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Research Article

Assessment of Rice Blast Disease using Hyperspectral Vegetation Indices

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ABSTRACT

Crop growth and yield are directly related to biotic and abiotic stress. Disease infection itself is a major cause of crop loss each year. Rice blast caused by the fungus *Pyricularia Oryzae* is one of the biggest threats to rice production in India. Determination of the disease by conventional method involves an investment of time, money, and manpower. On the other hand, remote sensing techniques are becoming very popular for real-time analysis of stress assessment. Keeping this view, a field experiment was conducted at ICAR-VPKAS, Almora to study the possibility of hyperspectral vegetation indices to assess the blast disease with 10 rice genotypes each for upland and irrigated conditions. The extent of disease severity was rated 0-9 based on the extent of the host organ covered by symptoms or lesions. 15 different vegetation indices having a higher correlation coefficient (>0.8) were calculated. The linear regression models were developed between these indices and disease scores. Out of those TVI and PVI based models performed best for blast disease severity assessment having R^2 and RPD values more than 0.86, 0.83, and 2.68, 2.41, respectively. So TVI and PVI based models can be used for detecting rice blast, which could be utilized to scan satellite data for regional mapping of blast-affected rice cropping regions.

Key words: Vegetation indices, Disease severity, Biotic stress, Rempte sensing

Introduction

Rice is the staple food of more than 1/3rd population of India as well as the World. The devils of high rice crop production are biotic and abiotic pressures, which must be avoided if India is to feed its expanding population. Numerous severe diseases affect rice, posing a serious danger to crop productivity. One of the main rice diseases, rice blast caused by the fungus *Pyricularia Oryzae*, results in yield losses of between 11.9 and 37.8% per hectare of grain (Chuwa *et al.*, 2015). This everlasting situation begs for proper monitoring and detection methods. There are so many conventional ways of disease detection but they are time-consuming and costly and most importantly it needs a skilled operation, so it is not possible to be applied in real-time detection and not that easy to employ at the field level limiting their scale of applicability. On the other hand, macro detection is based on a remote sensing approach. Remote sensing is a non-destructive method to detect plant stress at an early stage of development and holds great promise for the optimization of the management of commercially important agricultural crops. Remote sensing,

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basically spectral data in different scales including leaf, canopy, and whole field has been widely used in precession farming. Spectral data can also be useful in the case of non-destructive detection of disease and its extent of severity. For this purpose, the use of spectral data should be in an efficient manner because only a few ranges of the spectrum are useful. The spectral reflectance of the region which lies in the visible range of the electromagnetic spectra (400-700nm) depends on the plant pigment and the NIR region from (700-1500nm) region depends on the internal structure of the leaf and SWIR region (1500-2500nm) depends on water present (Sahoo *et al*., 2015). Based on spectral reflectance, researchers have developed vegetation indices to detect the particular stress present in crop. As a plant disease have a major effect on leaf chlorophyll and internal cell structure so a significant change in spectral response makes vegetation indices very useful for disease detection. Some investigation shows the potential of indices for disease detection and characterization. A vegetation index can be calculated by rationing, differencing rationing, differences, and sums and by forming linear combinations of spectral band data. The sensitivity of those indices is higher than individual spectral bands for the detection of biomass-related observation (Asrar *et al*., 1984). There are no such significant indices for disease detection but the existing physiological and biochemical indices are useful for disease studies. The indices like NDVI (Rouse *et al*., 1974), SIPI (Peñuelas *et al*., 1995), PRI (Gamon *et al*., 1992), ARI (Gitelson *et al*., 2001), GM1 and GM2 (Gitelson & Merzlyak, 1997), PSSRa, PSSRb, and PSSRc (Blackburn, 1998), TCARI/OSAVI (Haboudane *et al*., 2002) and ZM (Zarco-Tejada *et al*., 2001) were used for several studies. Devadas *et al*. (2009) showed that narrow band indices representing changes in non-chlorophyll pigment concentration and the ratio of non-chlorophyll to chlorophyll pigments proved more reliable in discriminating rust infected leaves from healthy plant tissue. But there is hardly any study to identify the appropriate VI for assessing the blast disease severity in India. The objective of the present study is to identify an appropriate VI-based regression model to assess rice blast and its severity.

