Effect of temperature on brown planthopper infestation in rice using hyperspectral remote sensing

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Hyperspectral remote sensing captures images in multiple wavelengths and is widely used to detect plant stress in agriculture. A study was conducted on brown planthopper (BPH) infestation in rice at various temperature regimes (15°C, 20°C, 25°C, 30°C and 35°C). The experimentation was done in the Environmental Control Chamber, Tamil Nadu Agricultural University, Coimbatore, India. The field spectroradiometer and vegetation indices were used to study the early and late infestations of BPH in rice. The results reveal that reflectance at certain wavelengths (550, 670 and 700 nm) indicates plant stress. Among the vegetation indices, MCARI performed better than NDVI, PRI, NDRE and SR for the detection of early and late infestation of BPH. Hence, hyperspectral reflectance from rice has been used to detect pest damage and improve management policies.

Keywords: Brown planthopper, hyperspectral sensor, plant stress, rice, vegetation indices.

IN order to recognize pest and disease infestations, spectral reflectance provides a profound understanding of the physiological, biological and chemical processes that occur in plants. Early detection and precise diagnosis of biotic stress using spectroscopic techniques have helped growers take preventive action[1]. Rice (*Oryza sativa* L) is an important staple food which provides 21% of global human per capita energy and 15% of per capita protein. According to the United States Department of Agriculture global rice trade will reach 47 million tonnes in 2022, less than earlier projections[2]. The climate model has predicted that in Tamil Nadu, rice yield will range from 0.7% to 6.3% under the low emission scenario and 4.1% to 20.1% in the high emission scenario between 2022 and 2050 (relative to 1971–2018)[3]. Among all pests of rice, the most destructive insect pest is the brown planthopper (BPH; *Nilaparvata lugens*) (Homoptera: Delphacidae), which causes 20–80% of yield loss and an annual economic loss of over US$ 300 million in Asia[4]. BPH eventually causes 'hopper burn' by draining sap from the xylem and phloem tissues, and also indirectly damages them by causing viral diseases such as the ragged stunt virus and the grassy stunt virus disease[5]. Pest management and crop protection are crucial in agriculture where reliable detection and forewarning are the current challenges[6]. As a result of climate change, adaptation and mitigation strategies such as holistic early warning systems, improved biological control agents, climate-resilient agriculture and new technological innovations such as pest modelling and remote sensing for early detection and pest forewarning have to be improved[7]. Remote sensing precisely forecasts the targeted insect pests, thereby reducing pest damage and management costs. The electromagnetic radiation reflected and emitted from the ground target is measured, recorded and processed in remote sensing based on the spectral characteristics of different living things[8]. Hyperspectral remote sensing involves the acquisition of visible, near-infrared and shortwave infrared images in several broad wavelength bands. Specific crop traits such as biochemical, biophysical composition and water content are related to the reflectance and absorption features in narrow bands[9]. In hyperspectral remote sensing, the stress due to leaf-water content is determined at 750–950 nm wavelength and the stress resulting from nutrient content and leaf dry matter (carbon) at 1000 nm in the NIR region[10]. Whereas, in the MIR region, the wavebands 1450 and 1975 nm are used to estimate the moisture content of leaves[11,12]. The reflectance in the wavebands at 640–680 nm (red region) and 680–740 nm (red edge region) is highly prone to stress due to pests and diseases[12–15]. The leaf reflectance in the red edge portion is strongly influenced by the chlorophyll content of the leaves[16]. The leaf folder infestation in rice[17] and thrips infestation in sugarcane[18] were sensed by the red edge portion of the hyperspectral remote sensing.

As climate change exacerbates the pest problem, there is a need for future pest management strategies. Farmers spray chemical pesticides on their crops to protect them, but this will have a detrimental impact on ecology, the environment and human health[19]. There is a lack of precise weather-based pest and disease forewarning services that eventually cut down on the cost of cultivation.

This study aims to assess the spectral reflectance of BPH-infected and uninfected rice plants using hyperspectral

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radiometers at different temperature levels and to derive vegetation indices for precise pest forewarning.

