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Development of Forecasting Model for Assessing Disease Risk and Non-Risk Period in Fusarium Wilt X Banana Pathosystem

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Abstract: Fusarium wilt caused by fungi *Fusarium oxysporum* f. sp. *cubense*, is one of the major production constraints of banana. The pathogen is soil-borne and produces chlamydospores responsible for its prolonged perpetuation in the soil. Banana being under perennial plantation, suffers a lot from this disease if, sufficient primary inoculum presents in the soil. Along with it, soil temperature (ST) and soil moisture (SM) have great influence in the epidemiology of this disease. The objective of this study is to develop a suitable forecasting model for its future use in computer simulation to predict the epidemic by feeding ST and SM data. The experiment was conducted with G9 variety of banana planted in Fusarium wilt endemic area for three consecutive years (2019-2021). With the initiation of the disease, SM and ST data was collected at a regular interval of 10 days and its corresponded effect on disease incidence was recorded. The model developed was Y'= -85.30 + 2.556 SM + 3.732 ST. The result showed both the factors have positive significant effect on disease progression. Among them, SM was more influential though the combination 60-65% SM and ST 30-35^{0}C played major role in disease establishment. Discriminant analysis unveiled, for each additional unit increase in SM and ST will increase the likelihood of being in disease risk group by 0.26 and 0.19 respectively that could be used for predictive purpose. The correctness of the model was determined with 72.3 % accuracy.

Keywords: AUDPC, Banana, Fusarium wilt, Disease modelling, Model evaluation

Banana (*Musa* spp.) holds a prominent position in the major food list being the fifth most economically valued agricultural food product (Hossain et al 2016). Among Asian nations, India stands as a preeminent producer of bananas, accounting approximately 25.7% of the global output (FAO 2021). Banana is highly nutritious and easily digestible and rich in potassium and calcium but low in sodium (Wall 2006). In Indian context, the nation contributes to annual production of 30.86 million tonnes of bananas in approximate 860,000 hectares, constituting around 21% of the global area (Thangavelu et al 2020, Musapedia 2021). Despite considerable research efforts dedicated to comprehending various aspects of the disease, substantial economic losses continue. Estimated yearly losses of banana by *Fusarium oxysporum* f. sp. *cubense* (Foc) in the world ranging from 60 to 90% including India (Bhuvanendra et al 2010). However, among the formidable challenges offered by biotic stresses, Foc gets the competitive advantages over the other pathogens by being majorly saprophytic (facultative parasite), having 4 different races, more than 20 vegetative compatibility groups and production of chlamydospores that can survive in the soil for more than 20 years (Niwas et al 2022). The pathogen penetrates the roots and spreads gradually till it reached the centre of the corm. After that, the plants produce characteristic symptom “quick wilting”. Purplish darker discoloration shows up in the xylem and get blocked. External leaves and pseudo-stem turn yellow and finally hang down. With the prevailing of conducive environments like soil temperature (25-30^{0}C) along with soil moisture (0.10 to 0.17 cm^3/cm^3) the symptoms become evident within 5-6 months of planting. The issue has been exacerbated by the prolonged monoculture of bananas (Perrier et al 2011), that is known escalate the incidence of Foc and consequently led to reduced crop yield with quality compromised (Shen et al 2017).

It is still challenging to manage the disease due to limited availability of the chemicals. Moreover, hazardous impact of chemicals in the environment through reiterate application should be equally counted (Panth et al 2020). To develop sustainable management practices crop rotation, biological control, use of resistant varieties and botanicals have been employed extensively but still the pathogen is proliferating all the year round and threatening the ecosystem (Rahman et al 2021). Hence, effort directed to find out the basis of survival advantage of Foc in soil under specific SM and ST combination and therefore, to determine the disease risk period. A predicting model will be developed to forewarn the stakeholders as well as to build up a holistic approach for sustainable and eco-friendly management of this disease.

MATERIAL AND METHODS

Study site and experimental layout: The experiment was conducted for three consecutive years (2019-2021) with banana cultivar G9 that was planted employing the heap method at a spacing of 1.8m X 1.8m, adhering to all recommended agronomic protocols. The experiment was laid out at the, College of Agriculture, Bidhan Chandra Krishi Viswavidyalaya, West Bengal (Lat: 23.31^0'N, Long: 87^{0}66' E and altitude: 36 m msl). The soil of the farm was clay loam in texture and belongs to the hyperthermic family with a pH of 7.3. No chemical was sprayed, and natural epiphytotic conditions were allowed for the disease establishment.

Disease scoring: Disease severity or percent disease index (PDI) was worked out to access the extent of damage caused by the disease using 0-9 scale (Mayee and Datar 1986). Details of the scale are: 0= no symptoms; 1=A few tiny necrotic patches that cover 1% or less of the leaf area; 3= A few tiny necrotic patches covering 1-5% of the leaf surface; 5= Coalescing spots expanding 6-20% of leaf area; 7= Spots grow in size and coalesce to reach 21-50% of the compound leaf area; 9= Spots expanding and merging to encompass at least 51% of the leaf area.

