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PLANT PATHOLOGY

Characterization of Rice Blast Disease Using Greenness Index, Canopy Temperature and Vegetation Indices

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ABSTRACT

Blast diseases cause economically important damage to rice. Protective treatments help producers to secure good quality crops. In contrast, curative treatments based on visually detectable symptoms are often riskier and less effective because diseased crop plants may develop disease symptoms too late for curative treatments. On the other hand, the effect of blast severity levels on crop physiology (greenness index and canopy temperature) and vegetation indices may help in early detection of rice blast. Keeping this view, a field experiment was conducted at ICAR-VPKAS, Almora to study the effect of different rice blast severity levels on canopy temperature, greenness index and hyperspectral vegetation indices with 10 rice genotype each for upland and irrigated condition. The extent of disease severity was rated 0-9 based on the extent of host organ covered by symptom or lesion. It was observed that canopy temperature and greenness index was significantly influenced by blast disease severity levels for both conditions. 8 different vegetation indices having higher correlation coefficient (>0.8) was calculated. The linear regression models were developed between these indices and disease score. Out of those, MTVI based model performed best for blast disease severity assessment having R^2 and RPD value more than 0.85 and 2.58 respectively. So MTVI based model can be used for detecting rice blast.

HIGHLIGHTS

- MTVI based model performed best for blast disease severity assessment.
- Canopy temperature positively correlates with blast severity levels and greenness index negatively correlates with blast severity levels.

Keywords: Blast disease, greenness index, canopy temperature, vegetation indices

Rice is the staple food of more than 1/3rd population of world as well as India. The area under rice cultivation in India is 43.86 Mha having a productivity of 2390 kg/ha (Ricepedia 2015). To feed the burgeoning population of India the production must be high but the devils of high crop production are biotic and abiotic stresses. Rice experiences lots of devastating disease which are real threat to crop production. Rice blast caused by fungus *Pyricularia oryzae* is one of the major diseases of rice which leads to a yield loss of grain yield losses of between 11.9 to 37.8 % per hectare were recorded (Chuwa *et al*. 2015). This everlasting situation begs for proper monitoring and detection methods. In contrast, curative treatments based on

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visually detectable symptoms are often riskier and less effective because diseased crop plants may develop disease symptoms too late for curative treatments. On the other hand, the effect of blast severity levels on crop physiology (greenness index and canopy temperature) and vegetation indices may help in early detection of rice blast. Greenness index is an important indicator of plant growth status. Plant disease showing various symptoms (chlorotic, necrotic etc.) must affect the status of plant greenness due to disease infection. The SPAD-502 meter measures the transmittance of red (650 nm) and infrared (940 nm) radiation through the leaf, and calculates a relative SPAD meter value that should correspond to the amount of chlorophyll present in the sample leaf (Minolta 1989). Bndara *et al*. (2016) found that severity levels of stalk rot fungi affected sorghum plant was significantly and negatively correlated with SPAD value, that is as the disease severity level increases greenness of plant decreases. Prabhakar *et al*. (2011) have studied the stress in cotton caused by brown leaf and revelled a significant linear relation between leaf hopper severity and chlorophyll having R^2 of 0.505. Marin-Ortiz *et al*. (2019) has also reported a decrease in plant pigment content for the diseased plant. The plant infected by pathogen shows the change in canopy temperature due to various physiological changes. Oerke *et al*. (2011) studied the scab disease (*Venturia inaequalis*) on apple leaves using thermo graphic and reported that leaf temperature increases with increase in severity levels. Lindenthal *et al*. (2005) have detected a pre-symptomatic of infection of cucumber downy mildew disease with thermography and found that with the development of downy mildew symptoms, maximum temperature difference increased by more than 2.0°C, about 1.4°C higher than for non-inoculated control leaves. The temperature difference allowed the discrimination between the infected and healthy leaves before the appearance of visible necrosis on leaves. On the other hand, remote sensing being non-destructive method to detect plant stress at an early stage of development holds great promise for the optimization of the management of commercially important agricultural crops. Spectral data can be useful in case of non-destructive detection of disease and its extent of severity. For this purpose the use of spectral data should be in efficient manner because only few ranges of the spectrum is 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 NIR region from (700-1500nm) region depends on internal structure of 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 major effect on leaf chlorophyll and internal cell structure so a significant change in spectral response makes vegetation indices very valuable for disease detection. Some investigation shows potential of indices for disease detection and characterisation. 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 1998b), 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. There is hardly any study to investigate the effect of different rice blast severity levels on canopy temperature, greenness index and hyperspectral vegetation indices in India. The objective of the present study is to investigate the relationship between canopy temperature and greenness index with disease severity and to identify appropriate VI based regression model to assess rice blast and its severity levels.