Materials and Methods

Experimental setup

In this present study, a field experiment was conducted at ICAR-Vivekananda Parvatiya Krishi Anusandhan Sansthan, Almora (29.59° N latitude, 79.64° E longitude and at an altitude of 1245 m above MSL) in the year of 2019. Almora is known as the hot spot of rice blast disease where the disease occurs naturally. 10 different genotypes of rice were grown for each irrigated condition and upland condition. Among them, some are blast susceptible and some are blast resistant and some are blast sensitive, taking 3 replications each laid in randomized block design.

Climate

Hawalbugh farm, Almora is situated at the foothills of the Himalaya whose climate is the temperate type with cold winter and moderate summer. The average annual maximum temperature is around 23°C and the average minimum temperature of 10°C. The annual average rainfall hovers more or less around the figure of 1,152 mm. For the rice blast disease to occur naturally the most congenial weather condition should be that air temperature must be 20-30°C during day time and much cooler during nighttime with prolonged leaf wetness (RH > 90%). Almora has the most suitable weather condition to occur blast naturally that is why Almora is one of the hotspot regions of rice blast.

Assignment of the score for different blast disease severity

In this study, 10 genotypes were cultivated each for rain-fed and irrigated conditions. Necrotic spots that are roundish, elongated, and have a dark brown edge that eventually covers the entire leaf are the classic symptoms of rice blast. According to the protocol outlined by International Rice Research Institute (IRRI, 1996), all genotypes of rice grown at the time of peak infection were scored based on the degree of disease infection and the area covered by the necrotic lesion (Table 1).

Collection of canopy reflectance of rice

Canopy reflectance of rice (under both rain-fed and irrigated conditions) was collected by employing

Table 1. Description of the different scores of rice blast disease (IRRI, 1996)

Rating	Description
Score 0	No lesion observed
Score 1	There is small brown specks of pinpoint size
Score 2	Small roundish to slightly elongated, necrotic gray spots, about 1-2 mm in diameter, with a distinct Moderately Resistant brown margin. Lesions are mostly spotted on the lower leaves
Score 3	Lesion type is same as in 2, but significant number of lesions on the upper leaves
Score 4	Typical susceptible blast lesions, 3 mm or longer infecting ≤ 4% of leaf area
Score 5	Typical susceptible blast lesions of 3 mm or longer infecting 4-10% of the leaf area
Score 6	Lesion type is same as in score 5 but infecting about 11-25% of the leaf area
Score 7	Lesion type is same as in score 5 infecting about 26-50% of the leaf area
Score 8	Typical susceptible blast lesions of 3 mm or longer infecting about 51-75% of the leaf area many leaves are dead
Score 9	Typical susceptible blast lesions of 3 mm or longer infecting ≥ 75% leaf area affected

a portable handheld ASD FieldSpec spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) for all disease severity levels (0–9). On a clear, sunny day at noon, the measurement was taken. The spectroradiometer was mounted with a 25° field of view and set at a nadir position at 50 cm from the canopy top. Measurements of reference reflectance and canopy reflectance were taken after the instrument had been tuned with a white reference panel called spectralon (Labsphere, Inc., Sutton, NH, USA). Each spectral measurement is the mean of the sample's 30 spectral scans. When there is a change in solar irradiation, optimization must be done in between the spectral observation. Spectral measurements of canopy reflectance were made between 350 and 2500 nm. In both irrigated and rainfed conditions, we have gathered 30 measurements of canopy reflectance for each disease severity level.

Pre-processing of canopy spectral reflectance

In order to improve the predictive power of univariate calibration models, spectral data are often pre-processed prior to data analysis as variation in the predictor variables that are unrelated to the response variable may reduce the predictive ability of the models. The aim of pre-processing is to reduce the effects of random noise and improve the signal-to-noise ratio. The most frequently used filter in spectral data analysis is Savitzky-Golay filter (Savitzky and Golay, 1964).

Calculation of spectral vegetation indices

The vegetation indices employed in this study include common narrow band indices which have sensitivity towards plant pigment (chlorophyll, xanthophyll *etc.*), structural, biochemical, and physiological properties of plants. Spectral indices (SIs) are mathematical combinations or ratios of canopy reflectance mainly in red, green and infrared spectral bands; they are designed to find functional relationships between crop characteristics and remote sensing observations (Wiegand *et al*., 1990). Using the plant canopy reflectance at different wavelengths, various narrow-band spectral indices were calculated. The equations and the references for these indices have been presented in Table 2.

Model development and its validation

First of all these indices were correlated with the score of the rice blast severity. The indices having a higher correlation coefficient ($r \leq 0.8$) were used to develop linear regression models for disease severity prediction using 2/3 of the total dataset. Then these prediction regression models were validated using spectral indices data for the remaining 1/3 dataset.

