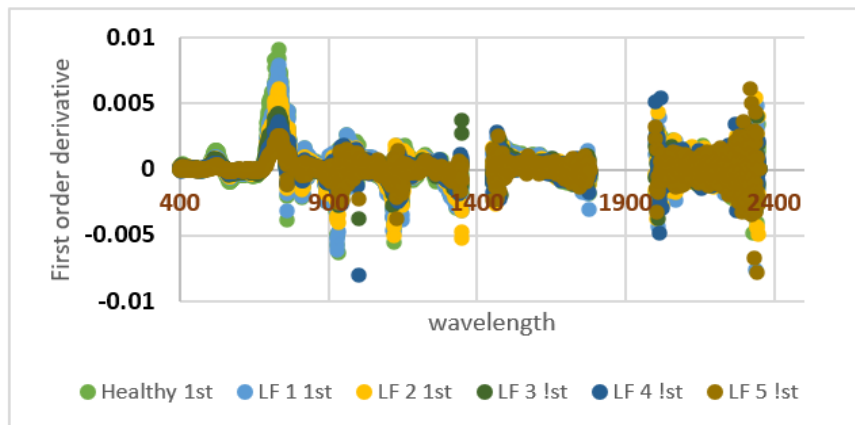


Fig 30 c. First order derivative *Naveen*, Mimic variety

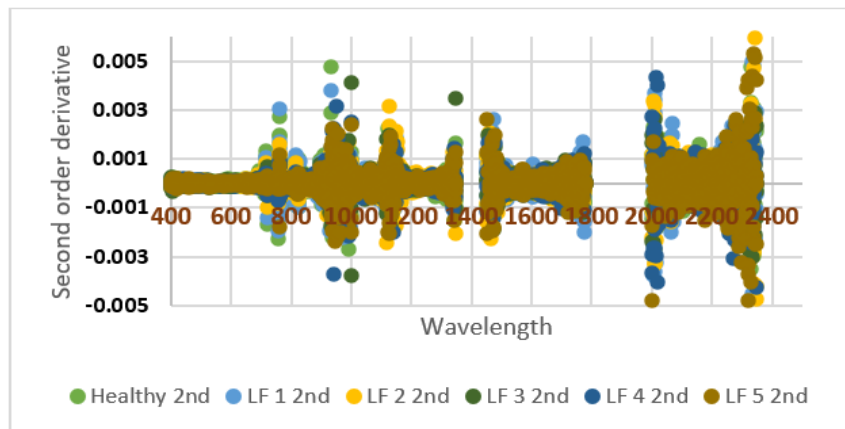


Fig 30 d. Second order derivative *Naveen*, Mimic variety

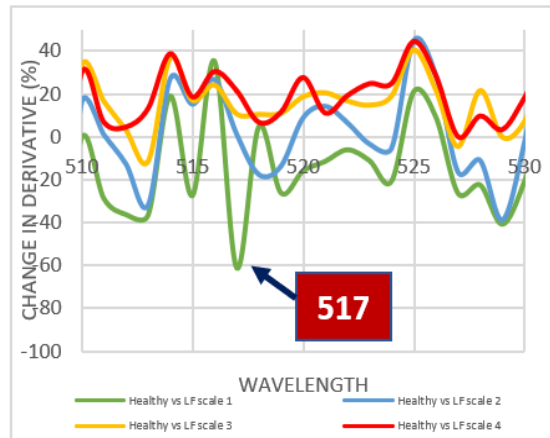


Fig 31 a. Change in derivative (%) 510-530, Farmers field

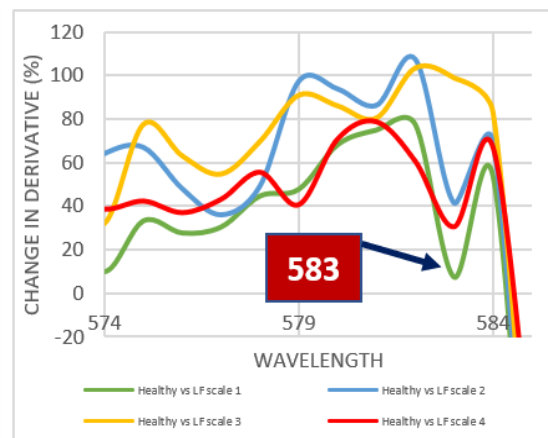


Fig 31 b. Change in derivative (%) 574-585, Farmers field

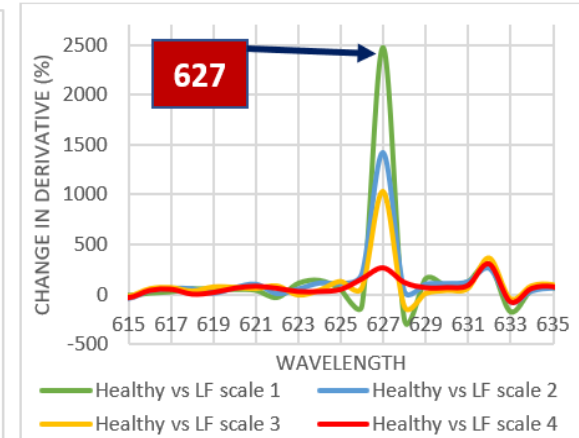


Fig 31 c. Change in derivative (%) 615-635, Farmers field

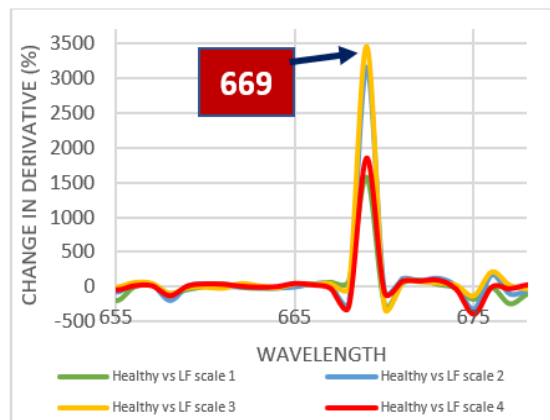


Fig 31 d. Change in derivative (%) 655-675, Farmers field

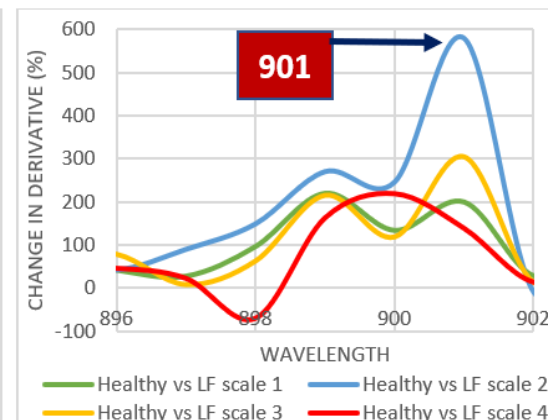


Fig 31 e. Change in derivative (%) 895-902, Farmers field

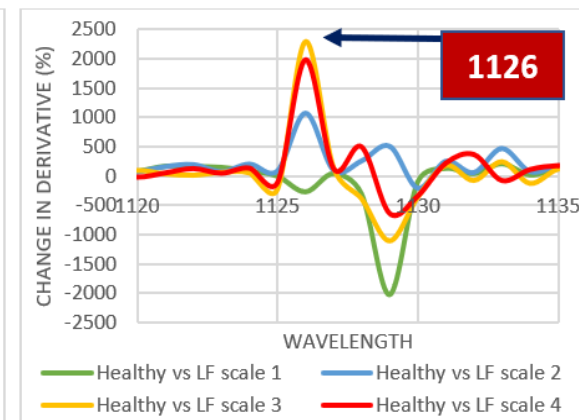


Fig 31 f. Change in derivative (%) 1120-1135, Farmers field

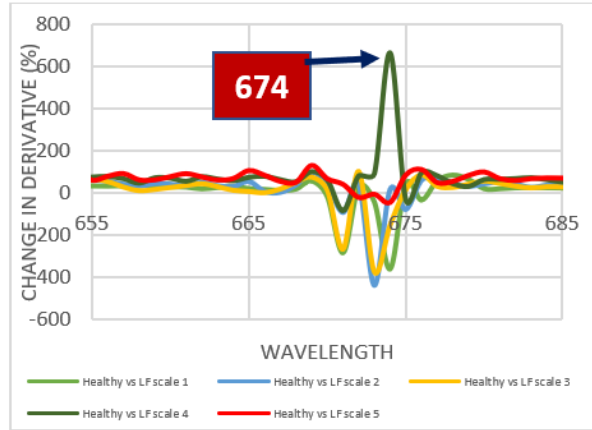


Fig 32 a. Change in derivative (%) 655-685, Naveen, mimic variety

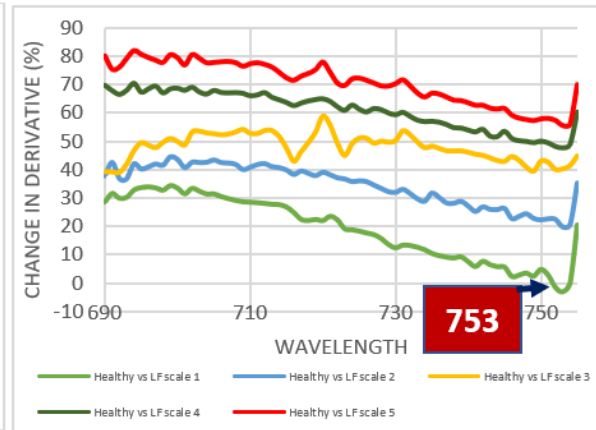