MATERIALS AND METHODS

Experimental setup

In this present study, a field experiment was conducted at o ICAR-Vivekananda Parvatiya Krishi Anusandhan Sansthan, Almora (29.59^0 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 Himalaya whose climate is temperate type with cold winter and moderate summer. The average annual maximum temperature is around 23°C and 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 night time with prolonged leaf wetness (RH > 90%). Almora has most suitable weather condition to occur blast naturally that is why Almora is one of the hotspot regions of rice blast.

Scoring of blast disease severity

In this study 10 genotypes were cultivated each for rain fed and irrigated condition. The typical symptoms of rice blast is necrotic spot roundish elongated with a district brown margin which gradually covers the whole leaf. At the time of peak infection, the all the genotypes of rice grown, were graded on the basis of extent of disease infection and the area covered by the necrotic lesion as per the protocol given by IRRI (1996) (Table 1).

Table 1: Description for different score of rice blast disease

Rating	Description
Score 0	No lesion observed
Score 1	There is small brown specks of pin point 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

Greenness index (SPAD) measurement

Chlorophyll content of the plant was measured by hand held SPAD-502 meter. This instrument is widely used for rapid, accurate and nondestructive measurement of chlorophyll content. This gives a unit less value of chlorophyll content which is comparable with other chemical measurement of chlorophyll. Under both conditions, 5 measurements for each treatment were taken.

Measurement of canopy temperature

Canopy temperature was measured by hand held IR thermometer which measures temperature without touching the object. This thermometer basically infers temperature from a portion of the thermal radiation sometimes called blackbody radiation emitted by the object being measured, there a laser is used to help aiming the thermometer. By knowing the amount of infrared energy emitted by the object and its emissivity, the object's temperature can often be determined within a certain range of its actual temperature

Measurement of canopy reflectance

Rice canopy reflectance was measured for all (0-9 scale) disease severity levels along with 10 different genotypes each for rainfed and irrigated condition with help of hand held ASD FieldSpec spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA). The measurement was taken at noon time on a clear sunny day. The spectroradiometer was mounted on with a 25° field of view and positioned at 0.5 m from the top of the canopy at nadir position. Prior to spectral reflectance measurement the instrument was optimized with white reference panel called spectralon (Labsphere, Inc., Sutton, NH, USA) and reference reflectance was measured followed by canopy reflectance measurements. Each spectral measurement is the average of the 30 spectral scan of the sample. Optimization needs to be repeated in between the spectral observation when there is a change in solar irradiance. Canopy reflectance was measured in the spectral range of 350-2500 nm. We have collected 30 canopy reflectance for each disease severity levels for both rainfed and irrigated condition.

Spectroscopic Data Pre-processing

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 is unrelated to 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 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 includes common narrow band indices which have sensitivity towards plant pigment (chlorophyll, xanthophyll etc.), structural, biochemical and physiological properties of plant. 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 higher correlation coefficient ($r \geq 0.8$) were used to develop linear regression models for disease severity prediction using 2/3 of total dataset. Then these prediction regression models were validated using spectral indices data for 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 the residual prediction deviation (RPD). The ratio of the standard deviation of the measured data (SD) to standard error of prediction (SEP) is designated as RPD which was also used to evaluate the prediction accuracy of the developed models (Willimas and Norris 2001).

$$RPD = SD/SEP$$

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

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

STATISTICAL ANALYSIS

"SPAD value and canopy temperature were statistically analyzed using analysis of variance (ANOVA) as applicable to randomize block design (Gomez and Gomez 1984) using OPSTAT software. The significance of the treatment effects was determined using F-test and the difference between the means was estimated by using least significance difference at 5% probability level.