The percent disease index (PDI) was calculated McKinney (1923)

$$\mathrm{PDI} = \frac{\sum[\text{No of leaves/scale} \times \text{scale value}]}{\text{Total number of observation} \times \text{highest scale}} \times 100$$

The values obtained from the above formula to evaluate disease severity were utilized to determine area under the disease progress curve (AUDPC) to quantify the disease over the period of time by Campbell and Madden (1990):

$$\mathrm{AUDPC} = \sum_{i=1}^{n-1} \left(\frac{\mathrm{Yi} + \mathrm{Yi+l}}{2}\right)(t_{i+1} - t_i)$$

where, Yi = proportion of disease at the i^{th} observation, *ti* = time in days at the i^{th} observation and n = total number of observations

Soil temperature measured using soil thermometer (Maxtech white pen-type soil thermometer Model name/ Number: DT-9)

Soil moisture data recorded using a moisture meter (Lutron digital soil moisture meter, Model name/ Number: PMS 714).

(Data collected every day in the morning hours and average of 10 days was considered)

Construction of mathematical models: Binary logistic analysis and discriminant analysis (Tabachnink and Fidell 1996) was done in the stepwise method for disease risk and non-risk period (1/0) as the dependent variable and soil moisture (SM) and, soil temperature (ST) as independent variables.

Binary logistic regression: This special type of regression designed for modeling a categorical dependent variable.

$\mathrm{Logit}(p) = b_o + b_1x_1 + b_2x_2 \ldots\ldots + b_kx_k$

$\mathrm{Logit}(p) = \ln[p/1-p]$

$p = 1/1 + e^{-\mathrm{logit}(p)}$

Where p is the probability of the event i.e disease risk (1) and non-risk (0).

Odds = p/(1-p) [p = presence of the event, (1-p) = 0 i.e., non risk.

$\mathrm{Odds} = p/1-p = e^{bi} X\, e^{b_1x_1} X e^{b_2x_2} X e^{b_3x_{3}} X \ldots\ldots X e^{b_kx_k}$

This means when a variable Xi increases by 1 unit, with all other factors remaining unchanged, then the odds will increase by factor e^{bi}

Discriminant analysis: This linear regression interprets the output differently. Dependent variable is an indicator variable expressed as

$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \ldots\ldots \beta_kx_k + e$

y= 1 if the observation falls within the group i.e., disease risk

y = 0 if it doesn't. (Here, it is no risk for the disease).

Data analysis: Data on ST and SM were computed and their effect on FWB was analysed through MS Excel and the level of significance and interaction effects were evaluated. The value of percent disease incidence was subjected to arcsine (Gomez and Gomez 1984). Binary linear regression and discriminant analysis was performed through Minitab statistical software (Minitab LLC, USA).

Mathematical equations developed by using logistic binary regression and additionally by discriminant analysis to assess the model both quantitatively and dynamically. Finally, the accuracy of the model was evaluated, and fitness was appraised to epitomize the real aspect of the banana X fusarium pathosystem.

RESULTS AND DISCUSSION

Set up of binary logistic regression equation and development of prediction model: Data was recorded on disease severity and correspondent SM and ST. Disease condition below 20% considered as disease no risk and above that considered as disease risk period. For developing binary logistic regression three years collective data were used to access the impact of ST and SM (independent variable) on the disease severity (dependent variable) of FWB. This is a special type of logistic regression equation used to prepare the model on categorical dependent variable within the probability (p) either 0 or 1 where, (p) stands for probability of the event assumed as disease risk (1) and non-risk (0). Both the predictors (SM and ST) confer statistically significant contribution to predict the disease severity of FWB as confirmed (Table1). The odd ratio of ST (1.08) designates every 1 unit increase in ST may cause rise in disease risk nearly 8%, whereas coefficient value of 2.43 and the odd ratio of 3.17 specifies SM tends to produce a higher disease risk of 3.17 times more in combination with ST when other factors remain unchanged in the model.

VIF (various implies factor) shows the correlation among the predictors (multicollinearity). VIF value 1.24 signifies SM and ST are moderately correlated in this model (Table 1). The goodness of fit displayed a high p-value ranging from 0.594 to 0.923 direct that model developed is good to accept (Table 2).

