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Effect of meteorological factors on rice sheath blight and exploratory development of a predictive model

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ABSTRACT

Sheath blight disease has become an important constraint in rice crop cultivation in Punjab in recent years. A field experiment was conducted during rainy (*kharif*) of 2007 and 2008 to investigate the influence of different meteorological parameters on sheath blight development as well as computation of a predictive model to predict the disease well ahead its appearance in the field. Correlation analysis showed that among all the meteorological factors considered, maximum air temperature and morning relative humidity were key factors to govern the disease in the field. A maximum temperature around 34°C and a minimum temperature around 26°C were found to be favourable for the spread of sheath blight after its establishment in the field. Again high morning relative humidity more than 90% facilitates spreading of the disease. A predictive model was developed with a coefficient of determination (R^2) of 0.8048 using statistical language R. A step-wise multiple regression analysis approach was adopted to identify the most appropriate predictive variables to constitute the model.

Key words: Meteorological parameters, Multicollinearity, Predictive model, Rice, Sheath blight

Rice sheath blight caused by *Rhizoctonia solani* Kuhn is the second most devastating disease in India and other tropical countries. Although, the disease was earlier considered as minor, became a major production limiting disease during recent years. In fact, this disease has turned out to be the most important disease in rice producing areas of north-western India due to absence of adequate resistant cultivars. Losses due to this disease have been reported to vary from 5 to 13.5% in Punjab (Thind *et al.* 2001). A 20–25 percent loss is expected when the infection reaches to the flag leaves. With the introduction of high-yielding varieties, there has been considerable increase in the dosage of nitrogen application, the number of plants/unit area and the number of irrigations. All these factors result in luxuriant plant growth, thick stand of the crop and constant humid conditions coupled with high temperature during rainy (*kharif*) season. Little was known regarding the influence of meteorological factors that influence the continuous build- up of sheath blight in the field. Weather-based prediction models have been used to forecast rice disease like bacterial leaf blight, blast disease (Calvero *et al.* 1996, Hashimoto *et al.* 1984) but there was very little initiative to model sheath blight incidence using epidemiological parameters, particularly in Indian condition.

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The objectives of this research therefore were to: (i) observe the effect of different meteorological factors associated with incidence of sheath blight, and (ii) develop a model to assist in predicting the incidence of the disease in the field.

MATERIALS AND METHODS

The field experiment was undertaken in the Research Farm of Department of Agricultural Meteorology, Punjab Agricultural University, Ludhiana (30°54' N; 75°48'E; 247 m) during *kharif* 2007 and 2008. The area is characterized by subtropical, semiarid climate with average annual rainfall of about 732 mm. The soil at the experimental site was sandy loam with a *p*H of 7.5. Two commercially cultivated rice varieties PR 115 (V_1) and PR 116 (V_2), plant height, pheno-phases and yield, were selected to investigate the effect of different meteorological parameters on the disease development. These varieties were planted under two different plant spacing viz. 20 cm×15 cm (S_1) and 20 cm × 20 cm (S_2). Fertilization, weed and insect control was done according to PAU package of practices for *kharif* crops. The sheath blight inoculum was prepared and cultures were mixed thoroughly for artificial inoculations in the field. In each plot 10–12 plants were inoculated randomly placing inoculum between leaf sheath and culms at three different stages, ie maximum tillering stage, leaf boot stage and grain-filling stage. A control was kept for each treatment. The control plots were protected from sheath blight attack by spraying the crop with Tilt (Propiconazole) 25 EC@ 200 ml in 200 liters of water when disease was noticed in the field and a second spray was given after 15 days. All experiments entailed a factorial split-plot design with four replicates. The main plot treatments were based on inoculation or non-inoculation with the sheath blight pathogen and subplot treatments were the two varieties (V_1 and V_2) and two different spacing (S_1 and S_2). Rice cultivars were arranged under above two spacing randomly in each subplot and within each subplot two seedlings/hill were transplanted. Transplanting was done on 15 June each year. For recording *disease incidence* (DI_{sh}), total number of infected plants in each plot was counted by observing characterizing symptoms.