RESULTS AND DISCUSSION

Scoring of blast disease infection

In this study, the disease severity levels were estimated by evaluating percentage of host tissue covered by the necrotic lessons of the disease and number and size of the lesson. The extent of rice blast severity was graded from 0-9 as per the guideline of IRRI. The severity level 0 depicts that the plant is healthy having no symptoms at all and the disease severity level 9 depicts that the plant is most severely affected by pathogen. The disease severity levels; in-between show various levels of infestation and severity level gradually increases from 0 to the level 9 (Fig. 1). Rice genotypes, BL 18 and DH 79 grown under rain fed and irrigated conditions respectively were assigned as level 9. Genotypes, VL 32475 and DH 94 grown under rain fed and irrigated conditions respectively were assigned as severity level 0. The details of other variety and their corresponding severity levels are shown in Table 3.

Greenness index of rice leaves as influenced by blast disease

In this study greenness index of leaves was represented by the greenness values of SPAD meter. Greenness index of rice leaves as influenced by different level of blast severity are presented in Table 4. SPAD value of rice leaves ranged from 8.5 to 42.2 and 2.2 to 40.6 for rainfed and irrigated conditions, respectively. It was observed that SPAD of rice leaves was significantly influenced by blast disease severity levels for both conditions. Result showed that with the increase in disease severity levels the SPAD value significantly decreases under both the conditions. Under rainfed condition, score 9 showed minimum SPAD value (mean=11.2) whereas score 0 (healthy plant) showed maximum SPAD value (mean=38.55) (Table 4). Similarly, under irrigated condition, score 9 showed minimum SPAD value (mean=9.05) whereas score 0 (healthy showed maximum SPAD value (mean=39.09) (Table 4).

Canopy temperature of rice as influenced by blast disease

Canopy temperature of rice as influenced by different level of blast severity is presented in Table 4. Canopy temperature ranged from 20.0 to 31.1°C and 21.9 to 31.6°C for rainfed and irrigated conditions, respectively. It was observed that canopy temperature was significantly influenced by blast disease severity levels for both conditions. Result showed that with

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

Sl. No.	Index	Formula	References
		Structural indices	
1	Lichtenthaler Indices (Lic1)	$(R_{790} - R_{680}) / (R_{790} + R_{680})$	Lichtenthaler *et al.* (1996)
2	Modified Triangular Vegetation Index (MTVI)	$1.2 * [1.2 * (R_{800} - R_{550}) - 2.5 * (R_{670} - R_{550})]$	Haboudane *et al.* (2002)
3	Normalized Difference Vegetation Index (NDVI)	$(R_{830} - R_{660})/(R_{830} + R_{660})$	Rouse *et al.* (1974)
4	Normalized Difference Water Index (NDWI)	$(R_{560} - R_{830})/(R_{560} + R_{830})$	McFeeters (1996)
		Biochemical indices	
5	Pigment-Specific Simple Ratio-b (PSSRb)	R_{800}/R_{635}	Blackburn, 1998
6	Water Band Index (WBI)	R_{970}/R_{900}	Wang *et al.* 2007
		Physiological indices	
7	Moisture Stress Index (MSI)	R_{1599}/R_{819}	Hunt *et al.* 2007
8	Photochemical Reflectance Index-2 (PRI2)	$(R_{531} - R_{570})/(R_{531} + R_{570})$	Gamon, 1992

