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**Research Paper**

# Forecasting model for disease risk period in chickpea x collar rot pathosystem

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## ABSTRACT

Collar rot caused by *Sclerotium rolfsii* Sacc. is one of the major biotic constraints of chickpea production worldwide. It is soil-borne fungi having wider host range and infection mainly occurs at the juvenile stage of crop growth resulting crop failure in no time. The pathogen is greatly influenced by soil temperature (ST) and soil moisture (SM) therefore, experiment formulated to develop a suitable forecasting model for its future use in computer simulation of plant disease prognostication by feeding only soil temperature and moisture data. The popular desi type chickpea variety Anuradha sown at different dates to get a range of soil temperature and soil moisture combination and its corresponding effect on disease incidence was recorded under natural epiphytotic conditions. The data obtained were analyzed using binary logistic regression and discriminant analysis to assess disease risk and non-risk period. The model developed was Y'= -73.9 + 1.251 SM + 0.017 ST. The outcome recorded, a unique statistically significant contribution of soil moisture (p value=0.029) on the establishment of the disease whereas, the effect of soil temperature was detected as statistically non-significant. The correctness of the model determined to predict the disease severity has 80 per cent accuracy.

***Keywords**: Collar rot, Chickpea, Forecasting model, Soil moisture, Soil temperature*

Chickpea (*Cicer arietinum* L.) is the third most important food legume grown over 52 countries in Asia, Africa, Europe, Australia, North America, and South America (FAOSTAT, 2019). In India, it is the major winter pulse crop grown mostly under rainfed conditions occupying almost all the states and rank first in production with 10.23 million tons which is 46 per cent of the total pulses production in India. (Anon., 2019). Chickpea is valued for its highly nutritive seed with protein content (38 %) and also a rich source of vitamins (A, D, and $B_6$), minerals (P, Ca, Mg, Fe, and Zn), fibre, unsaturated fatty acids and β-carotene (Jukanti *et al*., 2012) and therefore act as a good replacement of animal protein sources in a vegetarian diet. Chickpea could make a potential member of any cropping system due to its inherent capacity to fix atmospheric nitrogen (Flowers *et al*., 2010) that satisfy 80 per cent of nitrogen requirement thus improve soil health and fertility. The yield potential of chickpea is challenged by phytopathogens, climate changes as well as edaphic stresses, such as temperature, moisture which are recognized to be the main limitations of chickpea production (Ghanem *et al.*, 2011). Among biotic stresses, collar rot of chickpea caused by *Sclerotium rolfsii* infects the crop at early stages by parasitizing root and collar region of the plant thus, producing wilt-like symptoms accompanied by yellowing of the seedlings, rotting at the collar region. The disease usually arises in patches in the field (Hind, 2005) and under conducive environments like heavy rainfall and high soil temperature (25 - 30$^0$C), cause seed rot and seedling mortality ranges from 54.7 – 95.0 per cent in India (Sharma and Ghosh, 2017). This omnivorous soil borne pathogen is fast spreading and so destructive to do complete crop loss within 30 days. The whitish mycelial strand with conspicuous rape seed like sclerotia seen on the infected region. The dynamism of host-pathogen interaction depends upon the cross link between host, and the amount of inoculum that takes place at the interface of existing environment. With erratic changes in climatic conditions such as unpredicted rainfall, rise in temperature, changes in relative humidity, and soil moisture stress (Zhao and Running, 2010) are likely to influence the plant disease establishment, its dispersal, and epidemiology (Graham and Vance, 2003). Evidence suggests environment plays a crucial role in altering disease scenario in chickpea every year (Sharma and Pande, 2013). Conventionally, abridge of pathogen population can be possible by the application of different fungicide but recurrent use of it turns out to be uneconomical, especially where chickpea yields are low (Pande *et al*., 2005). The negative effect of fungicides on the environment has also been recorded by Javaid *et al*., (2020). Initial effort has

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been done to develop a resistant cultivar (Sharma *et al*., 2019) but no cultivar was found to confer true resistance against collar rot. Hence, effort piloted up to develop a forecasting model to forewarn the farmers bestowing information regarding the factors accountable for epidemic development as well as to develop a holistic approach for sustainable and eco-friendly management of this disease.