Evaluation is an important step of model verification, which determines how closely a model represents actual conditions. The accuracy of the models was assessed with the root mean squared error (RMSE), the coefficient of determination (R^2) and

Table 2. Details of spectral indices used for regression model development for disease severity prediction

Sl. No.	Index	Formula	References
		Structural indices	
1	Green Index (GI)	R_{554}/R_{677}	Zarco-Tejada *et al.* (2005)
2	Green Vegetation Index (GVI)	$(R_{682}–R_{553})/(R_{682}+R_{553})$	Kauth and Thomas (1976)
3	Modified Simple Ratio (MSR)	$(R_{800}/R_{670} – 1)/[(R_{800}/R_{670})0.5 + 1]$	Chen (1996)
4	Normalized Difference Vegetation Index (NDVI)	$(R_{830} – R_{660})/(R_{830} + R_{660})$	Rouse *et al.* (1974)
5	Perpendicular Vegetation Index (PVI)	$(R_{NIR} –\alpha R_{red} – b)/(1+\alpha 2)$ R_{NIR},soil = αR_{red}, soil+b	Richardson and Wiegand (1977)
6	Renormalized Difference Vegetation Index (RDVI)	$(R_{800} – R_{670})/[(R_{800} + R_{670})^{0.5}]$	Roujean and Breon (1995)
7	Second Modified Triangular Vegetation Index (MTVI2)	$[1.5(1.2*(R_{NIR} – R_{green}) – 2.5 (R_{Red} – R_{green})]/[(2 R_{NIR}+1)2 – (6 R_{NIR} – 5 R_{Red}0.5) – 0.5]0.5$	Haboudane *et al.* (2004)
8	TVI Triangular Vegetation Index (TVI)	$0.5 * [120 * (R_{750} – R_{550}) – 200 * (R_{670} – R_{550})]$	Broge and Leblanc (2000)
		Biochemical indices	
9	Pigment-Specific Normalized Difference-a (PSNDa)	R_{800}/R_{680}	Blackburn (1998)
10	Pigment-Specific Simple Ratio-c (PSSRc)	R_{800}/R_{470}	Blackburn (1998)
11	Modified Chlorophyll Absorption Ratio Index (MCARI)	$[(R_{700} – R_{670}) – 0.2 (R_{700} – R_{550})] (R_{700}/R_{670})$	Daughtry *et al*. (2000)
12	Normalized Difference Chlorophyll Index (NDCI)	$(R_{762}-R_{527})/(R_{762}+R_{527})$	Marshak *et al*. (2000)
		Physiological indices	
13	Normalized Difference Infrared Index (NDII)	$(R_{780}– R_{710})/(R_{780}– R_{680})$	Datt (1999)
14	Photochemical Reflectance Index (PRI)	$(R_{531} – R_{570})/(R_{531} + R_{570})$	Gamon (1992)
15	Red-edge Vegetation Stress Index (RVSI)	$r R_{714} + R_{752}/2-R_{733}$	Merton & Huntington *et al*. (1999)

the residual prediction deviation (RPD). The ratio of the standard deviation of the measured data (SD) to the standard error of prediction (SEP) is designated as RPD which was also used to evaluate the prediction accuracy of the developed models (Willimas.,2001).

RPD = SD/SEP

$$SEP = \sqrt{\frac{1}{n-1}\sum_{n=1}^{n}(Pi-Oi)^2}$$

Where P_i is the predicted value, O_i is the observed value and n is the number of samples.

Chang *et al.* (2001) classified prediction accuracies into accurate (RPD > 2), moderate (1.4 < RPD < 2), and poor (RPD < 1.4), although such a rule is still being debated (Bellon-Maurel *et al.*, 2010).

The coefficient of determination (R^2) gives an indication of the quality of trend conformity, with values of R^2 = 1.0 indicating a perfect fit, and lower values indicating less agreement of data.

The root mean square error (RMSE) was calculated to evaluate the fitness between the estimated and measured results.