Fig 32 b. Change in derivative (%) 690-755, Naveen, mimic variety

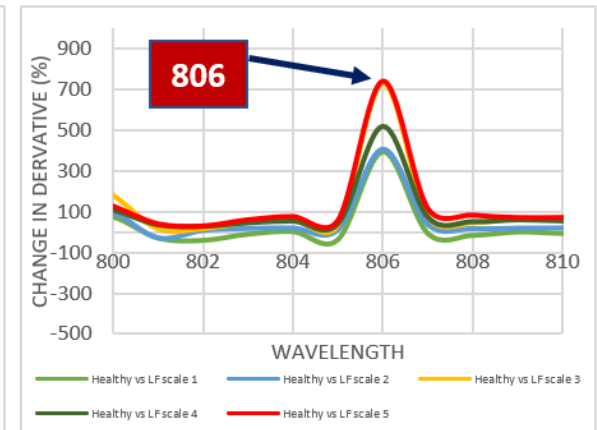


Fig 32 c. Change in derivative (%) 800-810, Naveen, mimic variety

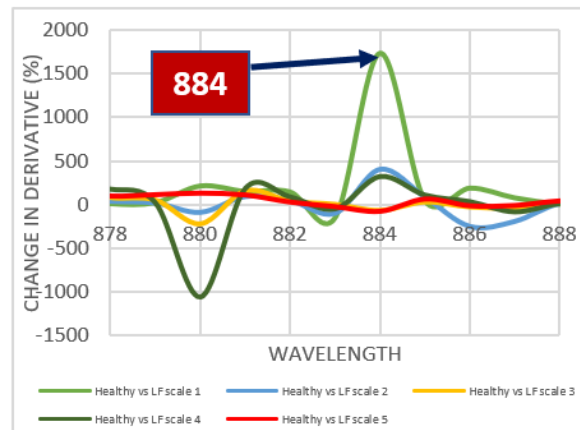


Fig 32 d. Change in derivative (%) 878-888, Naveen, mimic variety

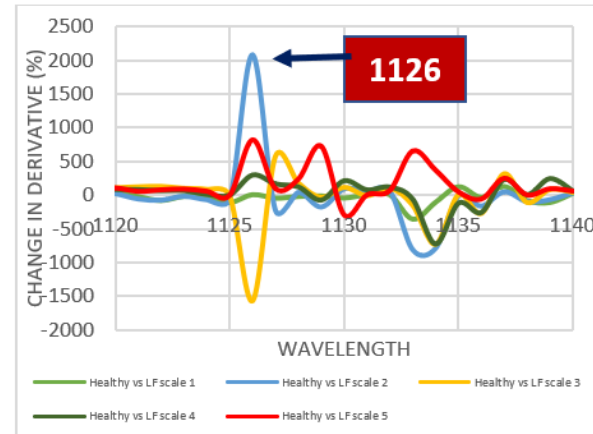


Fig 32 e. Change in derivative (%) 1120-1140, Naveen, mimic variety

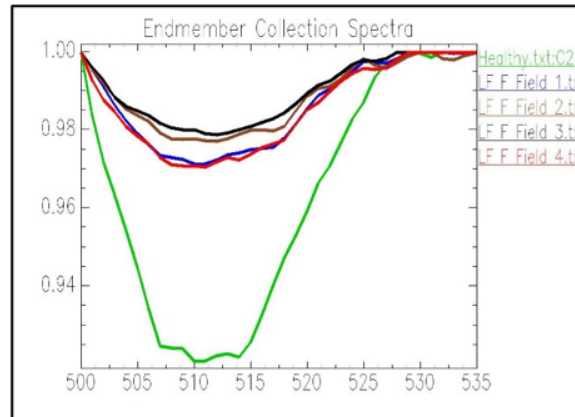


Fig 33 a. Continuum removal 500-535 (Farmers field)

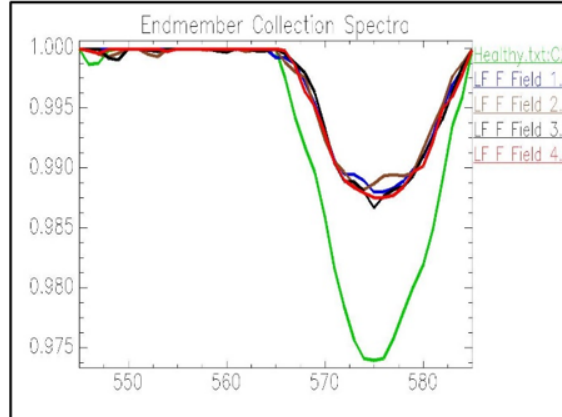


Fig 33 b. Continuum removal 540-590 (Farmers field)

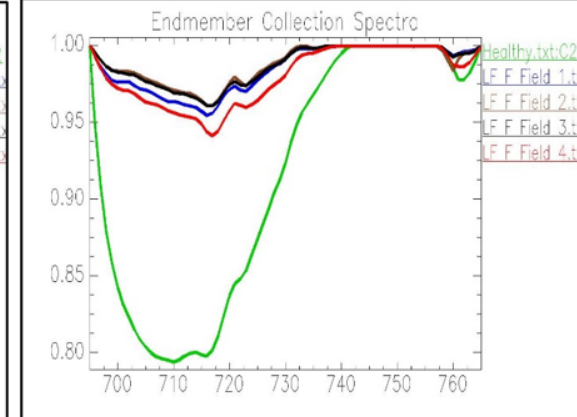


Fig 33 c. Continuum removal 695-765 (Farmers field)

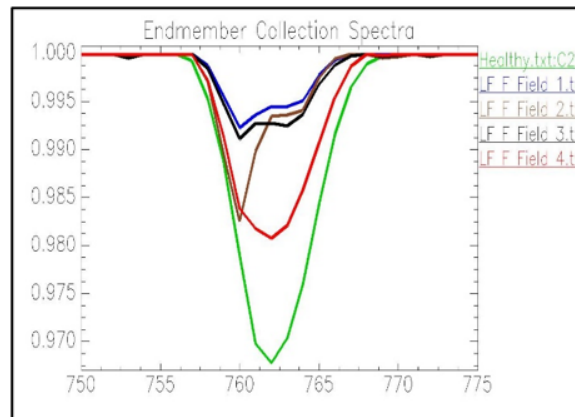


Fig 33 d. Continuum removal 750-775 (Farmers field)

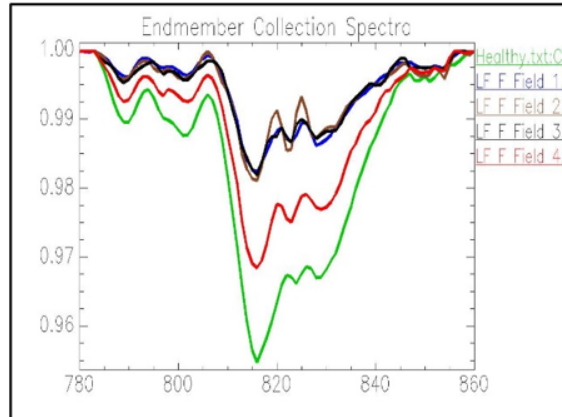


Fig 33 e. Continuum removal 780-860 (Farmers field)

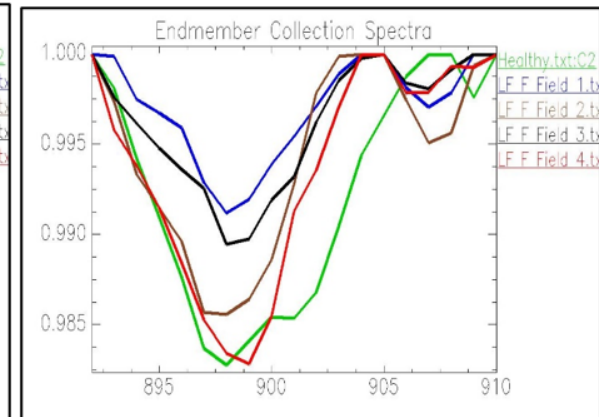


Fig 33 f. Continuum removal 890-910 (Farmers field)

