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Temporal dynamics and prediction model of sheath blight in rice under prevailing weather conditions

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Abstract

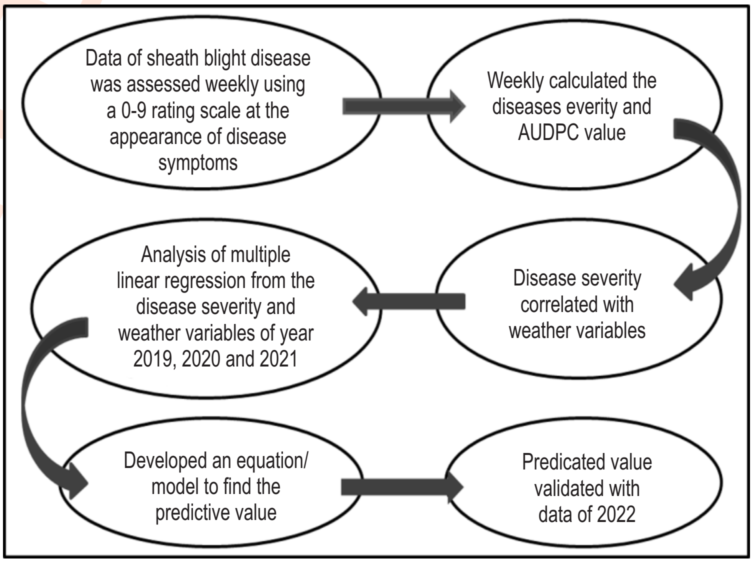
Aim: To study the effect of weather variables in the development of sheath blight in rice.

Methodology: The nursery of rice cv. PR 121 was raised in last week of May in four consecutive kharif seasons 2019 to 2022 and one-month-old seedlings were transplanted in the field. The sheath blight disease was assessed using a 0-9 rating scale at the appearance of first symptoms and correlated with weather variables *viz.,* maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity morning (RH_m), relative humidity evening (RH_e), rainfall (RF) and sunshine hours (SS). The multiple linear regression was applied to establish the relationship between weather variables and disease severity.

Results: Disease severity was highest when the maximum temperature was 30-33°C, minimum temperature was 21-24°C, morning relative humidity exceeding 95%, and evening relative humidity exceeding 65%. The disease severity showed a significant negative correlation with T_{min} (-0.93), T_{max} (-0.52), RH_e (-0.45) and RF (-0.41), while a positive correlation with RH_m (0.30). A predictive model with 0.88 coefficient of determination indicated that the weather variables can explain 88.0% of the variability in disease severity.

Interpretation: Sheath blight is a major destructive disease affecting rice in Punjab, with severity levels ranging 56.44% to 78.22% during the year 2019 to 2022. The predictive model developed to analyze the disease progression, yielded a R^2 value (coefficient of determination) of 0.88 and indicated that minimum temperature and rainfall were the key factors in the development of the disease.

Key words: Multiple regression, Predictive model, Sheath blight, Variance inflation factors, Weather variables



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Introduction

Sheath blight is a devastating disease of rice worldwide caused by *Rhizoctonia solani* Kuhn. It can result upto a 50% reduction in grain yield depending on the severity disease, infection rate and environmental conditions (Savary *et al.,* 2000; Willocquet *et al.,* 2004; Groth and Bond, 2007; Margani and Widadi, 2018; Yuan *et al.,* 2018). The disease was first identified in Japan (Miyake, 1910) and than has since been observed across temperate and tropical rice-growing regions worldwide Dasgupta, 1992; Sivalingam *et al.,* 2006). The disease significantly impacts rice production, threatening food security and farmer livelihoods (Ali *et al.,* 2023). In India, the occurrence of this disease was first reported in Gurdaspur, Punjab (Paracer and Chahal, 1963) and recorded yield loss, as high as 58.0 per cent in a cultivar Pusa Basmati-1 (Chahal *et al.,* 2003). The symptoms of the disease appears at the tillering stage on the leaf sheath as elliptical or oval to irregular, greenish-grey spots with brown margins at or above the water level (Singh *et al.,* 2016).

The infection mainly targets the leaf sheath and leaf blades, while in severe cases, the whole plant including the emerging panicles may be affected (Rangaswami and Mahadevan, 1998). Although, the disease can occur at any growth phase, rice crop is most vulnerable at tillering phase (Singh *et al.,* 1988). Lore *et al.* (2021) studied the temporal and spatial progression of sheath blight in rice varieties and observed that the spatial spread depends on the susceptibility level of a variety. *Rhizoctonia solani* is a highly destructive pathogen and spreads all across the world with a diverse host range and the ability to remain dormant under unfavourable conditions (Senapati *et al.,* 2022). In recent decades, the practice of producing a single crop species, high-yielding cultivars, extensive use of nitrogenous fertilizers, and dense crop canopy are the factors that lead to the spread and development of the disease (Savary *et al.,* 1995; Singh *et al.,* 2004). The spread of sheath blight is directly dependent on inoculum density, warm and high humidity conditions (Groth and Lee, 2003), maximum air temperature, morning relative humidity and leaf wetness (Biswas *et al.,* 2011) and high humidity after rainfall (Kasniya *et al.,* 2022).