Materials and methods

Experimental conditions

The response of temperature on BPH infestation was studied in a controlled chamber at five constant temperatures (15°C, 20°C, 25°C, 30°C and 35°C). The required temperatures were periodically checked in the controlled chamber using a HOBO weather analyzer. The relative humidity (RH) was sustained between 70% and 80%, and the photoperiod maintained was 12L : 12D. The nucleus cultures of BPH were collected from the BPH laboratory in the Department of Rice, Tamil Nadu Agricultural University (TNAU), Coimbatore, India (11.0102°N and 76.9374°E). In order to maintain a uniform and continuous culture of BPH, the insects were mass cultured for two generations to avoid infestation.

The susceptible rice variety (TN1) was chosen and grown under field conditions in the Paddy Breeding Station, TNAU, Coimbatore. After the 45th day from sowing, plants were transferred to an environmental control chamber (model no: GENESIS 44S-34 (2), M/s Genesis Technologies, Thane, Maharashtra, India) with pot culture (five seedlings per pot); the pot size was 10 cm × 13 cm. Twenty BPH adults were counted and transferred to the required treatments using an aspirator maintaining 20 adults per hill. The potted plants with adults were covered with mylar cages made of polyester film. The top was covered with wet muslin cloth fastened by a rubber band to prevent the escape of the released insects inside the environmental control chamber. The pots were then observed for the appearance of infestation symptoms throughout the experimental period at different temperature levels. The healthy plants were grown in an ambient environment (from a minimum temperature of 22°C to a maximum of 29°C, RH of 75%) without the release of BPH adults to distinguish infected plants from uninfected plants.

Spectral assessments

The rice plants on the 50th day (first reading) and 55th day (second reading) with BPH infestation were measured using a field portable spectroradiometer (Spectra Vista Corporation S/N 1500-002128, model-2009 GER 1500, New York, United States) covering the UV, visible and NIR wavelength (350–1050 nm). Readings of 512 channels were recorded at 1.5–3.2 nm bandwidth intervals using a silicon diode array in the instrument. The instrument was self-sufficient with an easily replaceable battery (SMARTPACK) and provided with data acquisition software (GER 1500 PC) for data processing. The software was used to obtain data from field portable spectroradiometer (GER 1500) and was also helpful to store and display the data graphically. The instrument was kept 1 m above the plant height, and the sighting laser was pointed close to the plant foliage at a 4° field-of-view. Before taking observations, the instrument was calibrated with white reference board to adjust the environment's light condition. Then the target samples were recorded by keeping the plants outside the controlled chamber under bright sunlight hours between 1100 and 1300 h IST, to represent the field situation. The spectral reflectance from infected rice plants was recorded twice, on the fifth and tenth days after the release of insects, under all temperature regimes in order to determine the early and late infestation of damage. The vegetation indices were derived from the rice canopy based on the acquired spectral reflectance (Table 1)[20–25].

Statistical data analysis

A general linear model was generated with a univariate ANOVA between temperature and spectral reflectance at various wavebands. A post hoc analysis with Duncan's homogenous test was employed to identify similar and statistically significant temperatures. The correlation and regression coefficients were analysed between spectral vegetation indices and different temperature levels.

Results and discussion

Spectral reflectance of BPH infestation

The results of the present study reveal that there is a significant difference ($P < 0.0001$) between various temperature levels and the spectral reflectance of rice on both the fifth and tenth days of BPH infestation (Tables 2 and 3). A significant difference was observed at G (490–559 nm), Y (560–584 nm), R (640–739 nm) in the visible region and NIR (740–925 nm). The damage levels of BPH at the vegetative to reproductive stages were specifically correlated with the wavebands from 426 to 690 nm. Whereas it was strongly correlated with the reflectance at 665, 670 and 690 nm (refs 15, 26). However, BPH infestation at the milk grain stage of rice was determined by the waveband at 765 nm (refs 12, 14). In the spectral wavebands, the visible region has high absorption of light by leaf pigments with less reflectance and transmittance[27]. The NIR domain has high reflectance and transmittance of light, where the cellulose and leaf pigments are almost transparent due to the internal scattering of air–cell–water interfaces within the leaves[28].