Mathematical equations developed by using logistic binary regression and additionally discriminant analysis were done to assess the model both quantitatively and dynamically. Finally, the accuracy of the model was checked and fitness was evaluated to represent the real aspect of the chickpea X collar rot pathosystem.

## MATERIALS AND METHODS

### *Experimental detail*

The experiment was laid out at the University Instructional Farm Jaguli, under Bidhan Chandra Krishi Viswavidyalaya, Nadia, West Bengal. The soil of the farm was sandy loam in texture and belongs to the hyperthermic family with a pH of 7.2. The experiment was designedin randomized complete block design with four replications. Plot size was 4m×5 m with spacing 30 x 10 cm. Local desi type chickpea variety 'Anuradha' was sown at 5 different dates *viz*. 26th November, 3rd December, 10th December, 17th December, and 24th December in both the experimental years i.e., 2018-19 and 2019-20 seasons. Proper recommended agronomic practices were followed, crop hygiene was maintained, no chemical was sprayed, and natural epiphytotic conditions allowed for the disease establishment.

### *Disease scoring*

Percent of infection recorded at the initiation of the diseases up to 30 DAS at 7 days intervals (Table 1) and computed as follows.

$$\text{Percent incidence} = \frac{\text{Total number of infected plants}}{\text{Total number of plants}} \times 100$$

Soil temperature was measured using soil thermometer (Maxtech white pen-type soil thermometer Model name/ Number: DT-9) Soil moisture data were recorded using a moisture meter (Lutron digital soil moisture meter, Model name/ Number: PMS 714) (Data were collected every day in the morning hours and average of 7 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.

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

$$\text{Logit (p)} = \text{In}[p/1-p]$$

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

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.

$$\text{Odds} = p/1-p = e^{bi}Xe^{b_1x_1}Xe^{b_2x_2}Xe^{b_3x_3}X \ldots\ldots\ldots\ldots Xe^{b_kx_k}$$

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 non risk for the disease).

### *Data analysis*

The data on soil temperature and soil moisture and their effect on collar rot was analysed through MS Excel and the level of significance and interaction effects were evaluated. The noted value of percent disease incidence was subjected to arcsine transformation (Gomez and Gomez, 1984) before analysis of variance (ANOVA) performed. Binary linear regression and discriminant analysis was executed through Minitab statistical software (Minitab LLC; USA).

## RESULTS AND DISCUSSIONS

### *Arrangement of disease severity data*

The data on soil temperature (ST) and soil moisture (SM) was obtained and its corresponding disease incidence was scored. The conditions where disease counted below 20% were considered as disease non risk period and above that considered as disease risk period. Based upon the data recorded over two experimental years binary logistic regression was performed to access the impression of these factors *viz*. soil temperature (ST) and soil moisture (SM). This logistic regression is a special type of regression designed for modeling a categorical dependent variable within the probability (p) either 0 or 1. Here, p is the probability of the event assumed as disease risk (1) and non-risk (0). The model contained two independent variables ST and SM. The ANOVA (Table 2) regarding the predicted disease severity of collar rot in chickpea revealed that soil moisture (SM) made a unique statistically significant contribution to the model confirmed by p value=0.029 (<0.05) whereas the effect of ST is not statistically significant p value=0.259 (>0.05). The odd ratio of ST (1.02) indicates every 1 unit increase in temperature minimally affects disease risk that is only 2%, provided other factors in the model remain controlled. On the other hand, the coefficient value of 1.25 and the odd ratio of 3.49 specifies soil moisture tends to produce a higher disease risk of 3.49 times more than soil temperature when other factors remain unchanged in the

**Table 1:** IIPR rating scale was followed for scoring the disease (Chaudhary, 2009)

| Sr No. | Reaction | Per cent mortality | Score |
|---|---|---|---|
| 1 | R- Resistant | <10 | 1 |
| 2 | MR- Moderately Resistant | 11– 20 | 2 |
| 3 | MS- Moderately Susceptible | 21 – 30 | 3 |
| 4 | S- Susceptible | 31 – 40 | 4 |
| 5 | HS- Highly Susceptible | > 40 | 5 |