The average relative humidity and temperature influence the vertical progression of sheath blight (Kumar *et al.,* 2016). Developing a stable resistant donor is challenging due to the complex nature of the pathogen and the polygenic nature of resistance among the rice genotypes. This lack of a stable resistant donor has hindered successful breeding for *R. solani* tolerance (Naveenkumar *et al.,* 2022). Consequently, sheath blight incidence has been rising in India (Laha *et al.,* 2016) and South Asia (Srinivasachary *et al.,* 2011) due to lack of genetic resistance. Hashiba (1984) investigated a model curve for forecasting the rice sheath blight on vertical development (ratio of the height of lesions to the plant height) based on temperature, relative humidity and susceptibility of leaf sheath. While, the horizontal development (percentage of the number of diseased hills) was produced on the basis of temperature, relative humidity between hills and quantity of sclerotia per unit area of paddy field. Similarly, the BLIGHTASIRRI model estimated the curve of vertical and horizontal development of sheath blight disease in rice (Kobayashi *et al.,* 1995). EPIRICE was most accurate model for predicting rice leaf blast and sheath blight epidemics in South Korea offering insights into epidemic locations, intensity, and temporal patterns (Kim *et al.,* 2015). Zeng *et al.* (2021) developed a linear regression model for predicting sheath blight lesion length based on genotypic and phenotypic data of 273 rice genotypes represented by the equation y= 34.44-0.56x, where y is the predicted value of lesion length and x is the total genotypic value.

Han *et al.* (2022) also developed a detection model based on images of lesions and damage grading of disease and provide a theoretical basis for the intelligent forecasting of rice sheath blight. The progression of rice sheath blight in relation to weather variables and exploratory development of prediction equations was developed by Sindhu *et al.* (2023). Climate change significantly impacts plant diseases by influencing pathogen evolution and host plant interactions, as well as fostering the emergence of new pathogenic strains (Singh *et al.,* 2023). In a recent study, Lahlali *et al.* (2024) observed that alterations in temperature, humidity, and precipitation patterns enhance the virulence and spread of various diseases. Indeed, the extreme weather event creates favourable conditions for disease outbreaks. The effects of climate change on different pathosystems can vary widely, ranging from positive to negative (Jeger *et al.,* 2021). Thus, coordinated efforts are needed to improve predictive capabilities and develop adaptive strategies to address these challenges.

Weather variables such as temperature, humidity, and rainfall are known to influence disease development, but there has been limited quantification of these factors. This study aims to identify and quantify the parameters that significantly contribute to sheath blight disease under field conditions, intending to formulate a predictive model for the disease.

Materials and Methods

Experimental details: Field experiments were conducted at Krishi Vigyan Kendra, Ropar (Latitude 30°58'06.8"N, Longitude 76°28'56.6"E) located in the sub-mountainous region of Punjab, India during four consecutive kharif seasons (2019, 2020, 2021 and 2022). The seed of paddy variety PR 121 was obtained from the Punjab Agricultural University, Ludhiana. During each year, nursery was raised on beds in last week of May. One-month-old seedlings were transplanted at spacing of 20 X 15cm in the plot size of 8 X 5m and the crop was raised following the PAU recommended agronomic practices for rice crop without spraying any fungicide. The data of weather variables like maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity morning (RH_m), relative humidity evening (RH_e), rainfall (RF) and sunshine hours (SS) were obtained from the meteorological observatory of Regional Research Station, Ballowal Saunkhri in the year 2019, whereas during 2020, 2021 and 2022, the data were obtained from meteorological observatory of *Krishi Vigyan Kendra, Ropar.*

Table 1: Disease scoring scale for sheath blight disease of rice (IRRI, 2013)

Scale	Relative lesion height
0	No infection
1	Vertical spread of the lesion up to 20% of plant height
3	Vertical spread of the lesion up to 21- 30% of plant height
5	Vertical spread of the lesion up to 31-45% of plant height
7	Vertical spread of the lesion up to 46-65% of plant height
9	Vertical spread of the lesion up to 66 -100% of plant height

Data collection and disease analysis: The disease data were assessed using a 0-9 rating scale (IRRI, 2013; Table 1) and recorded at the appearance of first symptom of disease. Twenty-five plants per plot were randomly selected in the 'Z' pattern to record the disease data under natural epiphytotic conditions. The selected plants were assessed at weekly intervals up to harvesting of crop. Disease severity was calculated using a standard formula of McKinney (1923). The area under the disease progress curve (AUDPC) is frequently used to combine multiple observations of disease progression into a single value. AUDPC value was estimated as per the equation given by Simko and Piepho (2012).

Correlation analysis and multiple linear regression equation: The correlation coefficients were calculated between various weather variables and disease severity. The best fit model was observed by using the value of coefficient of determination (R^2) and root mean square error (RMSE). A linear multiple regression analysis was used to examine the relationship between weather variables and the severity of sheath blight disease. As per regression equation: $Y = a + b_1X_1 + b_2X_2 + ... + b_n*X_n$. Where, Y represents the predicted sheath blight severity, and X_1, X_2, X_3, X_4, X_5 and X_6 represent the independent variables (T_{max}, T_{min}, RH_m, RH_e, RF and SS). The numbers accompanying the variables (b_1, b_2,…..etc.) are the coefficients assigned to each independent variable, indicating their impact on the predicted sheath blight severity 'a' represents the intercept of the regression line. The equation was developed to the disease severity and weather variables for the year of 2019, 2020 and 2021. Further, outcome of the predicative value was validated with the observed value of disease severity in the year 2022.