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

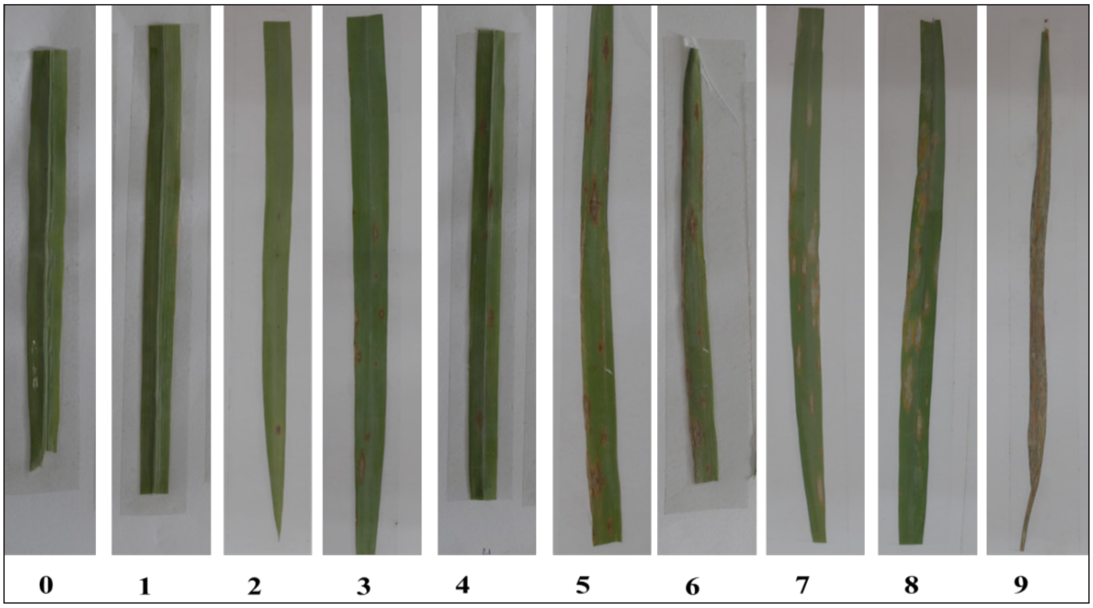

Fig. 1: Disease scoring of Rice Blast at VPKAS, Almora

the increase in disease severity levels the canopy temperature under both the conditions increases. Under rainfed condition, score 9 showed maximum canopy temperature (mean=21.67°C) whereas score 0 (healthy plant) showed minimum canopy temperature (mean=31.0°C) (Table 4). Similarly, under irrigated condition, score 9 showed maximum canopy temperature (mean=24.03°C) whereas score 0 showed minimum canopy temperature (mean=31.27°C) (Table 4).

Table 4: Greenness index (SPAD value) and canopy temperature of rice as influenced by blast disease

Disease score	SPAD value		Canopy Temperature (°C)	
	Rainfed (upland) condition	Irrigated (lowland) condition	Rainfed (upland) condition	Irrigated (lowland) condition
9	11.2	9.05	31	31.267
8	15.92	20.42	30	30.333
7	23.76	25.05	29.767	29.667
6	27.28	26.26	28.8	29.167
5	29.12	29.47	27.467	28.2
4	29.46	31.69	27.167	27.7
3	30.49	32.1	26.6	26.6
2	31.07	33.65	25.033	26.1
1	32.81	36.06	23.4	24.733
0	38.55	39.09	21.667	24.033
C.D.	3.849	3.786	1.997	1.875
SE(m)	1.365	1.343	0.667	0.626
SE(d)	1.931	1.899	0.943	0.885
C.V.	16.012	15.015	4.265	3.904

Response of leaf reflectance to variation in disease severity level

Generally a differential spectral response was witnessed with varying level of disease infestation. Fig. 2 shows the dynamic changes in leaf reflectance under different disease infestation levels. Different stress levels significantly influenced the spectral response of plant canopy in various wavelength regions which can be broadly divided into four spectral groups i.e. visible range (350-700 nm), near infrared range, NIR (700-1350 nm), SWIR I (1420-1800 nm) and SWIR II (1950 to 2350 nm). In the visible range, the healthy canopy experiences the lower reflectance at blue and red region and higher reflectance in green and also high in both NIR and SWIR-I and SWIR-II ranges. As the disease severity level progressed, the reflectance in visible region increases, basically at the red region the reflectance is more in the severely affected plant than the healthy plant. At this particular spectral region the spectral reflectance was mainly influenced by leaf pigment content. For blast infected plants, plant chlorophyll was almost damaged by the pathogen. Similar finding was also investigated by Kobayashi *et al.* (2016) for panicle blast disease detection. In the NIR region the reflectance of healthy plant is higher than infected and with the increase in disease severity level reflectance at NIR region gradually decreased. Due to the severe infection by the pathogen, the plant eventually starts producing the