Our results are in accordance with those of Prasannakumar *et al.*[12], who reported that BPH-infested plants have diminished spectral reflectance in the visible and NIR regions. In the present study, spectral reflectance from the visible and NIR regions showed a linear decrease from lower to higher temperatures (Figures 1 and 2). This indicates that infestation severity is high at extreme temperatures

Table 1. Derivatives of spectral index

Spectral index	Formula	Measurement
Photochemical reflectance index (PRI)	$(R_{531} - R_{570})/(R_{531} - R_{570})$	Leaf chlorophyll and leaf area index (LAI)[20]
Modified chlorophyll absorption reflectance index (MCARI)	$[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})] * (R_{700}/R_{670})$	Leaf chlorophyll and LAI[21]
Normalized difference vegetation index (NDVI)	$(R_{800} - R_{670})/(R_{800} + R_{670})$	Biomass, canopy structure, chlorophyll and LAI[22]
Normalized difference red edge (NDRE)	$(R_{790} - R_{720})/(R_{790} + R_{720})$	Vegetation density and condition, fertilizer demand and nitrogen uptake, chlorophyll content and LAI[23,24]
Simple ratio (SR)	(R_{695}/R_{420})	Leaf chlorophyll[25]

Table 2. Spectral reflectance of brown planthopper (BPH) infestation at various temperature levels on the 5th day after release

Wavelength	Healthy – 29°C	15°C	20°C	25°C	30°C	35°C	ANOVA
UV (350–399)	9.10 ± 0.68^{a}	5.19 ± 0.45^{b}	4.12 ± 0.42^{c}	3.99 ± 0.28^{c}	2.35 ± 0.21^{d}	1.55 ± 0.14^{d}	<0.0001
V (400–424)	4.34 ± 0.06^{a}	1.99 ± 0.04^{b}	1.32 ± 0.04^{b}	2.04 ± 0.03^{c}	0.80 ± 0.03^{d}	0.54 ± 0.02^{e}	<0.0001
B (425–489)	4.82 ± 0.04^{a}	2.30 ± 0.03^{b}	1.53 ± 0.03^{c}	2.09 ± 0.01^{d}	0.75 ± 0.00^{e}	0.57 ± 0.01^{f}	<0.0001
G (490–559)	9.97 ± 0.67^{a}	5.14 ± 0.34^{b}	3.81 ± 0.28^{c}	4.09 ± 0.23^{c}	2.02 ± 0.18^{d}	1.46 ± 0.12^{d}	<0.0001
Y (560–584)	16.75 ± 0.19^{a}	8.96 ± 0.08^{b}	6.97 ± 0.06^{c}	6.32 ± 0.05^{d}	3.77 ± 0.07^{e}	2.63 ± 0.03^{f}	<0.0001
O (585–639)	11.97 ± 0.22^{a}	7.08 ± 0.08^{b}	5.42 ± 0.07^{c}	5.01 ± 0.07^{d}	2.23 ± 0.07^{e}	1.82 ± 0.04^{f}	<0.0001
R (640–739)	14.66 ± 1.32^{a}	9.65 ± 0.92^{b}	7.62 ± 0.79^{b}	5.85 ± 0.40^{c}	3.03 ± 0.42^{d}	2.35 ± 0.27^{d}	<0.0001
NIR (740–925)	63.82 ± 0.38^{a}	47.05 ± 0.34^{b}	42.13 ± 0.38^{c}	27.89 ± 0.21^{d}	24.35 ± 0.20^{e}	15.32 ± 0.12^{f}	<0.0001

Table 3. Spectral reflectance of BPH infestation at various temperature levels on the tenth day after release