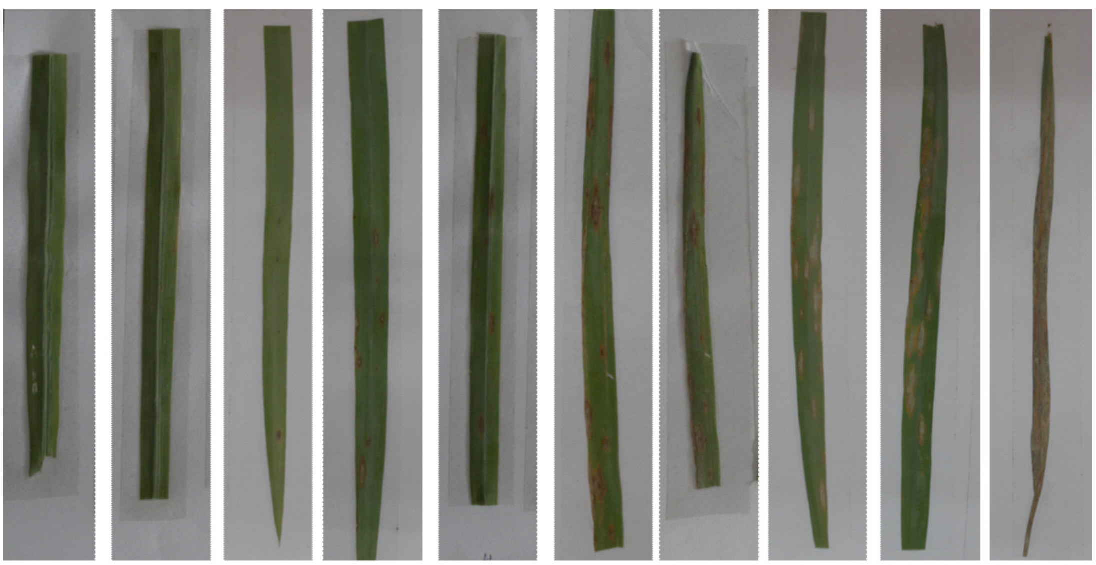
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_i - O_i\right)^2}$$

Where P_i is the predicted value, O_i is the observed value and n is the number of samples.

Result and Discussion

Blast disease infection and its scoring

In this study, the proportion of host tissue covered by the disease's necrotic lessons, as well as the quantity and size of the lessons, were used to estimate the disease severity levels. According to IRRI (1996) guidelines, the severity of the rice blast was rated on a scale of 0 to 9. The plant is found to be healthy and symptom-free at severity level 0, while the plant is found to be badly damaged by pathogens at severity level 9. The disease severity levels range from level 0 to level 9, with varying levels of infestation shown in Fig. 1. In this present study, rice genotypes BL 18 and DH 79 were found to be level 9 under rain-fed and irrigated conditions, respectively. Severity level 0 was ascribed to the genotypes VL 32475 and DH 94, which were cultivated under rainfed and irrigated conditions, respectively. Table 3 displays the specifics of different varieties and the respective severity levels.



0 1 2 3 4 5 6 7 8 9

Fig. 1. Disease scoring of Rice Blast at VPKAS, Almora

Table 3. Disease rating score (0-9) and entries details under field conditions at Almora, Uttarakhand

Rainfed (Upland) condition		Irrigated (lowland) condition	
Entry Name	Disease rating score	Entry Name	Disease rating score
BL-18	9	DH-79	9
DSN-140	8	Bala	8
DSN-120	7	DH-30	7
DSN-119	6	DH-33	6
BL-21	5	DH-34	5
BL-6	4	DH-32	4
BL-10	3	DH-44	3
BL-12	2	DH-49	2
VL 32473	1	DH-47	1
VL 32475	0	DH-94	0

Response of canopy reflectance to variation in disease severity level

In this study, differing levels of disease infestation showed different spectral responses. The dynamic changes in leaf reflectance at various disease infection levels are shown in Fig. 2 (Mandal *et al*., 2022). Different stress levels significantly influenced the spectral response of rice canopy in various wavelength regions which can be broadly divided into four spectral groups *i.e.,* visible range (350-700nm), near-infrared range (NIR) (700-1350nm), short wave infra-red region I (SWIR I) (1420-1800nm) and SWIR II (1950 to 2350nm). A healthy canopy has experienced lower reflectivity in the blue and red regions of the visible spectrum, higher reflection in the green region, and high reflectance in the NIR. The reflectance at the red region was higher in the seriously damaged plant than in the healthy plant as the disease severity level progressed. The spectral reflectance at the visible region is controlled by the level of leaf pigment. The pathogen almost caused damage to plant chlorophyll in blast-