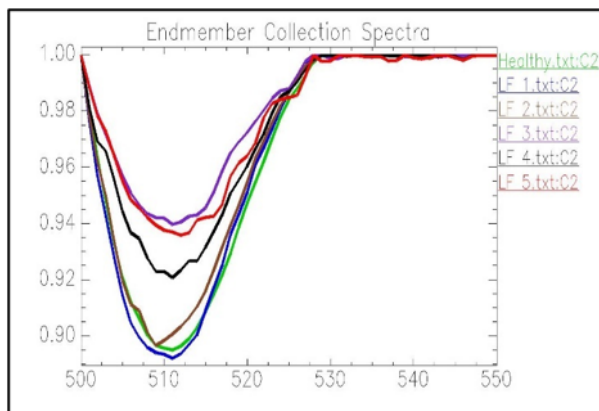


Fig 34 a. Continuum removal 500-550 *Naveen* (mimic variety)

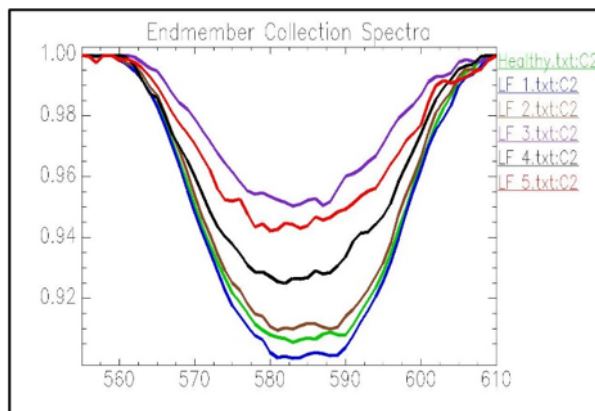


Fig 34 b. Continuum removal 555-610 *Naveen* (mimic variety)

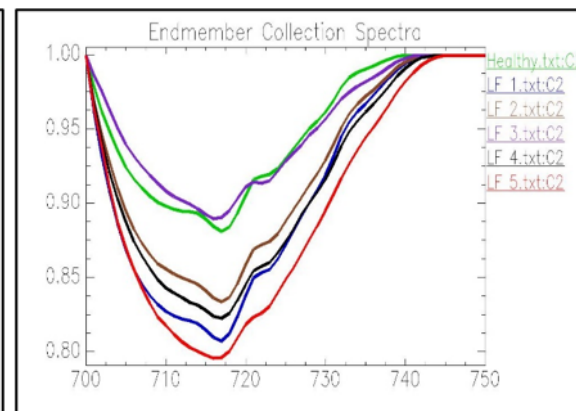


Fig 34 c. Continuum removal 700-750 *Naveen* (mimic variety)

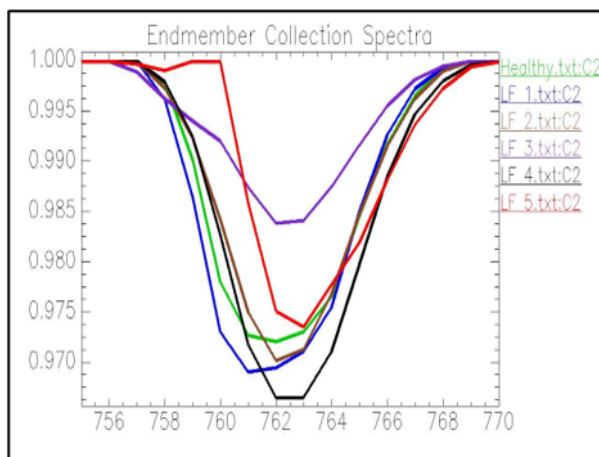


Fig 34 d. Continuum removal 755-770 *Naveen* (mimic variety)

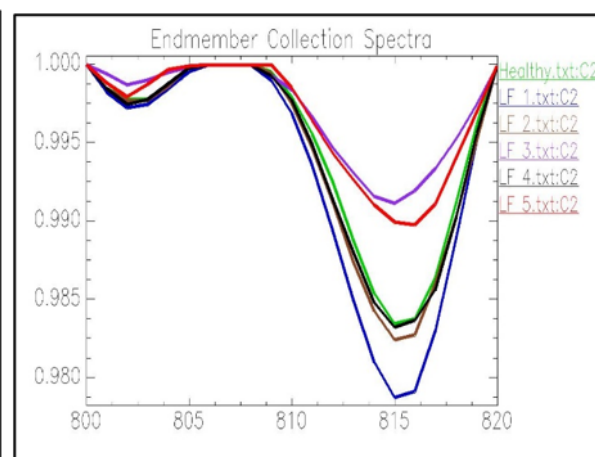


Fig 34 e. Continuum removal 800-820 *Naveen* (mimic variety)

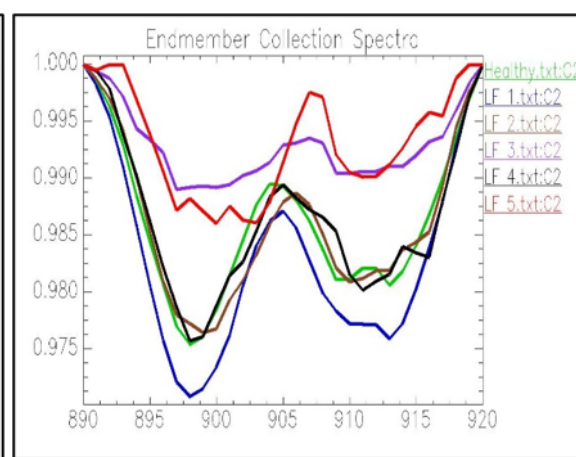


Fig 34 f. Continuum removal 890-920 *Naveen* (mimic variety)

The continuum removal was also performed to find out the exact location of absorption dips at specific wavelength. The continuum eliminated information of canopy spectral reflectance of farmers field during Rabi 2018-19 was presented in Fig 33a to Fig 33f. In the wake of removing the continuum utilizing the ENVI programming package, the absorption dips in the noticeable reach were unmistakably apparent at spectral bands *viz.*, 510, 575, 710, 762, 815 and 897 nm. Similarly, from continuum removed spectral information of the rice variety Naveen in controlled conditions revealed that there were six absorption dips at spectral bands of 510, 585, 718, 762, 815 and 897 nm, which were clearly observed after analysing with ENVI software (Fig 34 a to 34 f).

The central wavelengths selected from the derivative as well as continuum removal were subjected to unpaired 't' test for testing of significance at 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 nm interval. The pest sensitive spectral bands for farmers field and the same variety under controlled conditions are shown in Table 17. Seven spectral bands *i.e.*, 510, 583, 674, 762, 815, 897 and 1126 nm were found as most sensitive spectral bands for rice variety *Naveen* both under farmers field and the controlled conditions. The results also showed similarity with the spectral bands as recorded for rice variety TN1 in aforementioned table (Table 10). So, these spectral bands were considered as most sensitive spectral bands for rice leaf folder infestation irrespective of rice cultivar.

Table 16.1. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 1 (Farmers field, Rabi 2018-19)

Band width (nm)	Difference in 1 st derivative	Central wavelength (nm)	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	627	S	S	S	S	S	NS	NS	NS	NS	
	0.002	669	S	S	S	S	S	S	S	S	S	S
	0.002	710	S	S	S	S	S	S	S	S	S	S
	0.002	762	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S

Table 16.2. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 2 (Farmers field, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	627	S	S	S	S	S	NS	NS	NS	NS	
	0.002	669	S	S	S	S	S	S	S	S	S	S
	0.002	710	S	S	S	S	S	S	S	S	S	S
	0.002	762	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S

Table 16.3. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 3 (Farmers field, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	627	S	S	S	S	S	NS	NS	NS	NS	
	0.002	669	S	S	S	S	S	S	S	S	S	S
	0.002	710	S	S	S	S	S	S	S	S	S	S
	0.002	762	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S

Table 16.4. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 4 (Farmers field, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)									
			10	20	30	40	50	60	70	80	90	100
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S
	0.005	583	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	627	S	S	S	S	S	NS	NS	NS	NS	
	0.002	669	S	S	S	S	S	S	S	S	S	S
	0.002	710	S	S	S	S	S	S	S	S	S	S
	0.002	762	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S

Table 16.5. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 1 (*Naveen* in controlled condition, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 1 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	585	S	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	674	S	S	S	S	S	S	NS	NS	NS	NS	
	0.002	718	S	S	S	S	S	S	S	S	S	S	S
	0.002	753	S	S	S	S	S	S	S	S	S	NS	NS
	0.002	762	S	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	806	S	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	884	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S	S