**Table 2:** Binary logistic regression for predicting disease severity of collar rot in chickpea

| Predictor | Coefficient | SE | Z value | P-value | VIF | Odd ratio | 95% CI | |
|---|---|---|---|---|---|---|---|---|
| Constant | -73.9 | 31.2 | -2.37 | 0.018 | - | - | Lower | Upper |
| Soil moisture | 1.251 | 0.572 | 2.19 | 0.029 | 1.49 | 3.49 | 1.14 | 10.71 |
| Soil temp. | 0.017 | 0.331 | 0.05 | 0.259 | 1.49 | 1.02 | 0.53 | 1.95 |

**Table 3:** Goodness of fit

| Method | Chi-square | P-value |
|---|---|---|
| Pearson | 24.61 | 0.596 |
| Deviance | 18.40 | 0.891 |
| Hosmer-Lemeshow | 4.54 | 0.474 |

model. VIF (various implies factor) value indicates the correlation among the predictors (multi collinearity) and the value 1.49 denoted that the predictors (SM and ST) are moderately correlated (Table 2). The goodness of fit also testified and presented in Table 3 showed a high p-value ranging from 0.474 to 0.891 indicate that our model is good to accept.

***Development of model***

The model developed for collar rot of chickpea under West Bengal, India condition using Binary logistic regression is as follows:

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

Y'= -73.9 + 1.251 SM + 0.017 ST [$R^2$= 0.50 $R^2_{adj}$= 0.55]

Model explains that one has to put SM and ST value only and to get the Y'a value. If the value is above the cut off value then the disease will occur. Here, we take only two independent variables which could exert upto 50.79 per cent variance in the dependent variable. Adjusted $R^2$ value on the other hand indicates if we add more and more insignificant variables that have no effect on the dependent variable, $R^2$ value may increase but adjusted $R^2$ value will decrease. In this model high Adj $R^2$ value prove the goodness of the best fit of the developed model.

***Discriminant analysis***

ANOVA of discriminate analysis (Table 4) was also created to divulge how accurately the model can predict the disease severity. The result revealed that for each additional unit increase in SM it increases the likelihood of being in the disease risk group by 0.06 and it can be used for the predictive purpose. So, any given unit data of the independent variables predicted disease severity

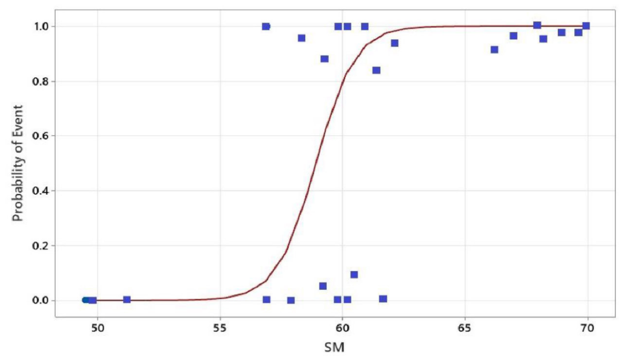


**Fig 1:** Binary classification (Sigmoid curve). Horizontal axis represents the SM (soil moisture) level and vertical axis represents probability events 0-1.

could be calculated and based on the cut-off value (=0.533) (Table4) determined through this analysis it can be predicted whether it falls in disease risk or non-risk situation. Any value above the cut-off value comes under disease risk (i.e., 1) and below it, likely to come under non-risk (0) provided other factors remain unchanged. From the p-value of Table 4, it is presented that SM had a statistically significant effect on the disease severity of collar rot of chickpea but the effect of ST was not statistically significant. Fig.1present a perfect sigmoid curve when plotted the event (disease risk) against soil moisture (SM). Most of the observed data falls between the probability level 0 and 1 and the cut-off point showing 0.5 which also matches with the calculated cut-off value (=0.533) of the model developed. The correctness of the model determined 0.80 that says the model would able to predict the disease severity with 80 per cent accuracy.