The model developed for fusarium wilt in banana under West Bengal, India condition using Binary logistic regression is as follows:

P (1) = exp(Y')/(1 + exp(Y')

Y'= -85.3 + 2.556 SM + 3.732 ST [R^2= 0.623 R^2_{adj}= 0.589]

Through this model, simply by putting SM and ST value Y' could be determined easily. If the value is higher than the cut off value, then the disease will take place. This study considered only two major independent variables (ignoring the other complex intermingled hidden factors that may influence the disease expression) which employ up to 62.34% variance in the dependent variable. Adjusted R^2 value indicates that the predictors chosen have influence on the disease severity. If other predictors added, R^2 value may increase but adjusted R^2 value will decrease but that might not have effect on the dependent variable.

Discriminant analysis: Further studies conducted to reveal how precisely the model can anticipate the disease severity (Table 3). The result divulged that for each additional unit increase in SM and ST the likelihood of getting the chance incremental disease risk group by 0.26 and 0.19 respectively which could be invariably used in predictive purpose. Therefore, in any given unit data of independent variables predicted disease severity could be easily estimated based on the cut-off value (=0.678) (Table 3). By determination of cut-off value through discriminant analysis situation would be predicted whether it falls in disease risk (if the value is above the cut-off value) or non-risk situation (if less than the cut-off value). p-value, precept both SM and ST and probably their combination too had a statistically significant effect on FWB as mentioned as p-value is less than 0.005 in both the cases. The SM and ST were plotted against the probability i.e. 0 to 1 to identify the event (disease risk) and the curve showed (Fig. 1), most of the observed data lies between the probability level 0 and 1 and the cut-off point also showing nearly 0.6 that do match with the determined cut-off value (=0.678) of the model. The correctness of the model computed 0.723 represented the accuracy of the model would be expected 72.3 % to predict the disease severity.

Adaptability of the model: To scrutinize the how far the model could be adapted two variables fitted probability (FITS_1) and delta deviance (DDEV_1) was introduced to decide over a particular event either disease risk or non-risk. Fitted probability was calculated and found that the data fit into the model with probability of 0.84 to 0.91 for being in state (1) i.e., disease risk period and is consistent in predicting disease risk. Whereas, low in predicting the second situation i.e., non-risk with probability 0.003 to 0.08 (Fig. 2). Delta deviance was used to show how far each event is from the pure fitted model. For better understanding these two variables were plotted against X and Y axis to display the deviance as a function of the fits to the model (Fig. 2). The Figure 2 shows two discrete curves involving two binary

Table 2. Goodness of fit

Method	Chi-square	P-value
Pearson	26.81	0.796
Deviance	17.90	0.923
Hosmer-Lemeshow	5.44	0.594

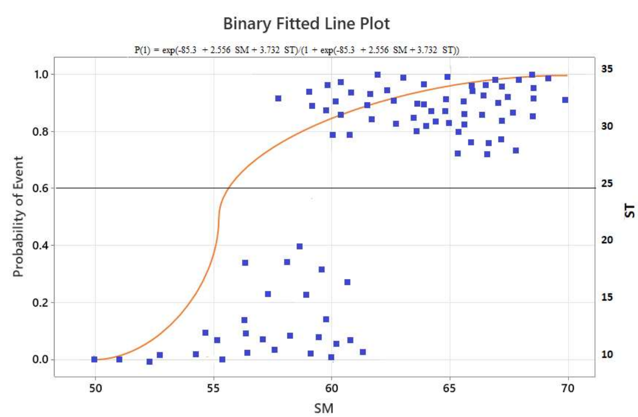

Fig. 1. Binary classification (Sigmoid graph)

Table 1. Binary logistic regression for predicting disease severity of fusarium wilt of banana

Predictor	Coefficient	SE	Z value	P-value	VIF	Odd ratio	95% CI	
Constant	-85.3	0.012	-3.47	0.008	-	-	Lower	Upper
SM	2.556	0.136	2.09	0.019	1.24	3.17	2.24	9.81
ST	3.732	0.234	0.15	0.024	1.24	1.08	1.35	2.67

SM = Soil moisture, ST = Soil temperature

Table 3. Discriminant analysis

	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%	Cut off value	Correct proportion	F value
Inter Cept	-4.954	0.765	-5.128	0.0006	-5.367	-2.453	0.674	0.723	0.004
SM	0.263	0.058	2.354	0.001	0.012	0.058			
ST	0.196	0.023	1.374	0.002	-0.003	0.032			

SM = Soil moisture, ST = Soil temperature

states (disease risk and non-risk). From top left to bottom right relates to event 1(disease risk). The experimental data which is a good fit to the model should have low delta deviance with probability 1 corresponding to disease risk. The data points that fit well to the disease risk period are clustered in the bottom right. Contrarily, the data displayed at the top left represent poor fit to the model. The other line of the data representing the disease non-risk viz. the data points with low delta deviance represented by bottom left showed good fit with probability corresponding to non-risk and the point at top right characterize a poor fit of the model (Fig. 2).