Table 16.6. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 2 (*Naveen* in controlled condition, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 2 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	585	S	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	674	S	S	S	S	S	S	NS	NS	NS	NS	
	0.002	718	S	S	S	S	S	S	S	S	S	S	S
	0.002	753	S	S	S	S	S	S	S	S	S	NS	NS
	0.002	762	S	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	806	S	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	884	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S	S

Table 16.7. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 3 (*Naveen* in controlled condition, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 3 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	585	S	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	674	S	S	S	S	S	S	NS	NS	NS	NS	
	0.002	718	S	S	S	S	S	S	S	S	S	S	S
	0.002	753	S	S	S	S	S	S	S	S	S	NS	NS
	0.002	762	S	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	806	S	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	884	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S	S

Table 16.8. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 4 (*Naveen* in controlled condition, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 4 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	
	0.005	585	S	S	S	S	S	S	S	NS	NS	NS	
600-800	0.002	674	S	S	S	S	S	NS	NS	NS	NS		
	0.002	718	S	S	S	S	S	S	S	S	S	S	
	0.002	753	S	S	S	S	S	S	S	S	NS	NS	
	0.002	762	S	S	S	S	S	S	S	S	S	S	
800-1000	0.005	806	S	S	S	S	S	S	S	S	S	S	
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	884	S	S	S	S	NS	NS	NS	NS	NS	NS	
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS	
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S	

Table 16.9. Unpaired t-test for testing of significance, Healthy vs leaf folder damage level 5 (*Naveen* in controlled condition, Rabi 2018-19)

Band width	Difference in 1 st derivative	Central wavelength	Healthy vs leaf folder damage level 5 at different interval in nm (Test of significance)										
			10	20	30	40	50	60	70	80	90	100	
500-600	0.005	510	S	S	S	S	S	S	S	S	S	S	S
	0.005	585	S	S	S	S	S	S	S	S	NS	NS	NS
600-800	0.002	674	S	S	S	S	S	S	NS	NS	NS	NS	
	0.002	718	S	S	S	S	S	S	S	S	S	S	S
	0.002	753	S	S	S	S	S	S	S	S	S	NS	NS
	0.002	762	S	S	S	S	S	S	S	S	S	S	S
800-1000	0.005	806	S	S	S	S	S	S	S	S	S	S	S
	0.005	815	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	884	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
	0.005	897	S	S	S	S	NS	NS	NS	NS	NS	NS	NS
1000-1200	0.005	1126	S	S	S	S	S	S	S	S	S	S	S

Table 17. Sensitive spectral bands for rice leaf folder infestation in *Naveen* variety

Canopy reflectance	Central wavelengths identified (nm)		Significant bands for leaf folder infestation in rice variety <i>Naveen</i>
	Derivative analysis (change in percentage of derivative)	Continuum removal	
Rice variety <i>Naveen</i> in Farmer's field	517, 583, 627, 674, 797, 901, 1126	510, 575, 710, 762, 815, 897	510 583 674
Rice variety <i>Naveen</i> in controlled conditions	674, 753, 806, 884, 1126	510, 585, 718, 762, 815, 897	762 815 897 1126

4.3.2 Validation of the ground truth data with satellite imagery using sentinel analysis

To assess the potential separability of classes of leaf folder damage Sentinel 2A spectral bands and derived vegetative indices were selected. Four Sentinel 2A spectral bands at a resolution of 10 m and six ones at a resolution of 20 m were used to create a signature analysis for this purpose. The experimental plot was selected in the farmers field at Aruha, Pipili. The mean surface reflectance value for field's pixels across all damage categories of *C. medinalis* was compared. Additionally, VI which are combination of the spectral bands were used to minimize the impact of other factors viz., soil brightness, atmospheric disturbances, while highlighting the sensitivity to vegetation. Six vegetation indices were selected to test their effectiveness in discriminating the damage level of *C. medinalis*.

Four bands of Sentinel-2A with 10 m resolution (Band 2, 3, 4 and 8) and three bands from 20 m resolution (Band 5, 6 and 7) were used for the analysis. The bands from 20 m resolution were determined to 10 m as well as five common VIs (NDVI, LAI, REPI, PRI and PSRI) were chosen for its ability to estimate leaf chlorophyll as well as carotenoid content. The ground truth data was recorded on 7th September, 2019 and cropland mask was produced from the Sentinel 2A map of 5th September 2019, when the vegetation was in the booting stage. The distinction between the cropland and other landcovers that included vegetation was observed.

The sentinel bands mentioned above were made composite using Arc map 10.3 software superimposing the experimental plot taken in shapefile format. The ground truth hyperspectral data were superimposed on the satellite imagery and hotspots were observed indicating the infestation of *C. medinalis* (Fig 35 a). Then the processed data was classified and crop masking was done to segregate healthy and infested samples (Fig 35 b).

The quality of the output of the classifier was evaluated through the Receiver Operating Characteristics (ROC) curve for deep learning model (Fig 35 c). The classification accuracy of 85.71 percentage was sufficient enough to predict that the validation model made using the combination of vegetative indices was correct. The training model (cross validation model using MATLAB) also confirmed an accuracy of 80 percent which replicates the ROC curve to be positively inclined.

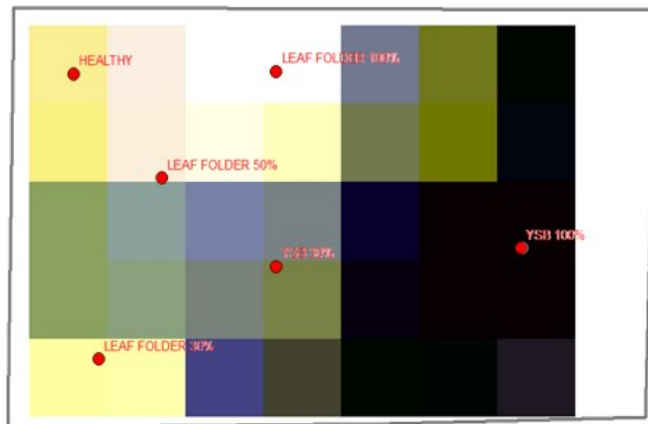
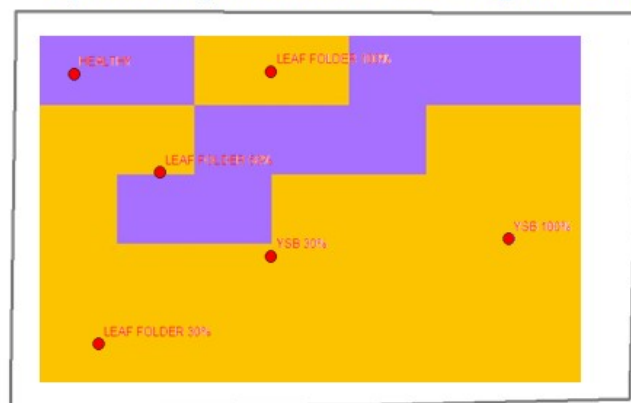
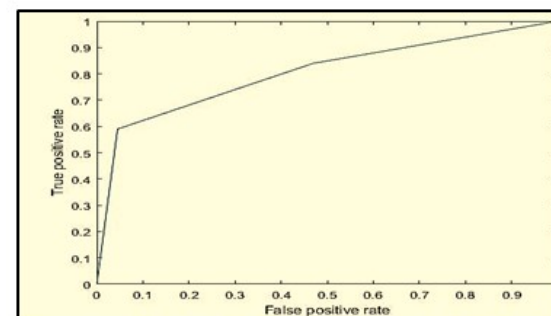


Fig 35 a. Sentinel 2A Composite map of the experimental plot at farmer's field using band 2 to 8