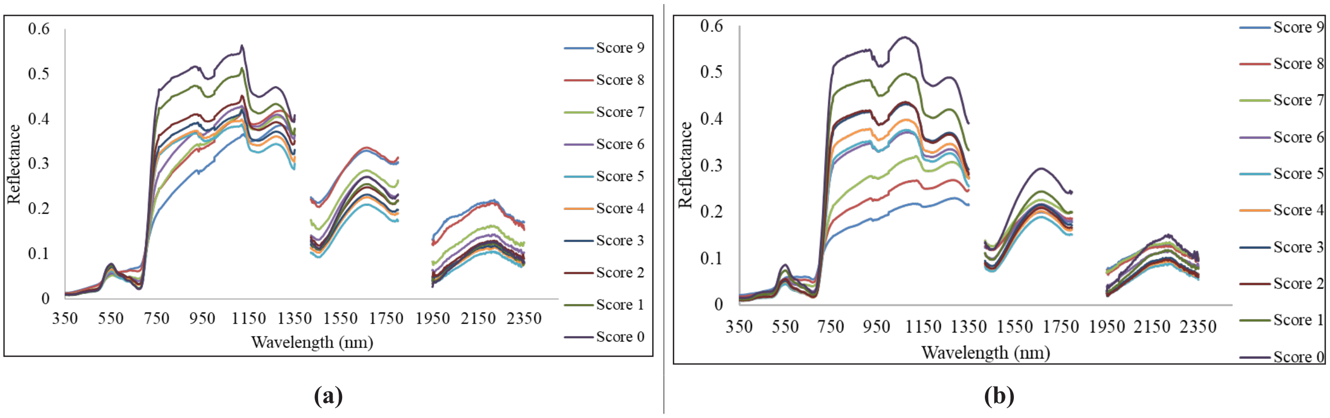

Fig. 2: Spectral reflectance of rice canopy under different disease severity levels at Almora under **(a)** Rainfed (upland) and **(b)** Irrigated (lowland) conditions

Table 5: 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	MTVI	Y=-13.388X+11.01	0.83	0.85	1.11	2.58
2	Lic1	Y=-15.58X+16.59	0.68	0.68	1.63	1.76
3	NDVI	Y=-17.10X+18.17	0.67	0.67	1.66	1.73
4	NDWI	Y=-28.63X+3.928	0.72	0.70	1.57	1.82
		Biochemical indices				
5	PSSRb	Y=-0.491X+8.954	0.56	0.57	1.87	1.53
6	WBI	Y=-52.97X+58.55	0.72	0.71	1.55	1.81
		Physiological indices				
7	MSI	Y=8.660X-1.537	0.69	0.65	1.51	1.89
8	PRI2	Y=50.03X+6.148	0.70	0.71	1.56	1.83

reactive oxygen species such as hydrogen peroxide and deposition of cellulose at the site of infection (Throdal-Christensen *et al*. 1997; Nishimura *et al*. 2003) which are the main causes of producing necrotic lesions leading to cell damage and finally death of the plant. Das *et al*. (2013) also reported the decrease in reflectance at NIR region for yellow mosaic virus infected soybean crop. In the SWIR region there was higher reflectance for the severely affected plant as compare to the disease infected plant. This may be attributed to the lower leaf water content for the blast infected plants.