Collinearity statistics analysis (Tolerance and VIF value): In statistics, collinearity is a situation where predictor variables in a regression model are correlated with each other. Tolerance value indicates the percentage of variance in an independent which close to 1 indicating low multicollinearity, while values closer to 0 suggest higher collinearity. It is calculated as $T=1-R^2$ Tolerance is the reciprocal of the variance inflation factor (VIF), which is another statistic used to detect collinearity. VIF values provide another measure of multicollinearity, where a value greater than 5 typically signals moderate multicollinearity, and values above 10 suggest a high level of multicollinearity. The VIF value was calculated as: *VIF=1/T.*

Statistical Analysis: The data were statistically analyzed for outcome of correlation and multiple linear regression using the Statistical Package for Social Sciences (SPSS Version 23).

Results and Discussion

The perusal of data showed that the highest disease severity of 78.22% was recorded in 2020, followed 71.56% during 2019. In contrast, the disease severity was lower (56.44%) in 2021 and (61.33%) in 2022 as Fig.1. The progression of disease severity from 2019 to 2022 is illustrated in Fig. 2, which shows a quantitative assessment of the cumulative disease severity experienced throughout the growing season. The higher AUDPC values typically indicate greater disease severity in the year. In 2019, the AUDPC value for disease was recorded at 2285. The severity of disease increased slightly in 2020, with the AUDPC rising to 2383. Subsequently, there was a notable decrease in disease severity in 2021, evidenced by decline in AUDPC to 1445. The trend continued in 2022, with a further reduction in disease severity, as indicated by the AUDPC value of 1170. Biswas *et al.* (2012b) studied microclimatic modifications due to cultural practices against sheath blight in Punjab. They found the highest disease severity at 68.40% in 2007 and 80.10% in 2008 with a spacing of 20 X 15cm in PR 115. In 2020, the disease severity was 78.22%, followed by 71.56% in 2019, both at the same spacing in PR 121. Disease severity decreased in 2021 (56.44%) and 2022 (61.33%). These variations underscore the influence of weather conditions on disease dynamics.

It was observed from the field conditions throught the study period that the disease infection initiated during the 28th-29th standard meteorological weeks (SMW) and increased rapidly from 38th-42th SMW under favorable environmental conditions (Fig. 3, 4). The disease progression exhibited a characteristic sigmoidal curve in all the years under investigation, where weather variables played a significant role. It was concluded that the disease severity was highest when the T_{max} was 30-33ºC and T_{min} was 21-24ºC (Fig. 3) along with RH_m exceeding 95% and RH_e exceeding 65% (Fig. 4). Boxplots for each individual parameter known to influence disease development (Fig. 5), illustrated their distribution across varying levels of disease severity and aiding in the quantification of different level of variable. Similar results have been previously reported by Dutta and Kalha (2011) that T_{max} 30°C and RH >90% favoured the development of disease; Henry and Devasahayam (2011) reported T_{max} 30-32°C and RH 96-97%; Biswas et al. (2011) mentioned maximum air temperature 34°C and RHm more than 90%; Biswas *et al*. (2012a) observed T_{max} between 33–34°C and T_{min} of 24–26°C with high relative humidity more than 90%; Bhukal *et al*. (2015) observed T_{max} 31-33°C, RH_m and RH_e >90%; Pal *et al.* (2016) found T_{max} 31-34°C; Ravali et al. (2021) revealed high temperatures (30-34°C) and high relative humidity (above 90%); Kasniya *et al.* (2022) reported high humidity after rainfall was found to be most conducive for the disease development. The disease was developed maximum at 38 to 42 SMW during the grain filling stage when crop canopy dense. Weather conditions with T_{max} of 30-33ºC, T_{min} of 21-24ºC,

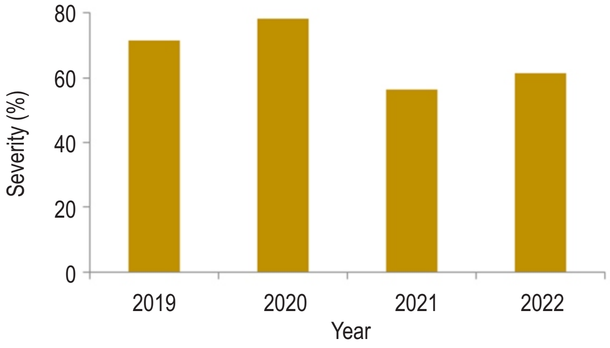

Fig. 1: Final disease severity of sheath blight of rice.