Performance test of the model: The performance of the binary classifiers are evaluated by ROC (receiver operating characteristic) curve. This analysis is mandatory to decide the optimum cut-off value and to consider the optimal decision threshold. For a specified cut-off value either positive or negative diagnosis could be done for every unit by comparing the data to the cut-off value. Though, there are the probabilities that the predicted situation not always match to the actual condition and the probable outcomes could be true positive, true negative, false positive, and false negative. Here, ROC curve plays an important role that plots the true positive rate or sensitivity against the false positive rate (1-Specificity) (Fig. 3) for all possible cut-off which is essentially a trade-off between true positive and false positive. The ROC curve provides a pictorial presentation of the fitness of the forecasting model against the false-positive rates. The diagonal line is the reference line that classifies the condition randomly. The threshold points at which the ROC curve reaches closer to the top left corner are the best for maintaining a true positive rate. The area under the ROC curve also depicts the overall performance of the forecasting model by providing a numerical value and here the value is 0.823 which conferred a pretty good impression for the model to determine the disease risk period of FWB.

The model developed through this study is proved to be acceptable to forecast FWB in a particular SM and ST situation and could be an incorporated in future study of plant disease epidemiology and forecasting system to predict the apparent disease situation. This model would be a great support to the growers for timely adoption of disease management practices based on prevailing atmospheric conditions that are the prime factors for the development of soil borne fungal pathogens. Several workers worked on epidemiology and disease forecasting for different pathosystems like on phytophthora blight in potato by Do et al (2012), early blight in tomato by Saha and Das (2013) and on collar rot of chickpea by Tamang and Saha (2022). These models have been successful in guiding the farmers by critically predicting the probable time of initiation of the disease based on either soil temperature and moisture data

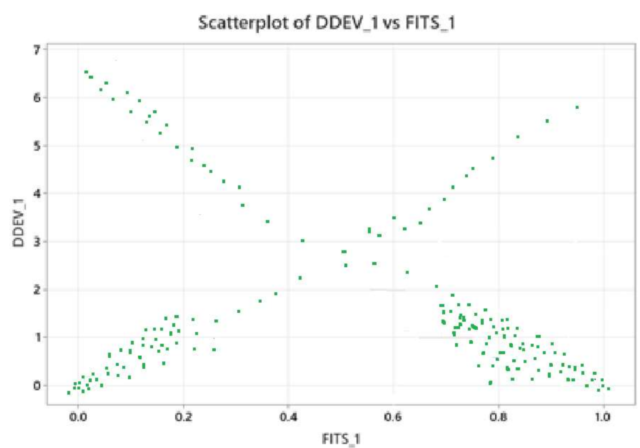

Fig. 2. Fitted probability Vs Delta deviance

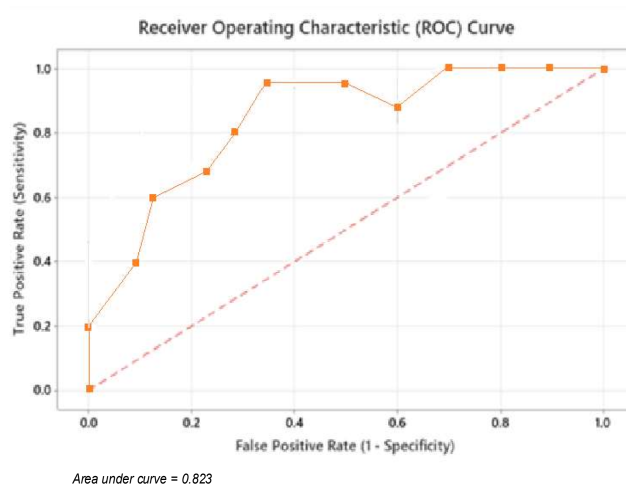

Fig. 3. ROC curve

or prevailing weather parameters and therefore guiding them toward the proper time for up-taking control measures.

CONCLUSIONS

Soil moisture and soil temperature are the critical factors for the development of fusarium wilt in banana. The combination of 60-65% soil moisture and soil temperature 30-35^{0}C are more conducive for the pathogen to create disease risk situation. Mathematical model developed and the accuracy of the model verified based on field data along with predicted disease situations which exhibited up to 72.3% precision in forecasting. Additionally, the threshold value determined from the realized data showed almost match with the predicted situation depicted through the model. Area under ROC covered 82.3% conveyed that the developed model would capably forecast the disease risk situation at any cut-off value by invalidating the effect of false-positive over true positive value. Therefore, it is highly imperative to have a precise tool to conjecture the situation vulnerable for ensuing the disease. Furthermore, when the disease occurs, the situation becomes pathetic for good crop stand leading toward total loss. This circumstance highly demands to have a definite forecast model to forewarn the farmers and the purpose has been served by this research. The present investigation holds scope to provide a vision to the researchers to develop a computer-simulated forecast model for fusarium wilt in banana.

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