Development of regression model and validation

A number of spectral indices have been selected for estimation of Blast disease severity levels with various combinations of wavelengths. Then linear regression model were developed among those indices and disease severity level. The best performing regression models between various indices and disease severity score (0-9) are shown in the Table 5. Out of biochemical, structural and physiological indices all the structural indices performed better than other. Among those indices, MTVI were found best for disease severity prediction with R^2 value of 0.83 for calibration, whereas during validation it could account maximum 85.0 % variability of observed severity level with RPD value of 2.58 (Table 5). Among the other indices, NDWI, WBI, MSI based regression models performed better for disease severity level prediction (Table 5). Spectral indices are nothing but the combination of mathematical equations of different spectral responses of different region of the spectra. Evaluation existing indices revealed that the structural indices perform the best for predicting the disease severity. Modified Triangular Vegetation Index are calculated as the areas of a hypothetical triangle in spectral space that connects green peak reflectance minimum chlorophyll absorbance and reflectance at NIR region. The fungus *Pyricularia* damages the internal structure of plant as well as the chlorophyll content. So, this index is influenced by the chlorophyll content and greenness of the plant and also sensitive to blast disease.

CONCLUSION

It can be concluded that canopy temperature was positively correlated with blast severity levels whereas greenness index was negatively correlated with blast severity levels. The spectral reflectance curve offers scope for potential use of the remote sensing technology to distinguish healthy and blast infected rice crop 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. MTVI based linear regression model was found best in this regard.

REFERENCES

Bandara, Y.M.A.Y., Weerasooriya, D.K., Tesso, T.T. and Little, C.R. 2016. Stalk rot fungi affect leaf greenness (SPAD) of grain sorghum in a genotype-and growth-stage-specific manner. *Plant Disease*, **100**(10): 2062-2068.

Bellon-Maurel, V., Fernandez-Ahumada, E., Palagos, B., Roger, J.M. and McBratney, A. 2010. Critical review of chemometric indicators commonly used for assessing the quality of the prediction of soil attributes by NIR spectroscopy. *TrAC Trends in Analy. Chem.* **29**(9): 1073-1081.

Blackburn, G.A. 1998. Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree leaves. *Int. J. Remote Sensing*, **19**(4): 657–75.

Chuwa1, C.J., Mabagala, R.B. and Reuben, M.S.O.W. 2013. Assessment of Grain Yield Losses Caused by Rice Blast Disease in Major Rice Growing Areas in Tanzania. *Int. J. Sci. and Res*. ISSN (Online): 2319-64.

Das, D.K., Pradhan, S., Sehgal, V.K., Sahoo, R.N., Gupta, V.K. and Singh, R. 2013. Spectral reflectance characteristics of healthy and yellow mosaic virus infected soybean (*Glycine max* L.) leaves in a semiarid environment. *J. Agrometeorology*, **15**: 36-38.

Devadas, R., Lamb, D.W., Simpfendorfer, S. and Backhouse, D. 2009. Evaluating ten spectral vegetation indices for identifying rust infection in individual wheat leaves. *Precision Agric.*, **10**(6): 459-470.

Gamon, J.A., Peñeulas, J. and Field, C.B. 1992. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sensing of Environ.*, **41**: 35–44.

Gitelson, A.A., Merzlyak, N.M. and Chivkunova, B.O. 2001. Optical properties and nondestructive estimation of anthocyanin content in plant leaves. *Photochem. and Photobiol.*, **74**: 38–45.

Gitelson, A.A. and Merzlyak, M.N. 1997. Signature analysis of leaf reflectance spectra: Algorithm development for remote sensing of chlorophyll. *Int. J. Remote Sensing*, **18**: 2691–97.

Gomez, K.A. and Gomez, A.A. 1984. Statistical procedures for agricultural research. John Wiley & Sons.

Haboudane, D., Miller, J.R., Trembaly, N., Zarco-tejada, P.J. and Dextraze, L. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sensing of Environ*., **81**: 416–26.

Hunt Jr, E.R. and Rock, B.N. 1989. Detection of changes in leaf water content using near-and middle-infrared reflectances. *Remote Sensing of Environ*, **30**(1): 43-54.

Kobayashi, T., Kanda, E., Naito, S., Nakajima, T., Arakawa, I., Nemoto, K., Honma, M., Toujyou, H., Ishiguro, K., Kitada, K. and Torigoe, Y. 2003. Ratio of rice reflectance for estimating leaf blast severity with a multispectral radiometer. *J. General Plant Pathology*, **69**(1): 17-22.