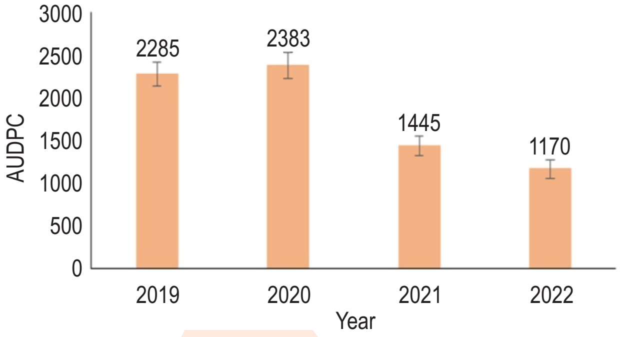

Fig. 2: Year wise AUDPC value of sheath blight disease of rice.

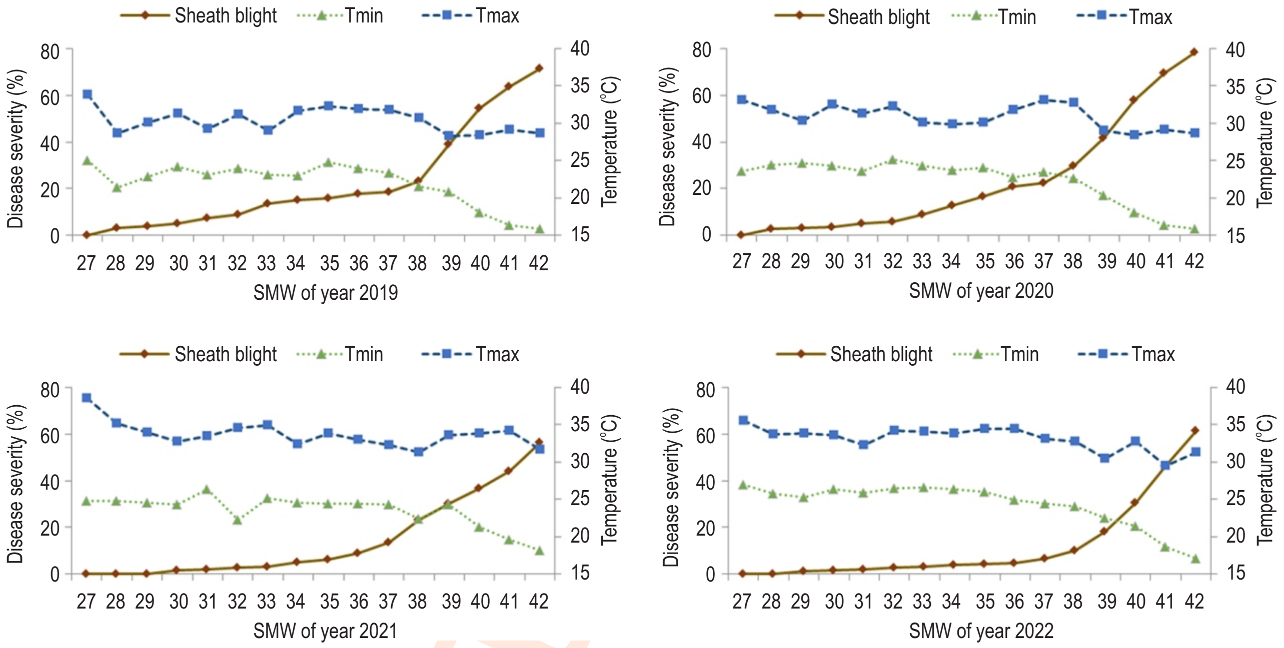

Fig. 3: Impact of maximum (T_{max}) and minimum (T_{min}) temperatures on progression of sheath blight disease in rice crop.

RH_m >95% and RH_e >65% created a humid and warm environment conducive to disease. Thakur *et al.* (2017) observed that T_{max} range of 30.5–32.6ºC during maximum tillering to panicle initiation stage of variety 'Swarna' favoured the sheath blight disease progression.

The correlation relationship between sheath blight disease severity and weather variables (maximum temperature, minimum temperature, morning relative humidity, evening relative humidity, rainfall and sunshine hours) from 2019 to 2022 is presented in Table 2. A strong negative correlation was observed between disease severity and minimum temperature of coefficient value varied from-0.95 to-0.98 at p<0.01 level of significant in all years. However, maximum temperature also showed a strong significant negative correlations during 2020 (-0.67) and 2022 (-0.75) at p<0.01 level of significance. Morning relative humidity exhibited strong positive correlations in 2020 (0.75) and 2022 (0.74), while evening relative humidity showed a strong negative correlations during 2019 (-0.69) and 2020 (-0.72) at p<0.01 level of significance. Rainfall had a weak negative correlation, significant only in 2020 (-0.50) at p<0.05 level of significance. Sunshine hours did not show a significant relationship in any year. In 2020 and 2022, most correlations were significant at p<0.01 level, indicating a strong relationship between weather variables and disease severity. Overall, the data provides valuable insights into the relationship between sheath blight disease severity and weather variables over multiple years,