■ Healthy ■ Pest infestation

Fig 35 b. Validation of experimental plot with satellite imagery



Cross-validation Training dataset Accuracy = 80%

Classification Accuracy = 85.71%

Fig 35 c. ROC curve of Ensemble Decision Tree (Adaboost) for Plant Biotic stress

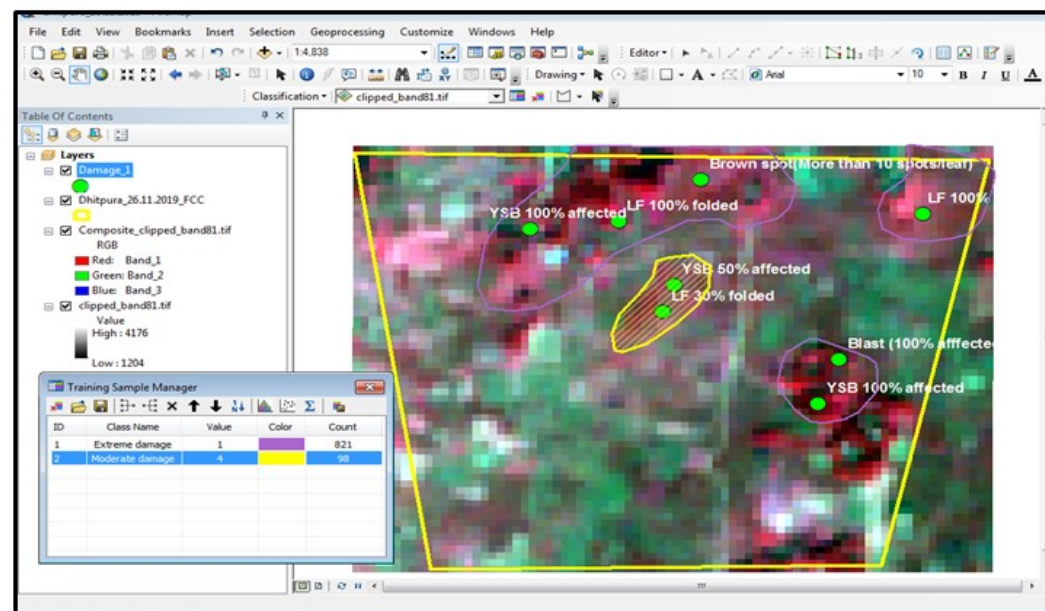


Fig 35 d. Validation by FCC map of the location indicating healthy and infested hotspots

Finally, the composite image was taken on ArcMap 10.3 by which and red, green and blue bands were set as Band 1, 2 and 3, respectively. Then the False Colour Composite (FCC) was derived which indicated the presence of infestation of *C. medinalis* in different colour codes (Fig35 d). The reddish-brown colour indicated the presence of severely infested area. The light red colour indicated the moderately infested area and the healthy vegetation was denoted by the green colour code.

CHAPTER -V

DISCUSSION

The results of field and laboratory experiments on "Assessment of leaf folder, *Cnaphalocrosis medinalis* (Guenée) damage in rice using ground based hyperspectral remote sensing techniques" conducted during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 at the farmer's field at Aruha, Pipili as well as ICAR-NRRI experimental fields at Cuttack have been presented in chapter IV. In the current chapter discussion in consideration of results obtained are presented.

5. 1 Discrimination of damage by *C. medinalis* in rice using the hyperspectral remote sensing techniques

Early detection of localized infestation of crop pest is the major goal of the hyperspectral remote sensing technique. The different objects in universe reflect, radiate and absorb the electromagnetic radiation incident upon that object and the specific reflection of energy is represented as electromagnetic spectrum. The spectral signature for different vegetation varies according to their biophysical and biochemical characteristics. So, reflectance value differs for healthy and infested vegetation. The fundamental approach for discriminating the pest damage is to detect the pest sensitive spectral bands from the electromagnetic spectrum. In view of scanty information on hyperspectral signature of crop pests in India, the present endeavour for evaluating the ground based hyperspectral remote sensing technique for assessing the damage of *C. medinalis* in rice is justified.

5.1.1 Spectral reflectance curve in relation to infestation of *C. medinalis* in rice

In the present study a ground-based ASD hyperspectral portable spectroradiometer was used to collect the remote sensing data set in the field. This device has been widely used for identification and characterization of different crop plants affected due to various biotic stress (Abdel- Rahman *et al.*, 2010 and Zhao *et al.*, 2013). The spectral signature of rice leaf and canopies in relation to infestation of *C. medinalis* presented through distinguished spectral curves for Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 interpreted that uninfested plant had higher reflectance in visible as well as near infrared region than infested plants for all the experimental season (Fig 15 to Fig 18). Changes in biological properties of photosynthetic pigments

caused by insect feeding resulted higher plant reflectance in visible region. Uninfested plants were comparatively green than the infested plants due to more absorption of blue (450 nm) and red (680 nm) radiation. Lower reflectance in the NIR band (700-1100 nm) observed in infested plants compared to healthy plants might be attributed due to leaf curling and shrinking caused by infestation of *C. medinalis* which could have resulted in incoming radiation scattering rather than reflectivity from leaf surface. Peak reflectance was observed at spectral bands of 520-540 nm which was comparatively higher in healthy vegetation in all the spectral curves. These variations in reflectance in this spectral band could be ascribed due to the presence and fluctuation of carotenoid. The reflectance value in each curve were found increased from 400 nm to the red edge shoulder. Each graph had small dip at spectral bands of 760-765 nm. This difference in magnitude between the graphs of canopy and leaf reflectance in the near infrared region was mostly attributable due to absorption of oxygen. The atmospheric disturbances were observed between 1350 and 1450 nm and 1780 and 2000 nm.

The spectral curves of healthy and damaged canopy of various crop by several insects and diseases showed a differential signature pattern (Dutta *et al.*, 2006, Vanegas *et al.*, 2018, Guo *et al.*, 2021 and Ji *et al.*, 2022). Huang *et al.*, (2012) found that as rice's leaf-roll rate due to *C. medinalis* increased, the reflectance from the leaves greatly increased in the blue (450-520 nm) and red (580-700 nm) regions and significantly reduced in the green (530-570 nm) and near infrared (700-1000 nm) regions. The leaves infested by *C. medinalis* had greater reflectance in the visible (430–470 nm, 490–610 nm, and 610–680 nm) and short-wave infrared (2080–2350 nm) regions. As compared to healthy leaves, the infested leaves had a reduced reflectance in the near infrared (780–890 nm) and short-wave infrared (1580–1750 nm) regions (Singh *et al.*, 2013). Zhao *et al.*, (2013) reported that reflectance in the visible range steadily decreased with increasing levels of *C. medinalis* damage in the same wavelength range, whereas it gradually increased in the NIR region. The obtained curves looked to have flattened, especially in the SWIR band (2000-2350 nm). The overall patterns of the spectral curves were flattened, especially in the visible and near-infrared spectrum (350-1350 nm). Wang *et al.*, (2018) found that when the population of *C. medinalis* increased, reflectance from the infested rice canopy considerably increased in the blue (450-520 nm) and red (580-700 nm) regions and reduced in the green (530-570 nm) and near infrared (700-1000 nm) regions.

When the leaf-roll rates increased during the booting stage, the reflectance dropped in the near-infrared spectral range. (Liu *et al.*, 2020). All these findings of previous researchers are in harmony to the results of present investigations.

5.1.2 Discrimination of infestation by *C. medinalis* through derivative analysis

Derivative analysis is used to reveal or enhance absorption features that are obscured by conflicting background absorption (Curran *et al.*, 1990, Filella and Penuelas, 1994). The instantaneous rate of change of a dependent variable with respect to an independent variable is represented by the first order derivative. The first order derivative provided the slope of the tangent line created at a certain point on the graph curve in terms of the graph derived from the experiments in three crop seasons. The graph's concavity or curvature was represented by the second-order derivative, which was the derivative of the first derivative. The graph of a function is upward concave if the second-order derivative value is positive.

First and second order derivative analysis were carried out using the reflectance data from three experimental seasons *viz.*, Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19 to identify the central wavelengths with maximum percentage change in derivative value. Six spectral wavelengths *i.e.*, 597, 672, 732, 806, 900 and 1131 nm were confirmed as central wavelengths from the derivative analysis during Rabi 2017-18 (Fig 20 a to Fig 20 f). The seven spectral wavelengths (411, 597, 672, 733, 806, 898 and 1130 nm) and six spectral bands (9596, 673, 757, 783, 806 and 1137 nm) were identified as central wavelengths from the derivative analysis of the canopy spectra during *Kharif* 2018-19 and Rabi 2018-19, respectively (Fig 21 a to Fig 22 f). The percentage change in derivative was highest at the spectral bands of 411, 597, 672, 733, 806, 898 and 1130 nm, for which these spectral bands were considered as central wavelengths based on leaf reflectance data (Fig 23 a to Fig 23 g).

Information on the hyperspectral spectroscopy of infestation by *C. medinalis* in rice as well as other insect pests through derivative analysis is scanty. But the findings of several studies revealed that the sensitive spectral bands were dictated by changes in the first order derivative. Liu *et al.* (2011) derived the derivative graphs of stressed leaves resulted due to infestation of *C. medinalis* had a smaller first order derivative (FDR) amplitude than normal leaves. Peak wavebands for the blue and green spectral areas were discovered at 521 nm and 569 nm, respectively. Stressed leaves, on the other

hand, shifted toward 5 nm-long wavebands, indicating that the red-light spectrum region was more susceptible to pest injury than the blue and green regions. The first and second order derivative graphs were also obtained for the rice crop infested by *C. medinalis* and the spectral discrimination between healthy and infested vegetation was done by identification of optimum bands (Huang *et al.*, 2012). Yang *et al.*, (2009) and Yang (2010) reported sensitive spectral bands through the derivative analysis for infestation of Russian wheat aphid and green bugs in wheat crop. The present results get ample support with the findings of these aforementioned researchers.