The meteorological factors evaluated consists eight variables that were tested for a correlation analysis with periodic disease incidence during *kharif* 2007 and 2008. These eight predictive variables were also tested for use in sheath blight predictive model. The eight predictive meteorological factors were: weekly maximum temperature (T_{max}), minimum temperature (T_{min}), mean air temperature (T_{me}) morning relative humidity (RH_m), evening relative humidity (RH_e), mean relative humidity (RH_{me}), sunshine hours (SSH) and total weekly rainfall (RF). All variables were determined from daily data collected from the Agrometeorological Observatory situated 150 m away from the experimental field. Data for the eight meteorological variables were subjected to correlation analysis to identify any variable(s) associated with DI_{sh}. In multiple linear regression, multiocollinearity, or correlation among predictor variables, is an important consideration. When multicollinearity is a problem, standard error for the estimates will tend to be large and parameter estimates may be illogical. To determine multicollinearity among variables, variance inflation factors (VIF) for each independent variable using statistical analysis software R (var. 2.9.0, *car* library) were worked out. Such problem was resolved by selecting appropriate combination of predictor variables which are not strongly correlated with each other and Akaike information criterion (AIC) can be used to select among models for an optimal combination of parsimony (limiting the model to the smallest number of parameters needed) and good fit. A lower AIC indicates a better model. A step-wise regression analysis was done to fit appropriate model with lowest AIC value by using step function in R (ver. 2.9.0–2009).

RESULTS AND DISCUSSION

Effect of different meteorological parameters on sheath blight incidence

Observations on DI_{sh} and different meteorological parameters were recorded weekly to investigate the probable functioning of those parameters on incidence of the disease. To express such relationship, correlation coefficients between different meteorological parameters and DI_{sh} were worked out for each treatment during rapid disease advancement period. The results showed whether a parameter was positively or negatively correlated with DI_{sh}.

Correlation analysis showed a strong positive association of maximum temperature (T_{max}) and morning relative humidity (RH_m) with DI_{sh} during both the years (Table 1). Corelation coefficients were found statistically significant with those two above mentioned meteorological parameters. Among the other parameters considered, only sunshine hours (SSH) showed a negative correlation with DI_{sh}, whereas others like minimum temperature (T_{min}), mean temperature (T_{me}), evening relative humidity (RH_e) and rainfall (RF) came out to be positively correlated. Such results signify that a relatively higher air temperature and relative humidity was more conducive to intensify disease incidence. A high and intermittent rainfall as well as lower sunshine hours, ie cloudy conditions helped in epidemic establishment of the disease in the field. Savary *et al.* 2001 reported that rate of disease increase at the onset of the epidemics was higher in the dry than in the rainy season, but it was higher afterwards during the rainy than in the dry season. Cloudy weather and rain showers were favourable for development of the disease (Anonymous 2007).

Boxplots (Fig 1) were prepared for every individual parameter considered being favourable in the disease

Table 1 Correlation coefficients between sheath blight incidence and different meteorological parameters under different treatments during *kharif* 2007 and 2008

Treatment	*Kharif* 2007								*Kharif* 2008							
	T_{max}	T_{min}	T_{me}	RH_m	RH_e	RH_{me}	RF	SSH	T_{max}	T_{min}	T_{me}	RH_m	RH_e	RHme	RF	SSH
S_1V_1	0.696*	0.12	0.29	0.59	0.33	0.39	0.47	–0.34	0.72*	0.12	0.29	0.71*	0.33	0.39	0.34	–0.41
S_2V_1	0.62*	0.09	0.26	0.79*	0.39	0.17	0.39	–0.31	0.68*	0.09	0.29	0.82*	0.39	0.17	0.42	–0.29
S_1V_2	0.72*	0.18	0.26	0.69*	.31	0.37	0.43	–0.31	0.78*	0.18	0.26	0.65*	0.31	0.37	0.51	–0.33
S_2V_2	0.56	0.67	0.44	0.66*	0.51	0.56	0.56	–0.35	0.63*	0.37	0.44	0.75*	0.51	0.56	0.37	–0.31

V_1 =PR-115, V_2= PR-116, S_1=20 cm × 15 cm spacing, S_2=20 × cm 20 cm spacing, Number of observations = 10, T_{max}= Maximum temperature (°C), T_{min} = minimum temperature (°C), T_{me}= mean temperature (°C), RH_m=morning RH (%), RH_e=evening RH (%), RH_{me} = mean RH (%), RF= rainfall (mm), SSH = sunshine hours