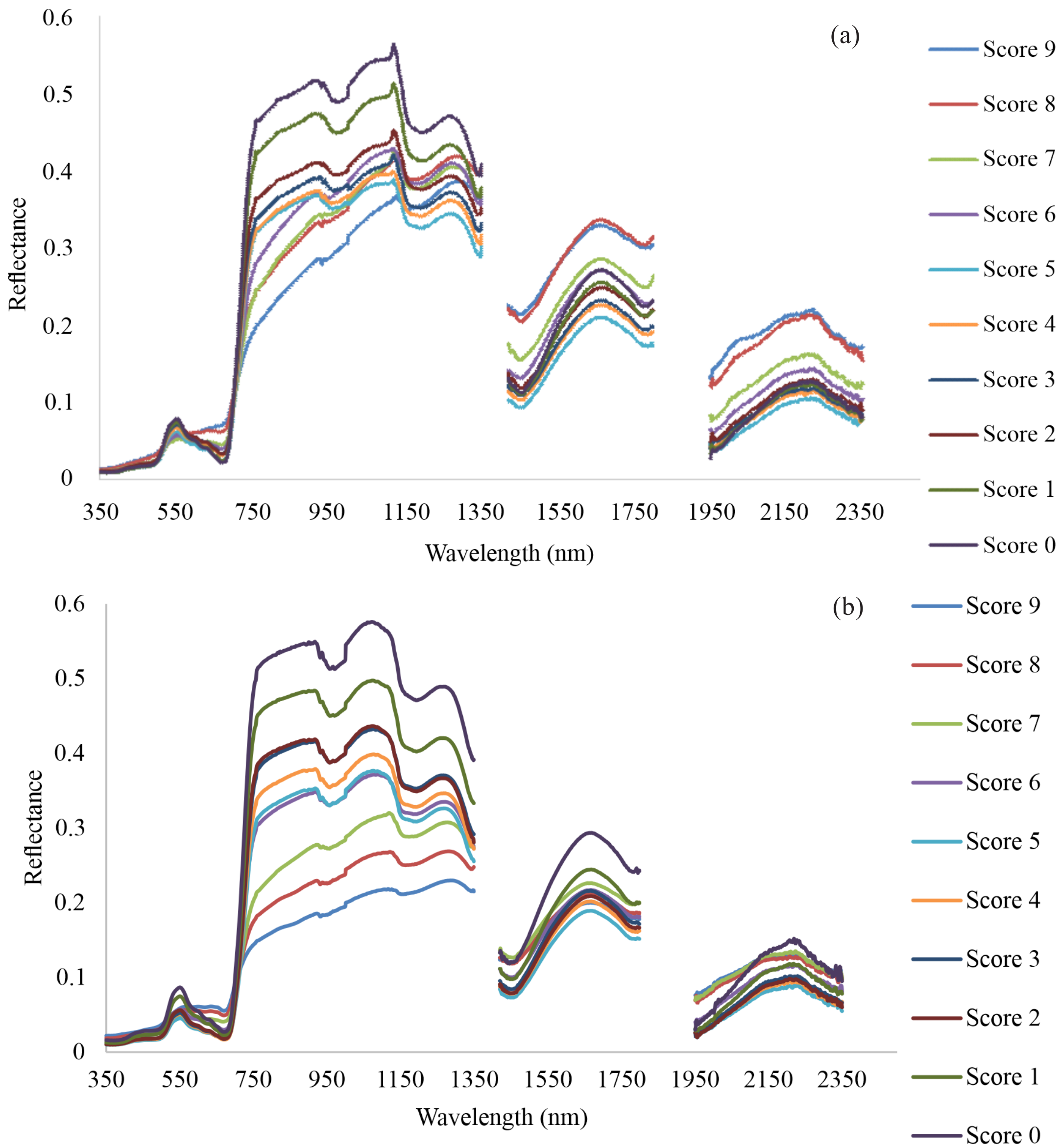


Fig. 2. Spectral reflectance of rice canopy under different disease severity levels at Almora under (a) Rainfed (upland) and (b) Irrigated (lowland) conditions (Mandal *et al.,* 2022)

infected plants. A similar finding was also investigated by Kobayashi *et al*. (2016) for panicle blast disease detection. The reflectance of healthy plants is higher in the NIR region than that of diseased plants, and as the severity of the disease increased, the reflectance in the NIR region steadily dropped. As a result of the pathogen's severe infection, the plant eventually begins to produce reactive oxygen species like hydrogen peroxide and cellulose deposition at the site of infection (Throdal-Christensen *et al*., 1997; Nishimura *et al*., 2003), which are the main causes of producing necrotic lesions that cause cell damage and ultimately cause the plant to die. According to Das *et al*. (2013), soybean crops infected with the yellow mosaic virus had a decrease in reflectance in the NIR range. When compared to the disease-infected plant, the seriously afflicted plant had higher reflectance in the SWIR area. This might be explained by the reduced water content of the leaves of the plants affected by the blast.