5.1.3 Discrimination of infestation by *C. medinalis* through continuum removal

As the hyperspectral remote sensing method needs vast volumes of data and thousands of bands so for identification of the most responsive band on the other hand is a challenging task. Data redundancy is the most reliable method for detecting sensitive bands. The best possible sensitive bands that clearly discriminates the healthy and infested samples were identified using continuum removal approach. The continuum is a convex hull fit over the top of a spectrum using straight-line segments that connect local spectra maxima. The first and last spectral data values are on the hull; therefore, the first and last bands in the output continuum removed data file are equal to one. When the continuum and spectra match, the image spectrum is equal to 1.0 and when absorption features appear, it is less than one (Huang *et al.*, 2004; Sowmya and Giridhar, 2017; Yousefi *et al.*, 2018).

Increase in reflectance for rice infested by *C. medinalis* was larger at blue bands and the red bands while it was smaller near the green bands. The healthy rice vegetation had a higher reflectivity than infested samples when the wavelength was greater than 680 nm. The continuum removal strategy which normalises the reflectance spectra to a range of 0-1 was used to compare the individual absorption. Eight spectral bands *viz.*, 505, 583, 669, 718, 815, 898, 934 and 1152 nm, eleven spectral bands *viz.*, 508, 578, 622, 646, 694, 762, 816, 898, 934, 1125 and 1150 nm and ten spectral bands *viz.*, 510, 580, 646, 706, 763, 815, 897, 935, 1122 and 1150 nm were identified as central wavelengths from the continuum removed canopy spectra during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19, respectively through ENVI software. Likewise, the continuum removed leaf reflectance during Rabi 2018-19 indicated six spectral bands

(515, 582, 718, 763, 815 and 897 nm) as central wavelength where absorption dips were observed (Fig 24 a to Fig 27f).

Information on discrimination of leaf folder damage in rice through the continuum removal approach could not be traced in literature. However, several researchers reported the sensitive bands specific to biological stress due to various factors other than insect pest infestation through this approach which supported potentially to the present findings. Zhao *et al.*, (2012) identified two sensitive regions (401-530nm and 550-730nm) with the sensitive bands 498 and 678 nm for rice vegetation infested by brown spot through continuum removal approach. The nitrogen stress in vegetation was distinguished from the continuum removed spectra (Kokaly, 2001). Sowmya and Giridhar, (2017) observed various sensitive bands *viz.*, 410 nm due to chlorophyll, 550 nm (peak in reflectance) due to Beta carotenoid and 760-940 nm (dip in reflectance) due to anthocyanins in the continuum removed graph in *Capsicum annum*.

5.1.4 Assessment of damage by *C. medinalis* by identification of pest sensitive spectral bands

Sensitive bands are essential for reducing data redundancy, choosing efficient bands and creating conversion models for hyperspectral remote sensing data. Therefore, it is crucial to precisely identify the bands or spectral areas that are most sensitive to the damage by insect pests. Though derivative analysis and continuum removal process for every band range of rice canopy (Var TN1), the central wavelengths were found during Rabi 2017-18, *Kharif* 2018-19 and Rabi 2018-19. The significance of the central wavelengths was examined using the unpaired 't' test, for ascertaining these wavelengths as pest-sensitive spectral regions. Seven spectral bands *viz.*, 515, 582, 673, 732, 815, 898 and 1130 nm were identified as the pest-sensitive spectral bands taking into account the reflectance of the leaf as well as the canopy during the three cropping seasons (Table 10). The reflectance from the leaf folder infested rice vegetation (rice variety, Naveen) in the farmer's field was also recorded using hyperspectral technology. The data analysis and comparison with the earlier study with rice variety TN-1 showed that the aforementioned spectral bands *viz.*, 515, 582, 673, 732, 815, 898 and 1130 nm were pest-sensitive bands regardless of rice cultivar.

Three spectral bands viz., 445 nm in heading, 757 nm in active tillering and 938 nm in booting were considered to be sensitive for rice leaf folder, *C. medinalis* (Yang *et al.*, 2007). Liu *et al.*, (2011) identified two spectral bands from the blue area i.e., 521 and 569 nm, as sensitive bands for *C. medinalis*. Similarly, after processing the spectrum data, seven sensitive regions viz., 503-521, 526-545, 550-568, 688-699, 703-715 and 722-770 nm from the leaf reflectance and a single sensitive spectral zone viz., 747-754 nm were identified for healthy and rice canopy infested by *C. medinalis*, respectively (Huang *et al.*, 2012). Zhao *et al.*, (2013) detected a spectral band (1141 nm) from short wave infrared (SWIR) range along with 424 nm and 758 nm for the rice plants infested by *C. medinalis*. Eight spectral bands viz., 716, 720, 733, 762, 766, 814, 816 and 896nm were recorded as sensitive spectral bands for rice leaf folder infestation (Adhikari *et al.*, 2020). Liu *et al.*, (2020) discriminated the damage in rice by *C. medinalis* and found that spectral bands viz., 410, 470, 490, 570, 625, 665 and 720 nm as the most sensitive spectral bands for leaf folder infestation. The present findings are in close conformity with the observations of these previous authors.

5.2 Relationship between the hyperspectral signature and the biochemical composition of rice leaves

Spectral reflectance is always associated with specific plant characteristics. Indices based on wave length in the visible and infrared regions of electromagnetic spectrum are being used in remote sensing technique to predict biochemicals of leaf and thereby various types of physiological traits. Plant stresses and senescence are visible as a reorganization or loss of pigments. Minor biochemicals such as specific defensive compounds may reveal more about their presence or absence by their concentrations. In the present investigation a great deal of variation between the hyperspectral signature of rice plants infested with *C. medinalis* with various biochemicals of rice plant viz., chlorophyll, phenol and carotenoids were observed.

a) Chlorophyll: Chlorophyll content is the most commonly used biochemical property of crops and its deficiency can be detected by remote sensing. Insect pests produce feeding stress in rice plants and thereby cause significant changes in the plant's nutritional composition as well as changes in the plant's biochemicals and enzyme levels. Chlorophyll content varies with differential degree of infestation of insect pests. The two primary photosynthetic pigments in plants are *chlorophyll a* and *chlorophyll b*.

In the present study the *chlorophyll a*, *chlorophyll b* and the total chlorophyll content was in the decreasing order with the increase in degree of leaf folder infestation. It was evident from the result that there was no significant reduction in *chlorophyll a* concentration up to 20 percent leaf damage due to insect. But there was a significant reduction in *chlorophyll a* concentration in rice leaves when the infestation rate further increased due to feeding and damage of rice leaf folder. The decrease in *chlorophyll a* concentration had a direct relation with extent of damage. As the percentage of leaf damage increased the *chlorophyll a* concentration gradually decreased simultaneously. Similar to *chlorophyll a*, the concentration of *chlorophyll b* was not influenced by insect feeding severely and the effects were marginal compared to the control up to 20 percent damage (healthy, grade 1 and grade 2). However, as the infestation rate increased, the concentration of *chlorophyll b* decreased significantly once more. The overall chlorophyll content was also reduced as the infestation rate increased. Four spectral bands viz., 515, 582, 597 and 672 nm were found sensitive due to chlorophyll absorption in the rice leaves infested by *C. medinalis* (Table 12.1). The peaks in the absorption spectra indicated that blue and red wavelengths were absorbed by chlorophyll molecules.

Meager information on variation in chlorophyll content in rice due to infestation of *C. medinalis* is available in published literatures. Zhao *et al.*, (2013) recorded the decreasing trend of chlorophyll in rice due to leaf folder infestation. The level of chlorophyll a, b and total chlorophyll were reduced due to leaf folder infestation in rice variety TN1 (Nayak *et al.*, 2019). The findings of these earlier workers corroborate with the present observation.

Information on spectral band sensitive due to chlorophyll absorption in the rice canopy infested by *C. medinalis* could not be traced in literature. However, the detection of chlorophyll absorption bands for other biotic stresses was reported in various plants. Maximum sensitivity to *chlorophyll a* concentration was found at 550-560 nm and 700-710 nm in maple and chestnut (Gitelson and Merzlyak, 1998). Riedell and Blackmer, (1999) found that the leaf reflectance from wheat in the spectral ranges of 625–635 and 680–695 nm was substantially connected with total chlorophyll concentrations in wheat plants infested by Russian wheat aphid and greenbug. Gitelson *et al.*, (2003), Dian *et al.*, (2016) and Sowmya and Giridhar, (2017) reported similar

spectral ranges related to chlorophyll absorption in several crop. All these observation by previous researchers are in full agreement with the present findings.

b) Phenol: Phenolics are the aromatic benzene ring compounds with one or more hydroxyl groups which play crucial role in physiological functions in plants to provide resistance against various biotic stresses. Phenolic phytoalexin generated by stressed or damaged plant kills or deters numerous insect pests.