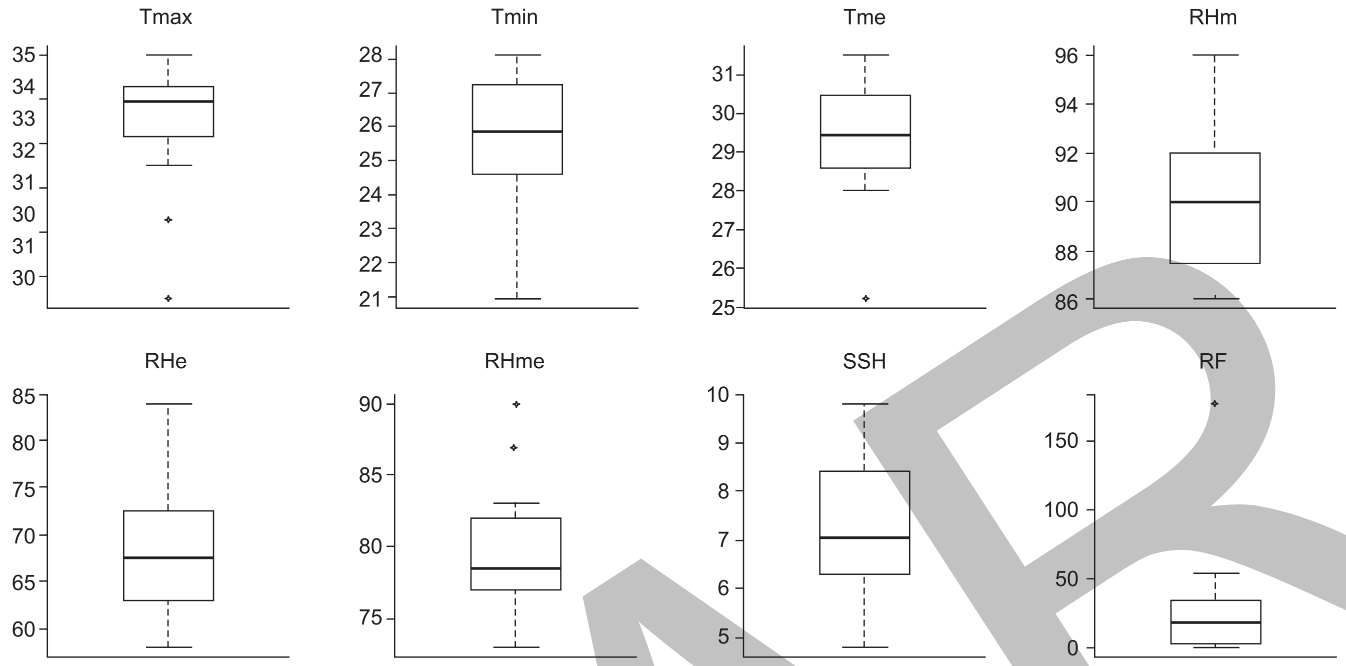

Fig 1 Boxplots showing distribution of the meteorological prameters considered conducive to the sheath blight development

development, to show their distribution throughout the disease incidence period. These helped to recognize different meteorological parameters quantitatively. A maximum temperature around 34°C and a minimum temperature around 26°C were found to be deciding factor for the spread of sheath blight after its establishment in the field. Higher morning relative humidity (>90%) as well as evening relative humidity (>70%) for most of the season facilitate in spreading the disease. Tiwari and Chaure (1997) also reported that mean temperature around 25°C and humidity range of 80–95% were optimum for disease development. Sunshine hours were also lower during active disease growth period.

