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Short communication

Weather-based modelling for the false smut disease of rice (*Oryza sativa* L.) in West Bengal

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Rice is a major staple crop throughout the world especially in the continent Asia. It is farmed in a variety of environments, from tropical lowlands to Himalayan Mountain terraces, having more than 80,000 local varieties. There are different biotic factors affecting the yield and quality of the rice grains among which false smut of rice is emerging as a major concern for rice growers throughout the rice growing regions in the world (Nessa *et al.,* 2015). False smut is caused by an ascomycetous fungus, *Ustilaginoidea virens*. Symptom of the disease involved conversion of few rice grains into greenish to orange colour smut balls in early stage which later changes to black in colour (Thapa *et al.,* 2023). Environmental factors such as temperature, relative humidity, rainfall, wind speed, and sunshine hours—have all been reported to play a significant role in influencing the severity of false smut (Sekhar *et al.,* 2022). However, the epidemiological understanding of this disease remains complex and sometimes inconsistent. The occurrence of disease has been reported from most rice growing regions in varying degree (Thapa *et al.,* 2022) depending on the climatic variation (Anbazhagan *et al.,* 2024). Alase *et al.,* (2021) suggested that reduced rainfall may elevate disease severity, while other researchers, such as Sanghera *et al.,* (2012), observed that heavy rainfall during the flowering stage significantly intensified the disease outbreak.

The statistical models are often useful for evaluating the association of weather variables with disease development (Ajith *et al.,* 2023). Prediction of disease outbreaks using such models enables the farmers to prepare and take preventive measures against the disease (Vaidheki *et al.,* 2023). However, a very little work has been conducted on prediction of rice false smut disease. In light of this gap, this study was undertaken to evaluate the effect of date of sowing and weather parameter on false smut disease severity and compared the linear and non-liners models to predict the disease progression.

A field experiment was conducted in Jagulia farm, B.C.K.V, Mohanpur (22°56’48”N, 88°32’18”E) West Bengal with the susceptible rice cultivar MTU7029, sown in three different dates i.e., 10th June, 10th July, and 10th August during the year 2018 and 2019 following a randomized complete block design with three replications. 30 days old seedlings were transplanted in plots with size 3 m × 5 m area. To ensure uniform disease pressure, *U. virens* isolate was identified using ITS primers (Acc no. MT002760.1) and its spore suspension was sprayed at the 50% flowering stage for each sowing date. Disease severity was recorded following the methodology of Singh and Dube (1978), starting from the initial appearance of symptoms and continuing at 5 days intervals until crop maturity.

To evaluate the effect of weather parameters and develop prediction models for rice false smut disease, metrological data were obtained from the Department of Agricultural Meteorology, Bidhan Chandra Krishi Vishwavidyalaya. The temporal dynamics of disease development were modelled using three non-linear growth models i.e., Logistic, Gompertz, and Monomolecular and compared against a Multiple Linear Regression (MLR) model.

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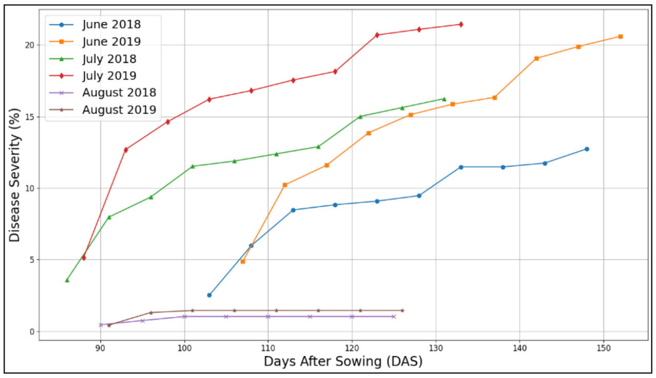

Fig. 1: Progression of False smut disease severity for the different sowing month during 2018-19

Logistic model: The Logistic model is denoted by X(t)=c/(1+b*exp(-a*t)) + e(t),

Gompertz Model: Gompertz Model is represented by X(t) = c*exp(-b*exp(-a*t)) + e(t),

Monomolecular model: Monomolecular model is denoted by X(t) = c-(c-b)*exp(-a*t) + e(t). Where X(t) represent the variable under study at time t, 'a' denote the intrinsic growth rate, 'c' the carrying capacity of the environment b = [b-X(0)]/X(0) and X(0) is the value of X(t) at t = 0 and e(t) is the error term. In general, the parameter 'a' is the coefficient of external influence emanating from the outside system.