Wavelength	Healthy – 29°C	15°C	20°C	25°C	30°C	35°C	ANOVA
UV (350–399)	8.85 ± 0.67^{a}	6.12 ± 0.43^{b}	3.68 ± 0.21^{c}	2.12 ± 0.13^{d}	1.51 ± 0.13^{d}	1.03 ± 0.09^{e}	<0.0001
V (400–424)	4.03 ± 0.06^{a}	3.21 ± 0.04^{b}	2.22 ± 0.02^{c}	1.23 ± 0.01^{d}	0.59 ± 0.01^{e}	0.40 ± 0.01^{f}	<0.0001
B (425–489)	4.53 ± 0.05^{a}	3.65 ± 0.05^{b}	2.46 ± 0.01^{c}	1.24 ± 0.01^{d}	0.63 ± 0.01^{e}	0.40 ± 0.01^{f}	<0.0001
G (490–559)	10.51 ± 0.77^{a}	6.49 ± 0.33^{b}	3.27 ± 0.13^{c}	2.11 ± 0.11^{d}	1.41 ± 0.09^{e}	0.89 ± 0.05^{e}	<0.0001
Y (560–584)	18.24 ± 0.20^{a}	10.21 ± 0.05^{b}	4.59 ± 0.05^{c}	3.23 ± 0.02^{d}	2.38 ± 0.02^{e}	1.50 ± 0.01^{f}	<0.0001
O (585–639)	13.05 ± 0.25^{a}	8.86 ± 0.06^{b}	3.49 ± 0.05^{c}	2.59 ± 0.03^{d}	1.87 ± 0.02^{e}	1.28 ± 0.01^{f}	<0.0001
R (640–739)	15.41 ± 1.36^{a}	11.24 ± 0.75^{b}	4.46 ± 0.38^{c}	3.06 ± 0.24^{c}	2.45 ± 0.23^{c}	1.83 ± 0.16^{c}	<0.0001
NIR (740–925)	59.13 ± 0.29^{a}	41.39 ± 0.26^{b}	26.62 ± 0.22^{c}	14.27 ± 0.11^{d}	13.36 ± 0.13^{e}	9.97 ± 0.10^{f}	<0.0001

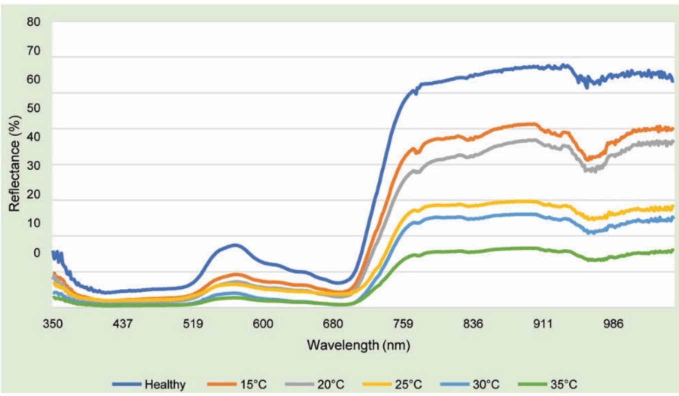

Figure 1. Reflectance of brown plant hopper (BPH) infestation on the fifth day.

due to insect feeding behaviour, which leads to the loss of plant pigments. At lower temperatures, the insect metabolism would be lower so that the feeding activity tends to decrease, whereas at higher temperatures the insect metabolism stimulates the efficiency of feeding behaviour for higher development rates[29–31]. Hence, the damage is maximum at extreme temperatures with a reduction in chlorophyll content. In chilli, the aphid damaged the chloroplasts by sucking the phloem tissues and altering the reflectance characteristics[32]. The study results are in accordance with

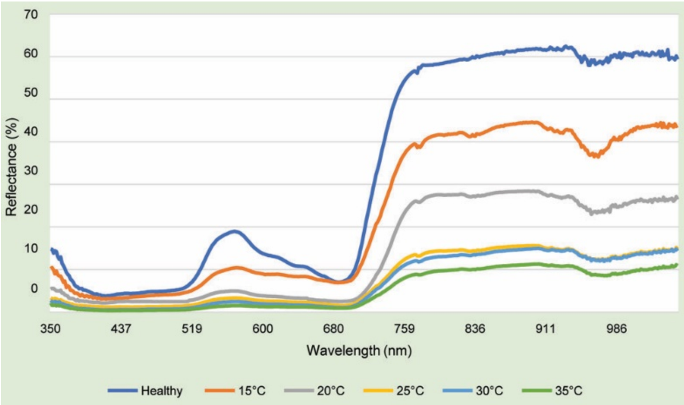

Figure 2. Reflectance of BPH infestation on the tenth day.