Development of a predictive model to estimate sheath blight incidence

Development of predictive model was attempted from meteorological and disease data collected in 2007 and 2008. Variance inflation factors (VIF) of eight predictive variables revealed several variables that were highly intercorrelated (ie condition of multicollinearity). High VIF values were observed in case of T_{max}, T_{min} and T_{me} as well as all the RH related variables (Table 2) that signified strong associationship among those variables. Hence if we choose all variables together, they will certainly hamper prediction

Table 2 Variance inflation factors (VIF) of individual predictive variables

Parameter	VIF
T_{max}	7.52
T_{min}	17.64
T_{me}	10.73
R_{Hm}	32.36
R_{He}	146.52
R_{Hme}	209.93
RF	3.70
SSH	3.38

T_{max}= Maximum temperature (°C), T_{min} = minimum temperature (°C), T_{me}= mean temperature (°C), RH_m=morning RH (%), RH_e=evening RH (%), RH_{me} = mean RH (%), RF= rainfall (mm), SSH = sunshine hours

Table 3 Step-wise multiple regression analysis for selecting appropriate predictive variables

Equation	AIC	R squared
DI_{sh}=179.26+16.01T_{max}-26.18T_{min}+9.27T_{me}-2.12RH_m-6.36RH_e+9.67RH_{me}+0.05RF-9.27SSH	99.09	0.83
DI_{sh}= -178.59+15.23T_{max}-24.80T_{min}+9.43T_{me}-4.54RH_e+5.86RH_{me}+0.06RF-9.12SSH	97.22	0.83
DI_{sh}=-203.33+14.21T_{max}-24.39T_{min}+8.88T_{me}-4.42RH_e+6.17RH_{me}-8.47SSH	95.38	0.83
DI_{sh}=-192.92+15.60T_{max}-18.02T_{min} -5.68RH_e+7.79RH_{me} - 8.72SSH	92.25	0.81

T_{max}= Maximum temperature (°C), T_{min} = minimum temperature (°C) T_{me}= mean temperature (°C), RH_m=morning RH (%), RH_e=evening RH (%), RH_{me} = mean RH (%), RF= rainfall (mm), SSH = sunshine hours