In the present study the lowest phenol concentration (3.25 mg/g) was observed in healthy leaves and it increased gradually with the percentage of infestation of *C. medinalis*. The rate of phenol content augmentation was lower because the test variety TN1 was a susceptible variety for rice leaf folder infestation. The leaves with more than 50 per cent infestation of *C. medinalis* contained highest phenol (4.79 mg /g) (Table 11.2). In the spectra of leaves and plant canopies, an absorption of phenolic compounds was observed at the SWIR region. This characteristic is most likely brought on by C-H bonds that are joined to the benzene ring in aromatics and phenols. Further study showed that among the identified spectral bands for infestation of *C. medinalis*, the spectral band of 1131 nm was found sensitive due to phenol absorption (Table 12.3).

Usha Rani and Jyothsna, (2010) found a substantial increase in phenol content in rice leaves infested by *C. medinalis*. In rice variety TN1 the total phenol content was increased by 23.85 per cent because of the enhance in defence mechanism against rice leaf folder (Punithavalli *et al.*, 2013). All these findings of previous researchers are in accordance with the present observation with respect to higher phenol content in the leaf folder infested leaves.

Information on phenol absorption spectral bands from rice canopy infested by *C. medinalis* could not be found in available literatures. However, particular spectral bands of phenol absorption were determined in other crops due to various biotic stresses. Kokaly and Skidmore (2015) found maximum absorptivity of phenol at 1130 nm. Total phenols in grape seeds were projected to exist between 1200 and 1450 nm in the NIR range (Zhang *et al.*, 2017). Yan *et al.*, (2021) examined the spectral signatures and demonstrated that the reflectance intensity decreased at approximately 1131.7nm and 1657.3nm, respectively in the phenol absorption curve. These experimental findings provide ample support to the present observations.

c) Carotenoid: Carotenoids are essential pigment in photosynthetic organs along with chlorophyll. These compounds absorb the light energy for use in photosynthesis as well as they protect chlorophyll from photo damage. Plants characterised by a lower carotenoids/chlorophyll a + b quotient are always less invaded by insect pest (Luczak, 1991). In the present study it was found that carotenoid content of rice leaves varied with leaf folder infestation. The concentration of carotenoid was lowest in rice leaves with more than 50 per cent damage (0.207 mg/g) by *C. medinalis* and highest (0.36) in the healthy leaves (Table 11.2). The correlation study further indicated that spectral bands of 515 and 582 nm were found sensitive due to absorption of carotenoid (Table 12.2). The spectral bands for carotenoid absorption were shown to be near the violet, green and blue region.

Information on relationship of carotenoid content with the incidence of *C. medinalis* in rice is lacking in published literature except the report of Nayak *et al.*, (2019) who found a similar declining trend in carotenoid pigment with increase in the infestation of *C. medinalis* in rice variety TN1. A declining trend of carotenoid level was observed in the leaves of *Nephtrolepis biserrata* infested with *Coccus hesperidum* in comparison to control plants (Golan *et al.*, 2015). Anjali *et al.*, (2017) found that the carotenoid content considerably decreased in medium infestation (200 aphids/plant) and high infestation (300 aphids/plant) in corn plant. Thus, the present observation confirmed the findings of these authors.

Scanning of literature showed no information on determination of sensitive band due to absorption of carotenoid under biotic stress condition due to insect pest attack. However, several researchers reported carotenoid absorption from spectroscopic studies of crops affected due to diverse biotic stresses. The ratio analysis of reflectance spectra revealed that the small peak at 500 nm was attributed to carotenoid (Car) absorption in spectrum (Chappelle *et al.*, 1992). Zur *et al.*, (2000) found a strong peak at 510 to 520 nm due to carotenoid content in the foliage. The reflectance near spectral bands, 510 nm and 550 nm were strongly related to carotenoid absorption (Gitelson *et al.*, 2003). The present findings are in partial agreement with the opinions of the above researchers.

5.3 Determination of vegetative indices for leaf folder infestation

Spectral vegetative indices are the mathematical combinations of various spectral bands primarily in the visible and near infrared region of the electromagnetic spectrum which normalize the plant reflectance. Reflectance variation due to different factors such as solar angle, background scattering and other unknown factors can be minimized by developing new vegetative indices which determine ultimately the sensitivity to damage by insect pests. In the present study some predetermined vegetative indices *viz.*, Normalized Difference Vegetation Indices (NDVI), Leaf Area Index (LAI), Red Edge Position Index (REPI), Photochemical Reflectance Index (PRI) and Photochemical Senescence Reflectance Index (PSRI) were computed using the spectral reflectance data of rice infested by *C. medinalis*.

a) NDVI: Normalized Difference Vegetation Index (NDVI) is the normalized difference of reflectance in NIR and red bands. This index is widely used for crop stress detection, because of its significant correlation with biomass and green leaf cover (chlorophyll content) (Curran, 1980). It measures the green vegetation over the surface and is determined from the visible (VIS) and near infrared (NIR) bands of the electromagnetic spectrum. This index normalises green leaf scattering in the near infrared wavelength and chlorophyll absorption in red wavelength. In the present study highest NDVI value of 0.77 was reported from the healthy vegetation of rice. A gradual decrease in NDVI value was observed with increase in infestation of *C. medinalis* (Table 14).

NDVI has also earlier been reported detecting insect pest infestation in several crops *viz.*, aphid and spider mite in cotton (Reisig and Godfrey, 2006), green bug and Russian wheat aphid in wheat (Yang *et al.*, 2009), soybean aphid in soybean (Alves *et al.*, 2015) and hessian fly in wheat (Bhattarai *et al.*, 2019). The present findings on decreasing trend of NDVI under biotic stress condition is well supported by the report of Rouse *et al.*, (1973) and Gitelson and Merzlyak (1994).

b) LAI: Leaf area index is a dimensionless quantity that characterizes plant canopy. Monitoring the distortion and change of LAI is essential for assessing the growth and vigour of vegetation. Canopy interception, evapotranspiration and gross photosynthesis are directly proportional to LAI. Emerging remote sensing technology can complement existing ground-based measurement of LAI for discriminating the damage by insect

pests. In the present study the value of LAI gradually reduced from 3.20 to 1.44 with increase in infestation of *C. medinalis* in rice. Hui *et al.*, (2009) also reported the use of the index (LAI) for detecting biotic stress due to insect attack in several crops.

c) REPI: Red edge position index (REPI) is sensitive to change in chlorophyll concentration. Increased chlorophyll concentration broadens the absorption feature and moves the red edge to longer wavelength. This is a sensitive indicator for various types of stress due to drought, insect pest attack and senescence. The position and the slope of the red-edge change under stress condition, resulting in a shift of the slope towards shorter wavelength. Position of red edge is defined as the position of the main inflexion point of the red NIR slope. This is also denoted as the red edge index.

Present study indicated that the position of red edge was reported at wavelength (spectral band) of 722 nm for healthy vegetation of rice and it gradually shifted towards the shorter wavelength and stationed at 707 nm for maximum infestation of *C. medinalis* (Grade 5). It was an expected phenomenon, that the presence of higher concentration of chlorophyll widened the absorption characteristics for which the red edge moved towards longer wavelength.

Several researchers *viz.*, Guyot and Baret (1988) and Luedeling *et al.*, (2009) have also reported the use of REPI for detecting biotic stress in crop plant. The present finding on shift of slope towards shorter wavelength are in accordance to the report of Vinoth Kumar *et al.*, (2016) while detecting the crop stress due to aphid and spider mite in brinjal.

d) PRI: Photochemical Reflectance Index (PRI) is derived from narrow band reflectance at 531 and 570 nm which measures the plant responses to stress. It is sensitive to changes in carotenoid pigment in live foliage. It provides a quick and non-destructive assessment of leaf physiological property (Penuelas *et al.*, 1995, Hilker *et al.*, 2010). PRI is based on short term reversible xanthophyll pigment changes accompanying plant stresses.

Present studies revealed a declining trend in the value of PRI from 0.17 to -0.14 with corresponding increase in infestation of *C. medinalis* in rice. Since carotenoid content is associated with PRI, so its value gets reduced as the infestation of *C. medinalis* increased. The use of this vegetative index was earlier found suited in

differentiating the stress due to insect pest infestation in several crops (Gamon *et al.*, 1997; Luedeling *et al.*, 2009; Garbalsky *et al.*, 2010 and Huang *et al.*, 2012).

e) PSRI: Photochemical Senescence Reflectance Index (PSRI) maximizes the sensitivity to the ratio of bulk carotenoids. An increase in PSRI indicates increased canopy stress. This tool is used for plant health monitoring and detection of physiological stress. Its value ranges from -1 to +1. For green vegetation it ranges for -0.1 to 0.2 (Penualas *et al.*, 1995, Merzlyak *et al.*, 1999).