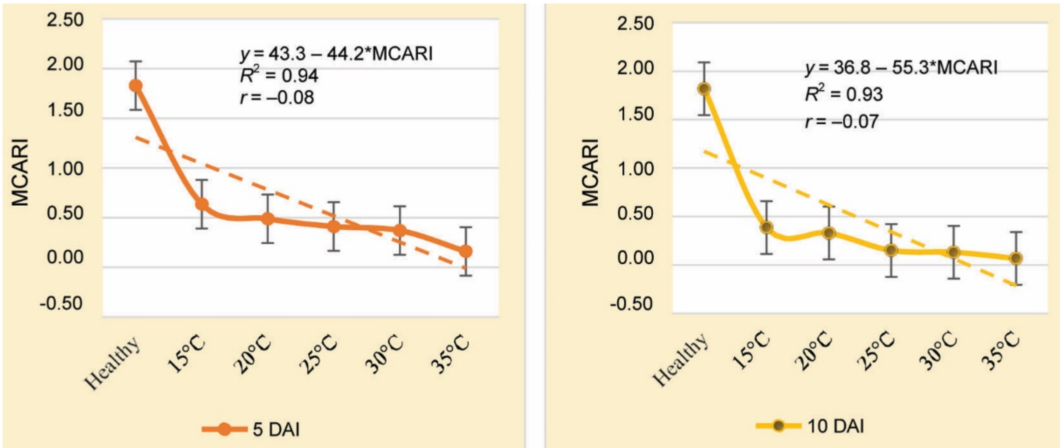

Figure 3. Modified chlorophyll absorption reflectance index with various temperature levels.

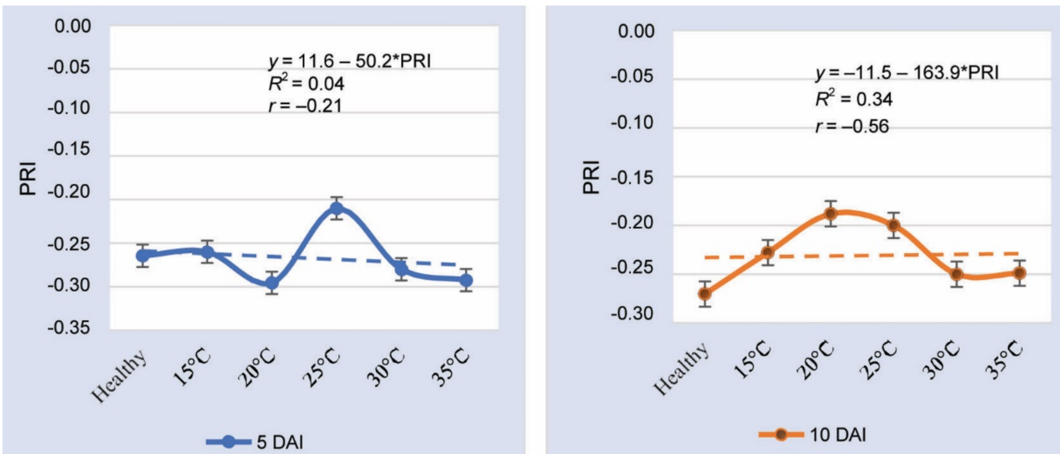

Figure 4. Photochemical reflectance index with various temperature levels.

cotton Aphids (*Aphis gossypii*) infestation where the visible (460–660 nm) and NIR (750–950 nm) waveband exhibited low level spectral reflectance[33]. Figures 1 and 2 show that the early infestation of BPH damage occurs at 30°C and 35°C on the fifth day itself, whereas on the tenth day, higher temperatures show hopper burn symptoms and lower temperatures show mild infestation.