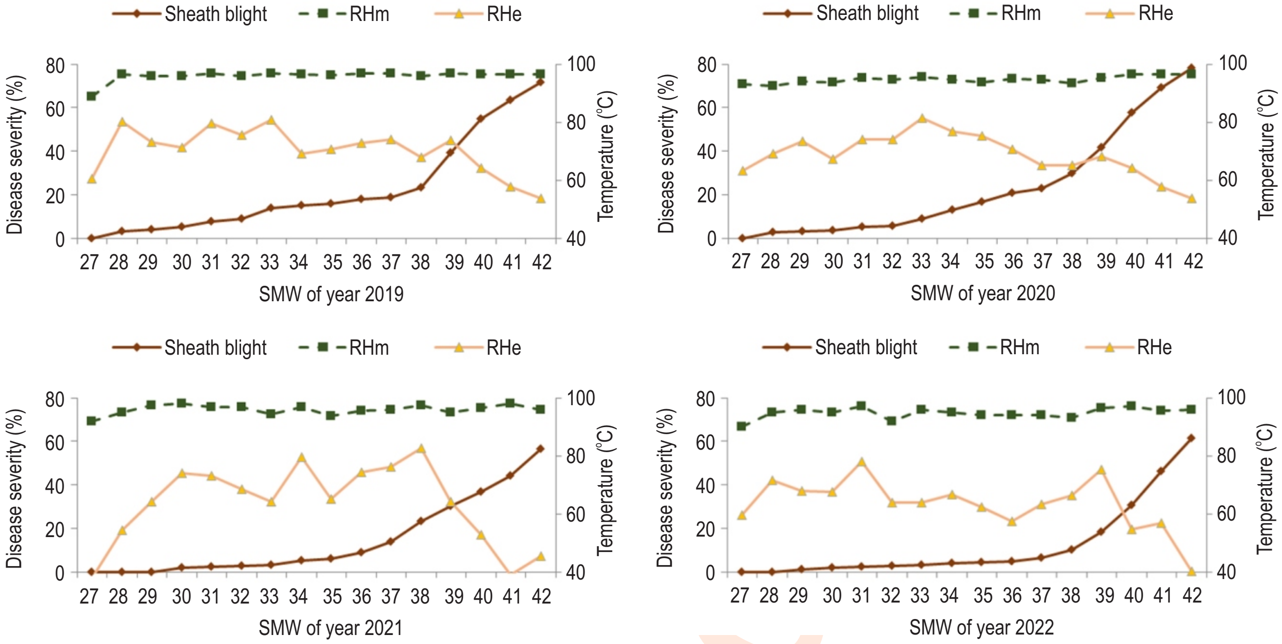

Fig. 4: Influence of morning (RH_m) and evening (RH_e) relative humidity on progression of sheath blight disease in rice crop.