Correlation analysis was performed using SAS 9.4 with PROC REG – for Multiple Linear Regression, PROC NLIN – for non-linear models, employing the Levenberg-Marquardt algorithm. Graphs were plotted with Python 3.8.2, employing the Matplotlib library.

Disease appearance and progression

The first visible symptoms of false smut appeared approximately two weeks after flowering, on average, at 105 days (June sowing), 87 days (July sowing), and 90.5 days (August sowing) after sowing. The highest disease severity was consistently recorded in July-sown plots, with disease severity of 20.60% and 21.44% during the respective years. In contrast, August-sown plots recorded the lowest severity, with values of 2.31% and 1.78% (Fig. 1).

Correlation analysis

Pooled correlation analysis revealed a statistically significant negative relationship between morning relative humidity and minimum temperature (RH) with false smut disease severity across all sowing windows. Notably, minimum temperature emerged as the most influential factor, showing a strong and highly significant negative correlation with disease severity for across the months: June (–0.77), July (–0.86) and August (-0.83) (Table 1). Taken together, these results confirm that minimum temperature and morning relative humidity were the most consistent and impactful meteorological parameters associated with false smut disease severity.

Table 1: Correlation of weather parameters with false smut disease severity (On the basis of pooled values of 2018 and 2019)

Parameters	June	July	August
Rainfall	-0.35	-0.32	-0.96
Tmax	0.52	-0.79	-0.17
Tmin	-0.77	-0.86	-0.83
RH-I	-0.48	-0.57	-0.96
RH-II	0.22	-0.35	-0.24
BSH	0.22	0.15	0.51
WS	0.11	0.23	-0.97

Though the infection occurs, particularly during the flowering stage, disease development occurs ranging from 111 to 136 days after sowing (Saha *et al.,* 2020), which corroborates the current study's observations. previous studies have reported a negative correlation between false smut severity and meteorological variables such as rainfall, minimum and maximum temperature, and relative humidity has also been documented by several authors (Saha *et al.,* 2020) supporting the present results. However, Anbazhagan *et al.,* (2024) reported a positive correlation of relative humidity with false smut severity, contradicting our results although their results align with present finding regarding minimum temperature.

Model performance

To evaluate model performance across varying weather conditions, separate models were constructed for June, July, and August sown crops. The MLR models with backward selection method identified minimum temperature for Jun and July and maximum temperature, minimum temperature, and wind speed (August) as the most significant predictors, influencing disease severity (Table 2). Due to the sigmoidal disease progression, non-linear models were applied to using the parameters: intrinsic growth rate (a), carrying capacity (c), and time (t). The carrying capacity (c) was found to be highest for July sown crops across all models: Monomolecular:21.739, Logistic:20.631, Gompertz:20.981. The intrinsic growth rate (a) varied across models and months. The Logistic model recorded the highest intrinsic growth rate in June sown (0.506), while August exhibited higher growth rates in the Monomolecular (0.396) and Gompertz (0.755) models. These results suggest that although disease intensity was highest in July, the speed of disease progression varied depending on environmental conditions and model type.

Model performance were evaluated using two criteria i.e., R^2 and RMSE. Among the models, non-linear models performed better than MLR with the Logistic models exhibiting the highest R^2 (0.998) in July. The lowest R^2 was recorded for the MLR model (0.849), indicating inferior predictive capability. Lower RMSE values in august is likely due to the lower infection rates (Table 2). These results suggest Logistic model to be precise and dependable for false smut disease prediction

From a predictive modelling perspective, the present study demonstrates the superior performance of non-linear growth

Table 2: Description of false smut disease progression using mathematical models across sowing months.