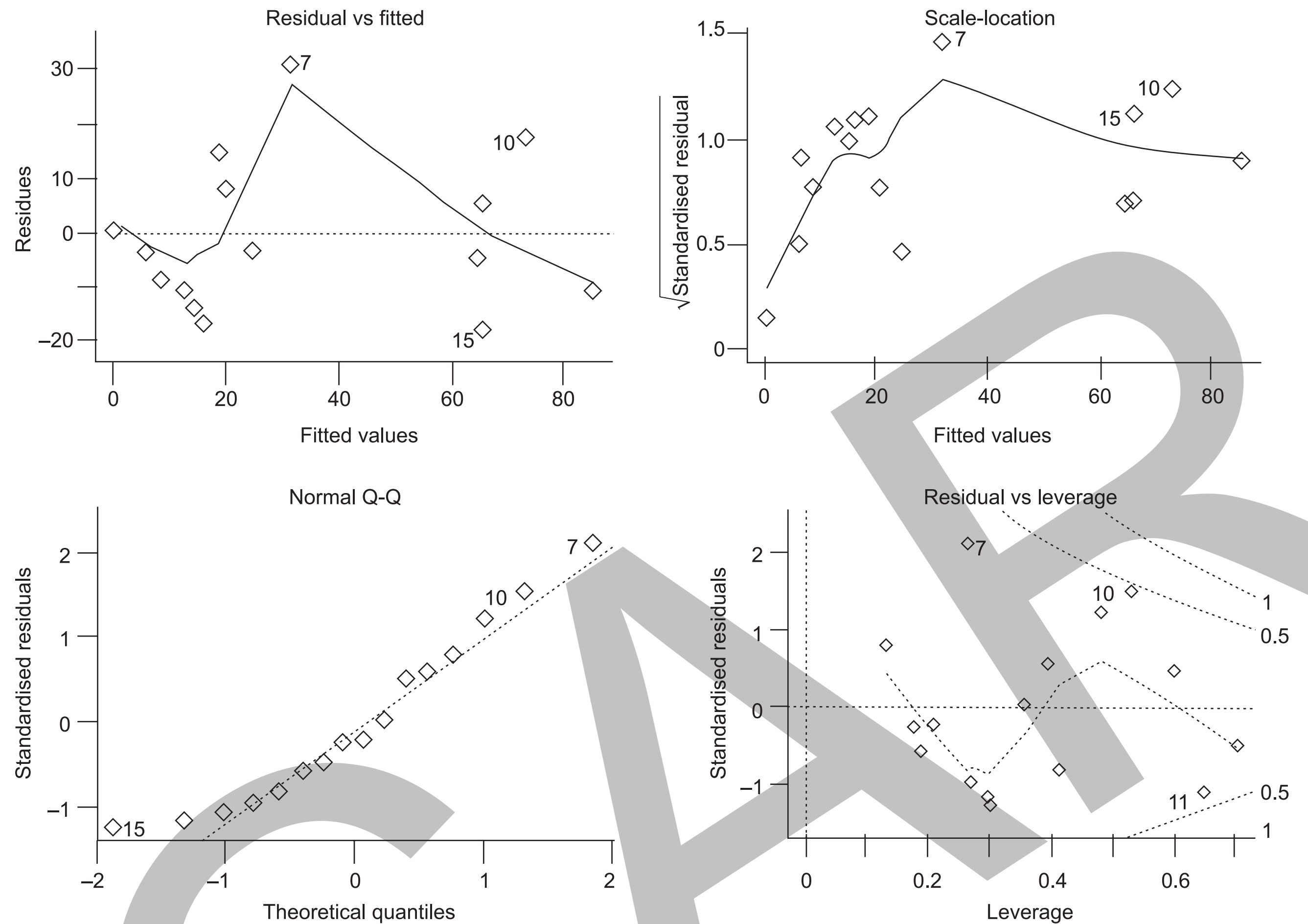

Fig 2 Diagnostic plots of the predictive model

of the model in a real time situation. So, a step-wise multiple regression analysis approach helped to identify the most appropriate predictive variables to constitute the model with lowest AIC value of 95.25 (Table 3). The model came out to be:

DI_{sh}= 192.92+1560 T_{max} - 18..02T_{min} - 5.68 RH_e + 7.79RH_{me} - 8.72SSH (R^2=0.8048)

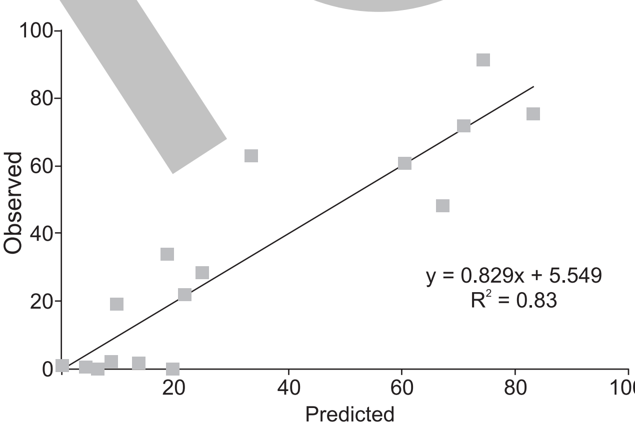

Fig 3 Performance of the predictive model (DI_{sh})

with a multiple R^2 value of 0.8048 which indicates that the predictor variables explain 81% of the variance in the response variable. Probability values for the coefficients of T_{max}, T_{min}, RH_e and RH_{me} were found statistically significant

Table 4 Descriptive statistics of predictive model

	Coefficient	Standard error	t stat	p value
Intercept	–192.94	263.45	–0.732	0.481
Tmax	15.61	6.85	2.278	0.045*
Tmin	–18.02	5.04	–3.571	0.005**
RHe	–5.68	2.72	–2.092	0.062
RHme	7.78	3.89	1.997	0.073
SSH	–8.72	5.25	–1.659	0.127

Signif. Codes: ‘** 0.01 ‘*’ 0.05 ‘.’ 0.1 level
Residual standard error: 17.06 on 10 degrees of freedom, Multiple R-squared: 0.8048, F statistic: 8.245 on 5 and 10 DF, p value: 0.002549

T_{max}= Maximum temperature (°C), T_{min} = minimum temperature (°C), T_{me}= mean temperature (°C), RH_m=morning RH (%), RH_e=evening RH (%), RH_{me} = mean RH (%), RF= rainfall (mm), SSH = sunshine hours

(Table 4) and p value (0.0025) was small enough to suggest that predictive variables were appropriately chosen. The diagnostic plots (Fig 2) of the model also signify good predictability of the model if a new set of meteorological data fitted into it. Observed verses predicted plot (Fig 3) also depicted a good association between them. So, this model can be used to predict sheath blight incidence and thus fungicide application schedule can be arranged accordingly and subject to further evaluation under field conditions.

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