Spectral indices for BPH infestation

The capability and sensitivity of detecting crop growth status and vegetation, indices are frequently utilized. It is a crucial method for monitoring plant stress in agriculture[34]. The results of the present study reveal that the modified chlorophyll absorption reflectance index (MCARI) was

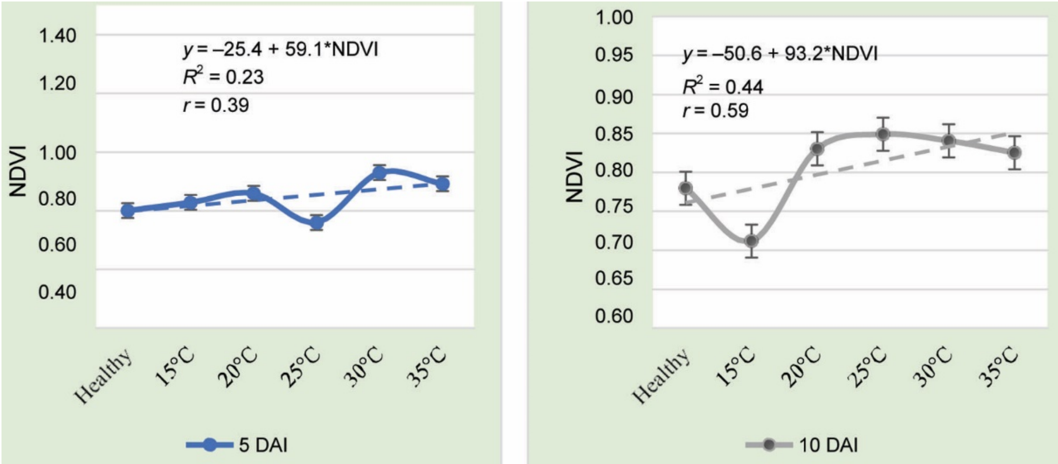

Figure 5. Normalized difference vegetation index with various temperature levels.

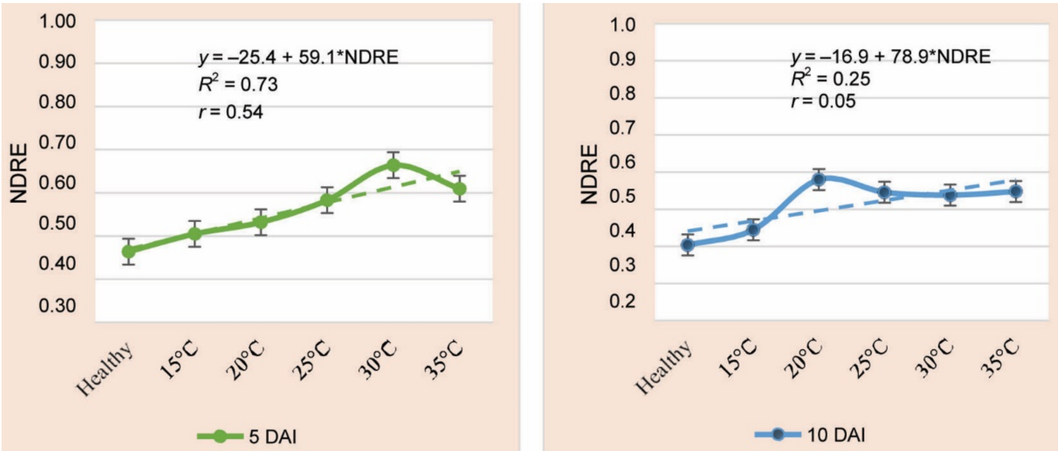

Figure 6. Normalized difference red edge with various temperature levels.