Sowing month	Equation	R^2	RMSE
Multiple linear regression			
June	36.872−1.361×Tmin	0.658	1.913
July	26.927−1.083×Tmin	0.849	6.847
August	1.377−0.268×WS+0.032× Tmax−0.066×Tmin	0.812	0.443
Logistic model is denoted by X(t)=c/(1+b*exp(-a*t)) + e(t)			
June		0.940	0.798
July		0.998	1.195
August		0.932	0.001
Gompertz Model is represented by X(t) = c*exp(-b*exp(-a*t)) + e(t)			
June		0.954	0.697
July		0.997	1.071
August		0.945	0.012
Monomolecular model is denoted by X(t) = c-(c-b)*exp(-a*t) + e(t)			
June		0.970	0.566
July		0.995	0.912
August		0.960	0.912

models, particularly the Logistic model, over MLR in simulating the progression of false smut disease. This conclusion aligns with previous work in plant disease modelling. The Logistic model's superiority has been demonstrated across various cereal pathosystems by Tamang *et al.,* (2020).

The present study highlights that, minimum temperature and relative humidity play a pivotal role in influencing the severity of false smut disease with a significant negative correlation with disease incidence. Among the models tested, the logistic growth model consistently provided the best statistical fit, demonstrating its robustness in capturing the sigmoidal nature of disease development. The model's ability to accurately identify critical predictors and their influence on disease progression, positions it as a powerful tool for both epidemiological research and practical field-level forecasting.

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REFERENCES

Ajith, S., Debnath, M. K., Gupta, D. S., Basak, P., Bandyopadhyay, S., Kheroar, S. and Hr, R. (2023). Comparative evaluation of penalized regression models with multiple linear regression for predicting rapeseed-mustard yield: Weather-indices based approach. *J. Agrometeorol.,* 25(3): 432-439. https://doi.org/10.54386/jam.v25i3.2185

Alase, S., Nagaraja, A., Pramesh, D. and Prasanna, K. M. K. (2021). Influence of weather parameters on false smut disease development in rice. *Mysore J. Agric. Sci.,* 55(4): 320-325.

Anbazhagan, P., Theradimani, M., Ramamoorthy, V., Vellaikumar, S., Hebziba, S. J. and Oviya, R. (2024). Influence of weather parameters on rice false smut disease progression in Tamil Nadu, India. *J. Agrometeorol.,* 26:115-119. https://doi.org/10.54386/jam.v26i1.2334

Nessa B, Salam MU, Muzul-Haque AHM, Biswas JK, Abdul-Latif M, Ali MA, Ansari TH, Ahmed M, Parvin N, Zakaria M, Baki I, Islam S, Islam M. and Galloway J. (2015). Rice false smut disease at different flowering times. *Bangladesh Rice J.* 19(2):28-34.

Saha M., Chakraborty A. and Bhattacharya K. (2020). Aerobiology, epidemiology and disease forecasting of false smut disease of rice in West Bengal, India. *Aerobiologia.* https://10.1007/s10453-020-09631-1.

Sanghera GS, Ahanger MA, Kashyap SC, Bhat ZA, Rather AG, and Parray GA. (2012). False smut of rice *Ustilaginoidea virens* under temperate agro-climatic conditions of Kashmir, India. *Elixir Biol Tech.,* 49:9827-9831.

Sekhar YC, Kamalakannan A, Gopalakrishnan C, Paneerselvam S, Rajesh S, and Ganapati PS (2022). Influence of weather factors on rice false smut disease development (*Ustilaginoidea virens*) in Tamil Nadu. *Biol. Forum Int. J.,* 14(4):543-547.

Singh, R. A. and Dubey, K. S. (1978). Assessment of loss in seven rice cultivars due to false smut. *Indian Phytopathol.,* 3: 186-188

Tamang S, Kumar S, Das S, and Mahapatra S (2020). Role of abiotic factors on disease progression of spot blotch of Wheat. *Indian Phytopathol.,* 74(1):263-269.

Thapa, S., Mahapatra, S., Baral, D., Lama, A., Shivakoty, P. and Das, S. (2022). Status of false smut of rice in different districts of West Bengal. *Oryza,* 59(2), 167-171.

Thapa S., Mahapatra S., Baral D., Chatterjee A., Shivakoty S., Subba B. and Das S. (2023). Morpho-molecular variability of different isolates of *Ustilaginoidea virens* causing false smut of rice. *Arch. Phytopathol Plant Prot.,* 56(6):489-502.

Vaidheki, M., Gupta, D. S., Basak, P., Debnath, M. K., Hembram, S. and Ajith, S. (2023). Prediction of potato late blight disease severity based on weather variables using statistical and machine learning models: A case study from West Bengal. *J. Agrometeorol.,* 25 (4):583-588. https://doi.org/10.54386/jam.v25i4.2272