In the present investigation, the value of PSRI was maximum (0.18) for the highest grade of leaf folder damage (grade 5) whereas lowest value of 0.03 was observed for the healthy vegetation. The reason might be ascribed due to loss of chlorophyll as a result of insect attack. An increase in PSRI value representing the plant stress condition was earlier reported by Dutta *et al.*, (2009).

f) Relationship between various combination of spectral bands and chlorophyll

The relationship between a number of two band and three band sensitive spectral indices and the chlorophyll content was determined by plotting the regression graph. Three numbers of two band indices *viz.*, (R_{515}/R_{732}) , $(R_{732}-R_{515})$ and $\{(R_{732}-R_{582})/(R_{732}+R_{582})\}$ and three numbers of three band indices *viz.*, $\{R_{732}/(R_{515}+R_{673})\}$, $\{R_{815}/(R_{568} \times R_{732})\}$ and $\{R_{815}/(R_{673}+R_{582})\}$ were established specifically for the leaf folder infestation in rice utilising two and three band combinations (Fig 28 a to Fig 28 f).

The photochemical reflectance index $(R_{550}-R_{531})/(R_{550}+R_{531})$ along with newly developed two-band spectral index $(R_{490}-R_{470})$ as well as three-band spectral index $(R_{400}-R_{470})/(R_{400}-R_{490})$ showed a good correlation for estimating leaf-roll rates in rice infested by *C. medinalis* (Liu *et al.*, 2020). Huang *et al.*, (2012) utilized the bands from blue, red and red edge region i.e., 542, 670 and 730 nm to formulate the vegetation indices like PRI and NDVI based on the spectral reflectance from the rice canopy infested by *C. medinalis*. The present findings are in close conformity with the remarks of these previous authors.

5.4. Validation of ground truth hyperspectral data with the satellite imagery by Sentinel 2A analysis

The ground truth hyperspectral data was validated using Sentinel 2A images. ArcMap 10.3 was used to create composite images of the Sentinel bands (13 bands). Then ground truth hyperspectral data were superimposed on the satellite imagery and hotspots were observed indicating the presence of insect pest occurrence. Results showed that the infested vegetation due to leaf folders, *C. medinalis* were observed along with the healthy crop area in the particular location. The Receiver Operating Characteristics (ROC) curve with classification accuracy of 85.71 percentage was obtained for the data set. A False Colour Composite (FCC) was created by superimposing the shapefile of the experimental plot on the composite image to reveal hotspots with various colour codes. Dark red denoted the presence of highly infested places, whereas light red depicted locations that were moderately infested. The imagery's use of green symbolised healthy vegetation (Fig 35 a to Fig 35 d).

Similar protocols were followed to validate the hyperspectral data set of the healthy and Fall Army Worm (FAW) damaged maize crop locations (Champagne, 2019). The sentinel bands (Band 2, 3, 4, 5, 6, 7 and 8) used in the experiment are identical to that of present research. The false colour composite was derived from the sentinel analysis which determined and discriminated the healthy and infested locations based on different colour codes. The red colour described the presence of infested area while the green colour code indicated the healthy vegetation. Moso *et al.*, (2021) investigated the anomaly detection in two fronts: application to the GPS logs of combine harvesters and detection of crop damage in crop dataset. Validation of ROC curve was obtained by the Sentinel data analysis. ROC curve with classification accuracy 0.8 to 0.9 was considered to be excellent. Ali *et al.*, (2021) also validated the multitemporal Normalized Difference Vegetation Index (NDVI) extracted from nine Sentinel-2 imagery cover the whole summer season. The supervised nearest neighbourhood object-based classification method was employed which classified the map with an overall accuracy of 95 per cent and a kappa coefficient of 0.93. Murguia-Cozar *et al.*, (2021) reported that the quadratic SVM model was the best classifier of maize crop phenology, with an overall accuracy of 82.3 percentage while discriminating the phenological stages of maize crops (*Zea mays* L.) in Sentinel 2 satellite image. The present observations are in consonance with the findings of the above researchers.

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ANNEXURE I

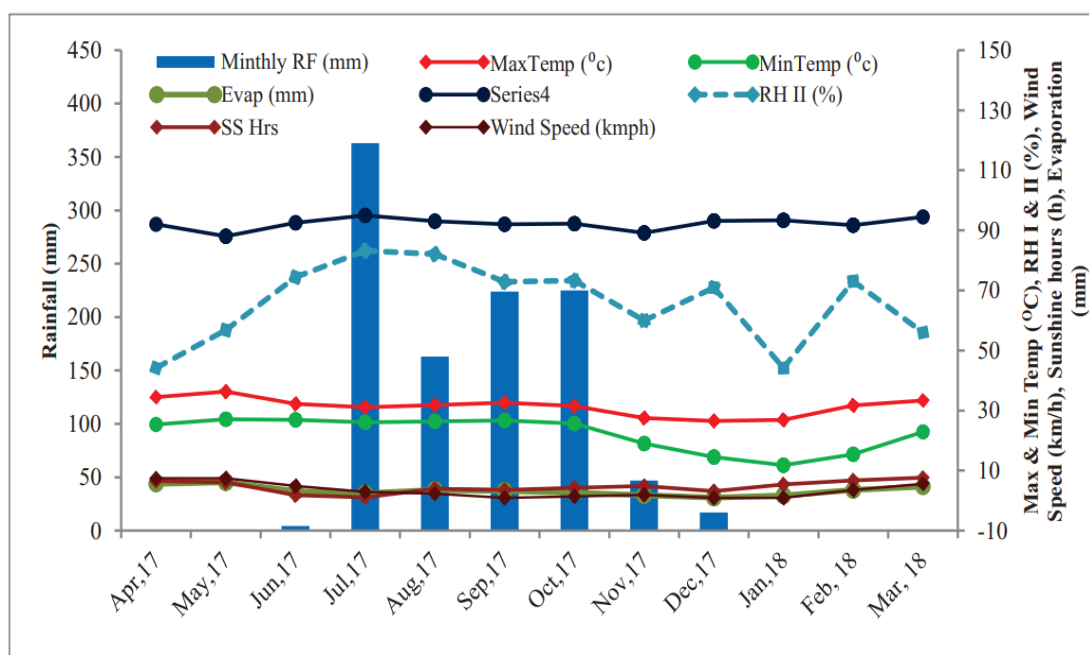


Fig I. Meteorological Data during April, 2017 to March, 2018 at ICAR-NRRI, Cuttack

(Annon., 2018)

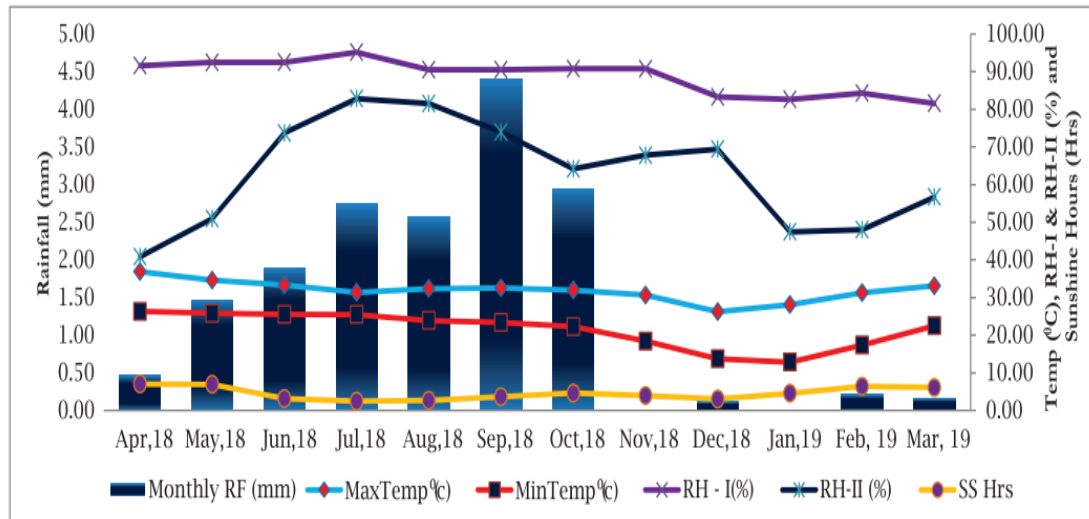


Fig II. Meteorological Data during April, 2018 to March, 2019 at ICAR-NRRI, Cuttack

(Annon., 2019)