Development of regression model and validation

A number of spectral indices have been selected for the estimation of blast disease severity levels with various combinations of wavelengths. Then linear regression models were developed among those indices and disease severity levels. The best-performing regression models between various indices and disease severity scores (0-9) are shown in Table 4. Out of biochemical, structural, and physiological indices, all the structural indices performed better than others. Among those indices, PVI, RDVI, and TVI were found best for disease severity prediction with R^2 values of 0.83, 0.81, and 0.84 respectively for calibration, whereas during validation those indices could account for a maximum of 82.8, 82.6, and 86.1% variability of observed severity level with RPD value of 2.41, 2.39 and 2.68, respectively (Table 4). Among the other indices, RDVI, MTVI2, MCARI, and RVSI based regression models performed better for disease

Table 4. Regression model for disease score prediction using Spectral indices

Sl. No.	Index	Calibration equation	R^2 (calibration)	R^2 (validation)	RMSE	RPD
		Structural indices				
1	GI	Y=-2.6675X+10.251	0.75	0.78	1.36	2.11
2	GVI	Y=11.57X+7.563	0.75	0.78	1.36	1.36
3	MSR	Y=-16.28X+17.38	0.67	0.67	1.64	1.74
4	NDVI	Y=-17.10X+18.17	0.67	0.67	1.66	1.73
5	PVI	Y=-189.7X+2.359	0.83	0.83	1.19	2.41
6	RDVI	Y=-19.38X+13.99	0.81	0.83	1.19	2.39
7	MTVI2	Y=15.05X+11.79	0.77	0.79	1.30	2.20
8	TVI	Y=-0.362X+10.78	0.84	0.86	1.07	2.68
		Biochemical indices				
9	PSNDa	Y=-15.88X+16.87	0.68	0.68	1.63	1.75
10	PSSRc	Y=-0.338X+10.22	0.64	0.60	1.48	1.55
11	MCARI	Y=-23.79X+8.486	0.71	0.74	1.47	1.94
12	NDCI	Y=-26.24X+23.06	0.51	0.48	2.07	1.38
		Physiological indices				
13	NDII	Y=-14.90X+6.926	0.72	0.70	1.57	1.82
14	PRI	Y=51.84X+4.484	0.67	0.70	1.65	1.73
15	RVSI	Y=299X+10.11	0.79	0.79	1.30	2.19

severity level prediction (Table 4). Spectral indices are nothing but the combination of mathematical equations of different spectral responses of a different region of the spectra. Evaluation of existing indices revealed that the structural indices perform the best for predicting disease severity. Out of all the indices, TVI and PVI are the best-suited indices for rice blast indicated by R^2 and RPD values more than 0.8 and 2, respectively during validation. The triangular vegetation index (TVI) is calculated as the areas of a hypothetical triangle in spectral space that connects green peak reflectance minimum chlorophyll absorbance and reflectance at the NIR region. So, this index is influenced by the chlorophyll content and greenness of the plant. In the case of blast disease as discussed earlier the plant becomes necrotic so the pathogen damages chlorophyll and cell structure, so TVI can be a good index for disease severity measurement. On the other hand in the case of perpendicular vegetation Index (PVI), the formula itself depicts that it depends on the reflectance of NIR and red region. The reflectance from these two regions depends on the chlorophyll content and internal structure of the plant leaf. The fungus *Pyricularia* damages the internal structure of plants as well as the chlorophyll content. So, these two indices TVI and PVI are sensitive to the blast disease.

Conclusion

The present study can be concluded that the spectral reflectance curve offers scope for the potential use of remote sensing technology to distinguish healthy and blast-infected rice crops in a rapid and cost-effective manner from large and continuous rice growing areas. Spectral indices based linear regression models can be used for the assessment of blast severity levels. TVI and PVI-based linear regression models were found best in this regard. In spectral space, the regions of a hypothetical triangle connecting the green peak reflectance lowest chlorophyll absorbance, and reflectance in the NIR region are used to calculate TVI. On the other hand, PVI also considers NIR and Red region which is crucial for disease stress. As a result, these indices are influenced by the amount of chlorophyll in the plant, how green it is, as well as the interior structure of the leaf. Given the nature of the disease and the fact that becoming a necrotic pathogen destroys cell structure and chlorophyll, TVI and PVI may be a useful tool for determining the severity of Rice Blast disease.

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