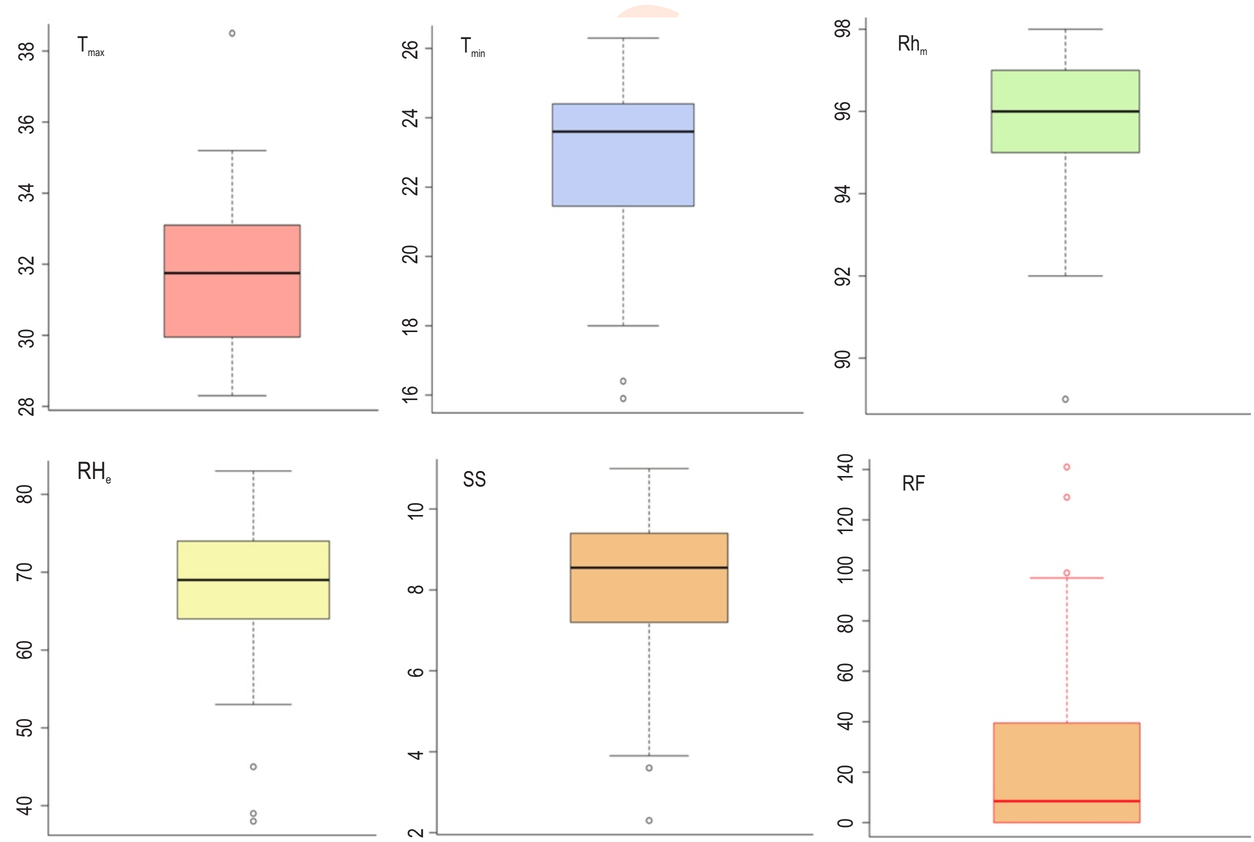

Fig. 5: Boxplots showing distribution of weather variables considered conducive for development of sheath blight disease of rice.

Table 2: Year wise correlation analysis of sheath blight disease severity with weather variables

Year	Correlation coefficient					
	T_{max} (ºC)	T_{min} (ºC)	RH_m (%)	RH_e (%)	RF (mm)	SS (h)
2019	-0.44 ^{NS}	-0.95**	0.30 ^{NS}	-0.69**	-0.34 ^{NS}	0.48 ^{NS}
2020	-0.67**	-0.97**	0.75**	-0.72**	-0.50*	0.39 ^{NS}
2021	-0.40 ^{NS}	-0.87**	0.40 ^{NS}	-0.18 ^{NS}	-0.22 ^{NS}	0.41 ^{NS}
2022	-0.75**	-0.98**	0.74**	-0.28 ^{NS}	-0.19 ^{NS}	0.42 ^{NS}

** Correlation significant at 0.01 level (two tailed); * Correlation significant at 0.05 level (two tailed); NS: Non-significant

Table 3: Correlation analysis of sheath blight disease severity with weather variables from the pooled data of year 2019, 2020 and 2021

Weather variable	Correlation coefficient
T_{max} (ºC)	-0.52**
T_{min} (ºC)	-0.93**
RH_m (%)	0.30*
RH_e (%)	-0.45**
RF (mm)	-0.41**
SS (h)	0.12

** Correlation significant at 0.01 level (two tailed); * Correlation significant at 0.05 level (two tailed); NS: Non-significant

Table 4: Parameter coefficient for fitting of multiple regressions from the pooled data of year 2019, 2020 and 2021

Parameter	Coefficient	Standard error	t state	p value
Intercept	157.839	81.097	1.946	0.058
T_{max} (ºC)	-0.656	1.367	-0.480	0.634
T_{min} (ºC)	-6.480	1.209	-5.359	0.000**
RH_m (%)	0.451	0.853	0.528	0.600
RH_e (%)	-0.169	0.292	-0.578	0.567
RF (mm)	-0.075	0.037	-2.047	0.047*

Significance codes:‘**0.01‘*’0.05; R-squared: 0.880, Adjusted R-squared: 0.865, Standard error of the estimate: 8.05; F-statistic: 61.34 on 5 and 42 DF, Significance p<0.05; RSME = 2.32, MSE = 7.22 and MAE = 2.68

highlighting the importance of certain weather conditions in influencing disease outcomes.

In conclusion, temperature and relative humidity were the most influential factors in sheath blight disease severity with varying significance across the years. Similar results were also recorded by Kaur *et al.* (2015) who observed a negative correlation of sheath blight disease with maximum and minimum temperatures, evening relative humidity and total rainfall while, whereas a positive correlation between morning relative humidity and sunshine hours. Thind *et al.* (2008) also reported a significant positive correlation between disease severity and crop age, while a significant negative correlation between disease severity and minimum temperature and number of rainy days. Biswas *et al.* (2011) demonstrated a strong positive association between maximum temperature and disease severity.

For the estimation of the predicative model, correlation was analyzed from the pooled data of disease severity and weather variables of years 2019, 2020 and 2021. In the pooled results, disease severity showed a significant negative correlation with T_{min} (-0.93), T_{max} (-0.52), evening relative humidity (-0.45) and rainfall (-0.41), suggesting that these factors contribute to reduced disease severity. But positive correlation with RH_m (0.30) suggested that higher morning humidity might increase disease severity. However, sunshine hours showed a non-significant relationship with disease severity (Table 3). The weather variables showed a significant correlation with disease severity which was implied to estimate in predication model (maximum temperature, minimum temperature, relative humidity morning, relative humidity evening and rainfall). However, sunshine hours were not incorporated in predication model due to non-significant relationship with disease severity in pooled analysis.