Lichtenthaler, H.K., Gitelson, A.A. and Lang, M. 1996. Nondestructive determination of chlorophyll content of leaves of a green and an aurea mutant of tobacco by reflectance measurements. *J. Plant Physiol.*, **148**: 483– 493.

Lindenthal, M., Steiner, U., Dehne, H.W. and Oerke, E.C. 2005. Effect of downy mildew development on transpiration of cucumber leaves visualized by digital infrared thermography. *Phytopathology*, **95**(3): 233-40.

Marín-Ortiz, J.C., Gutierrez-Toro, N., Botero-Fernández, V. and Hoyos-Carvajal, L.M. 2020.Linking physiological parameters with visible/near-infrared leaf reflectance in the incubation period of vascular wilt disease. *Saudi J. Biological Sci*., **27**(1): 88-99.

McFeeters, S.K. 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sensing*, **17**(7): 1425-1432.

Minolta. 1989. Chlorophyll Meter SPAD-502 Operation Manual. Minolta Camera Co., Osaka, Japan.

Nishimura, M.T., Stein, M., Hou, B.H., Vogel, J.P., Edwards, H. and Somerville, S.C. 2003. Loss of a callose synthase results in salicylic acid-dependent disease resistance. *Science*, **301**(5635): 969-972.

Oerke, E.C., Fröhling, P. and Steiner, U. 2011. Thermographic assessment of scab disease on apple leaves. *Precision Agric.*, **12**(5): 699-715.

Peñuelas, J. and Filella, I. 1998. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. *Trends in Plant Sci*., **3**: 151–156.

Prabhakar, M., Prasad, Y.G., Thirupathi, M., Sreedevi, G., Dharajothi, B. and Venkateswarlu, B. 2011. Use of ground based hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). *Computers and Electronics in Agric.*, **79**(2): 189-198.

Ricepedia. 2015. Agricultural Statistics at a glance. https://www.nfsm.gov.in/StatusPaper/Rice

Rouse, J.W., Haas, R.H., Schell, J.A. and Deering, D.W. 1974. Monitoring vegetation systems in the Great Plains with ERTS. *Proc.* 3rd Earth Resources Technology Satellite-1 Symposium. Greenbelt, MD, NASA. pp. 301–17.

Sahoo, R.N., Ray, S.S. and Manjunath, K.R. 2015. Hyperspectral remote sensing of agriculture. *Current Sci.*, pp. 848-859.

Savitzky, A. and Golay, M.J.E. 1964. Smoothing and differentiation of data by simplified least squares procedures. *Ann. Chem*., **36**: 1627–39.

Thordal-Christensen, H., Zhang, Z., Wei, Y. and Collinge, D.B. 1997. Subcellular localization of H_2O_2 in plants. H_2O_2 accumulation in papillae and hypersensitive response during the barley—powdery mildew interaction. *The Plant J.*, **11**(6): 1187-1194.

Wang, Y.Y., Chen, Y.H., Li, J. and Huang, W.J. 2007. Two new red edge indices as indicators for stripe rust disease severity of winter wheat. *J. Remote Sensing-Beijing*, **11**(6): 875.

Wiegand, C.L., Richardson, A.J., Escobar, D.E. and Gerbermann, A.H. 1991. Vegetation indices in crop assessments. *Remote Sensing of Environment*, **35**: 105-119.

Williams, P.C. 2001. Implemenation of near infrared technology. In Near infrared technology in the agricultural and food industries. (Eds. P.C. Williams & K.H. Norris). American Association of Cereal Chemists. St. Paul, Minneesota, pp. 145-171.

Zarco-Tejada, P.J., Miller, J.R., Mohammed, G.H., Notlamd, T.L.L. and Sampson, P.H. 2001. Scaling-up and model inversion methods with narrow-band optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data. *IEEE Transactions on Geoscience and Remote Sensing*, **39**: 1491–1507.