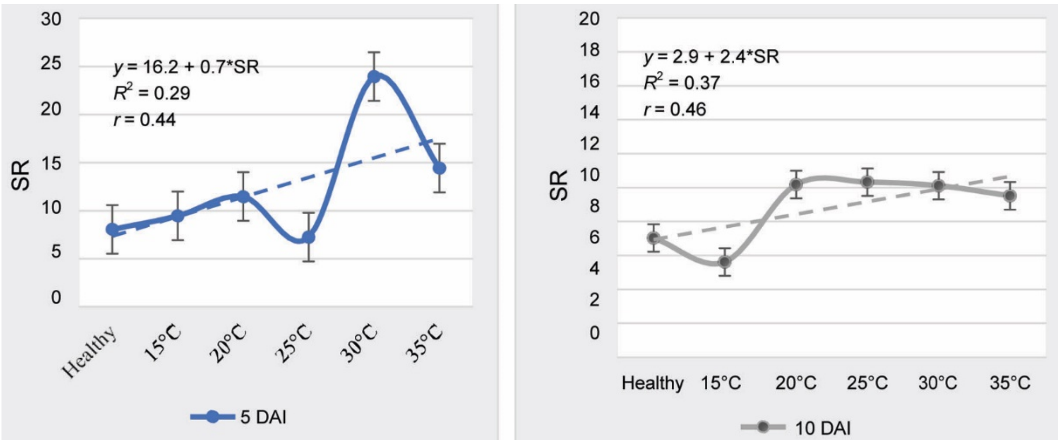

Figure 7. Simple ratio with various temperature levels.

negatively correlated with different temperature levels on the fifth day ($R^2 = 0.94$) and tenth day ($R^2 = 0.93$) after the release of BPH (Figure 3). It decreased linearly from lower to higher temperatures with a consistent increase in hopper burn symptoms. The negative correlation shows that temperature is highly conducive to insect behaviour and exceeds the threshold limit required for survival at extremely high temperatures. In rice, $MCARI_{710}$ is considered a superior spectral index to estimate the population of BPH and its damage under different levels of nitrogenous fertilizer[35]. Similar results were obtained in grapevines, where an early infestation of *Grape phylloxera* damage was assessed through MCARI[36]. Photochemical reflectance index (PRI), normalized difference vegetation index (NDVI), normalized difference red edge (NDRE) and simple ratio (SR) were complex to interpret, and they did not follow the trend of lower to higher infestation. These indices were zigzag with various temperature levels on both the fifth day (R^2 = 0.23, R^2 = 0.73, R^2 = 0.04, R^2 = 0.29 respectively) and tenth day (R^2 = 0.44, R^2 = 0.25, R^2 = 0.34, R^2 = 0.37 respectively) after the release of BPH (Figures 4–7). The disparity between these indices is due to their lack of ability to diagnose a specific type of stress because they are based on broad wavebands[37]. The above indices (PRI, NDVI, NDRE and SR) were developed based on plant photosynthetic activity, which has a high correlation with plant nitrogen content. This makes it possible to evaluate vegetation density and conditions during rice harvest without stress due to pests and diseases[38,39]. In soybean, the estimation of chlorophyll content was higher in MCARI than in NDVI and NDRE[40]. In wheat, the aphid infestation density was more highly correlated with MCARI than PRI and NPCI[41]. The indices NDVI and SR failed to detect rice BPH infestation[42]. In rice, active transportation of phloem sap to the root is disrupted by continuous feeding and stylet probing of BPH. It enhances leaf senescence by accumulating proteolytic products, free amino acids and amides in the leaf blades[43–46]. Our findings show that MCARI performs better at capturing leaf senescence and loss of chlorophyll in BPH-infected rice plants. This detection of early symptoms (leaf senescence) was done using the sensitive wavebands (670, 700 and 550 nm) in the mathematical derivation of MCARI.

Conclusion

BPH infestation in rice at different temperature levels reveals that at lower temperatures, the appearance of symptoms is delayed during the early days, similar to healthy plants. At higher temperatures, symptoms appear as early as the fifth day, based on the derived spectral indices. It indicates that as the temperature increases, the pest-feeding behaviour also increases. Rapid infestation occurs between 30°C and 35°C, in which more than 50% of the damage occurs from the fifth to the tenth day. At 35°C, symptoms reached hopper burn from fifth day onwards. This leads to a higher application of pesticides over a short period in the entire field, resulting in a lower yield. Hence, MCARI (R^2 = 0.94) is the best index to sense early infestation of BPH compared to PRI, NDVI, NDRE and SR in all the temperature regimes. Hence, the above methodology is useful to detect BPH infestation in rice over large-scale mapping and is highly useful to smallholder farmers for effective pest management.

Conflict of interest: The authors declare that there is no potential conflict of interest.

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