Table 4 presents an overview of the overall performance and fit of the regression model used to analyze the relationship between weather variables and disease severity. R^2 value (0.880) represents the coefficient of determination, indicating the proportion of variance in the dependent variable (severity) that is explained by the independent variables (weather variables). Approximately 88.0% of the variability in sheath blight disease severity can be explained by the weather variables included in the model. Standard error is an estimate of the standard deviation of the residuals (the differences between observed and predicted values of the dependent variable). In this model, the standard error of the estimate was 8.05, indicating the average amount by which the actual severity values might deviate from the predictive values. The F-statistic tests the overall significance of the regression model. In this case, the F statistic was 61.34, with associated degrees of freedom (df1=5, df2=42), and a significance level (0.05). A small p-value (typically <0.05) suggests that the regression model was significant. Minimum temperature was observed as a highly significant predictor (p<0.01), indicating a strong negative relationship with disease severity. The data on sheath blight severity and weather factors were subjected to multiple linear regression analysis and the regression equation is given as $Y (\%) = 157.839 - 0.656\,X_1 - 6.480\,X_2 + 0.451\,X_3 - 0.169\,X_4 - 0.075$

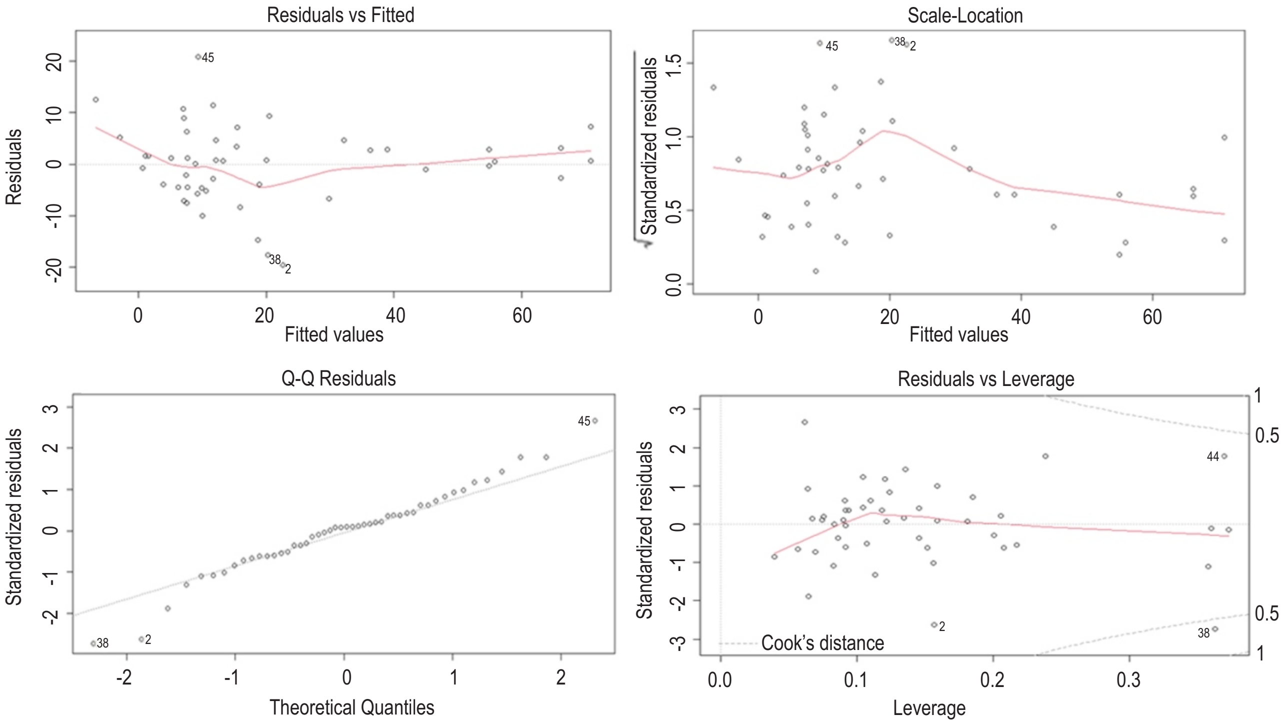

Fig. 6: Diagnostic plots for predicative model.

X_5. The predictive model for estimating sheath blight exhibited a high degree of accuracy and reliability, with an R^2 of 0.880, indicating strong explanatory power, and relatively low error metrics (RMSE = 2.32, MSE = 7.22, and MAE = 2.68) signifying good predictive performance. This model effectively estimated sheath blight disease severity, supported by historical data and regression analyses.

The model's accuracy and reliability, supported by low error metrics and strong correlations, underscore the importance of weather variables in predicting sheath blight severity. Biswas *et al.* (2011) developed a multiple regression equation for sheath blight disease severity (R^2=80.48%), highlighting a strong relationship with maximum and minimum temperatures. Sindhu *et al.* (2023) created a predictive model related to weather variables, yielding an R^2 value of 0.804-0.848, emphasizing maximum temperature and morning relative humidity. In the current study, a predictive model achieved an R^2 of 0.88, identifying minimum temperature and rainfall as significant factors for disease progression. Bhukal *et al.* (2015) also reported a regression equation for sheath blight on scented Basmati CSR 30 (R^2: 0.59-0.88) and non-scented HKR 127 (R^2: 0.76-0.92), underscoring the role of minimum temperature. Similarly, Kaur *et al.* (2015) found minimum temperature, evening relative humidity, and rainfall critical in determining disease severity. The diagnostic plots (Fig. 6) indicated the model's strong predictability of disease with meteorological data. Additionally, the observed versus predicted plot (Fig. 7) showed a strong correlation, reinforcing the model's reliability.

Table 5 presents the tolerance and variance inflation factor (VIF) values, which assessed the presence of multicollinearity among the independent variables (weather variables) in a regression model. In this case, the tolerance values ranged from 0.13 to 0.78. Some variables (T_{max}, T_{min} and RH_e) have relatively low tolerance values (0.15, 0.13 and 0.15), indicated higher multicollinearity with dependent variable (severity). VIF values provided another measure of multicollinearity, where a value greater than 5 typically indicated moderate multicollinearity, and values above 10 suggest a high level of multicollinearity. In this case, the VIF values ranged from 1.28 to 7.88. Three variables (T_{max}, T_{min} and RH_e) had VIF values above 5 (6.59 to 7.88), indicating moderate to high multicollinearity with dependent variable (severity), which might affect the stability of regression coefficients.

The model was evaluated by comparing the disease severity of sheath blight which was observed in the year 2022. Fig. 8 illustrates that the model exhibited optimal performance, with predictive values falling within a range of ±15 percent. It indicated that the model neither under-estimated nor over-estimated the predictive value of disease. This information is crucial for understanding the potential redundancy among the predictors and assessing the stability and reliability of regression coefficients in the model.

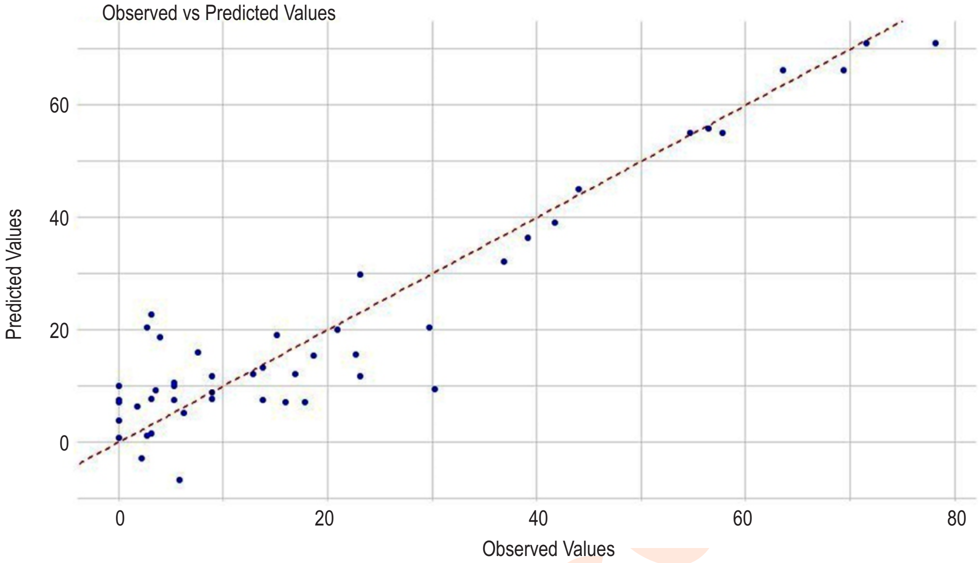

Fig. 7: Performance of predicative model.

Table 5: Collinearity statistics of individual weather variables for sheath blight disease severity

Weather variable	Collinearity Statistics	
	Tolerance	VIF value
T_{max} (ºC)	0.15	6.59
T_{min} (ºC)	0.13	7.88
RH_m (%)	0.68	1.48
RH_e (%)	0.15	6.61
RF (mm)	0.78	1.28

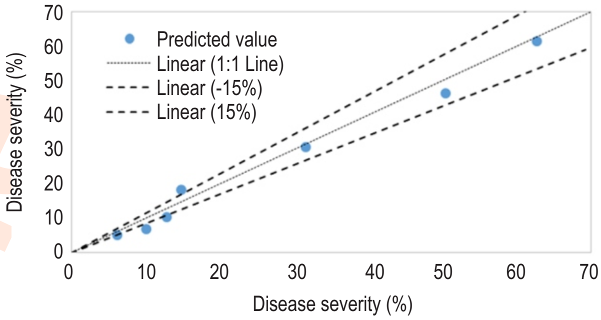

Fig. 8: Quantify the over/under-estimated the predictive model.

In conclusion, the study demonstrated that sheath blight disease in rice exhibited a characteristic sigmoidal progression and was significantly influenced by specific weather parameters. The multiple regression model, which explains 88.0% of the variability in disease severity, confirmed minimum temperature and rainfall as a significant predictor. The minimum temperature enhances moisture retention, particularly in the evening, creating favourable microclimatic conditions that increase the survival of sheath blight disease. These findings underscore the significant effect of specific weather conditions on sheath blight development and provide a reliable predictive model for estimating disease severity, aiding in effective disease management and planning for the scheduling of fungicide applications.

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Authors' contribution: P.K. Kasniya: Conceived, conceptualized, conducted investigations and writing original draft; **G.S. Makkar:** Conceptualized experimental framework and manuscript editing; **M. Kumar:** Statistically analysis of data, manuscript writing, revision and editing; **R. Singh:** Interpreted the results; **A. Singh:** Prepared experimental framework and interpreted the results; **J. Singh:** Collection of weather data; **V.S. Adarsh:** Statistical analysis of data; **P.P. Gopinath:** Theoretical support for statistical analysis; **A. Kumar:** Interpreted the results.

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