***Adaptability of the model***

Now, to analyze how good the model is, two new variables FITS_1 that is the fitted probability of a particular event (disease risk or non-risk) was calculated and the data showed the model has got a probability of 0.75 to 0.92of being in state 1 (disease risk) which is consistently followed for predicting disease risk but got low probability (0.001 to 0.07) in predicting the second situation i.e., non-risk (Fig. 1). Another variable DDEV_1 is the delta deviance was considered which shows how far each particular event is from

**Table 4:** ANOVA of discriminant analysis

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Cut off value* | *Correct proportion* | *F value* |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -3.132 | 0.834 | -3.753 | 0.0008 | -4.845 | -1.420 | 0.533 | 0.80 | 0.006 |
| Soil moisture | 0.061 | 0.015 | 3.549 | 0.001 | 0.023 | 0.086 | | | |
| Soil temp. | 0.024 | 0.028 | 0.856 | 0.399 | -0.033 | 0.082 | | | |

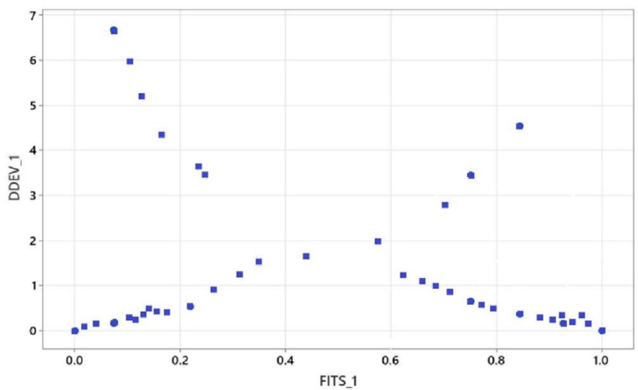


**Fig 2:** Fitted Probability vs. Delta deviance. Horizontal axis represents fitted probability value 0-1 and vertical axis represents delta deviance.

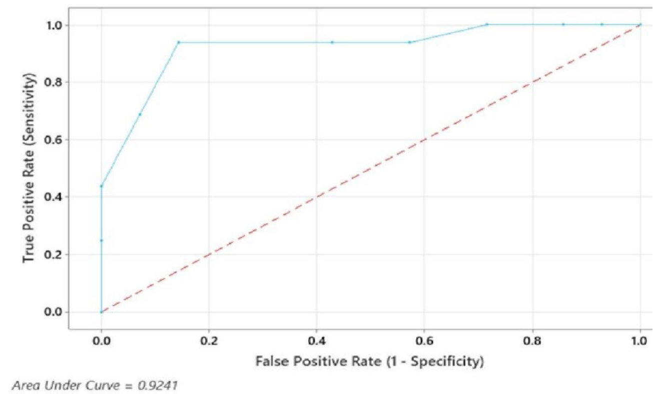


**Fig 3:** Receiver operating characteristic (ROC) curve. Horizontal axis represents false positive rate with probability value 0-1 and vertical axis represents true positive rate with probability 0-1.

the pure fitted model and it could be useful to display the deviance as a function of the fits plotting these two variables on an XY graph (Fig. 2).

The graph shows two distinct curves relating to the two binary states (disease risk and non-risk). The curve from top left to bottom right relates to event 1 that is disease risk. In experimental data which is a good fit to the model have low delta deviance will be expecting probability of 1 corresponding to disease risk. So, records that fit well to the disease risk period (probability 1) are displayed in the bottom right and the point in the top left is the poor fit of the data. Similarly, another line is for data representing the disease non-risk. Records that show low probability corresponding to non-risk and with low delta deviance are presented in the bottom left represent a good fit and the point at top right represent a poor fit (Fig. 2).

***Performance test of the model***

ROC (Receiver operating characteristic) curve analysis is mandatory to measure the performance of the binary classifiers. The analysis may also be used to limit the optimum cut-off value or optimal decision threshold. For a specified cut-off value a positive or negative diagnosis is thru for each unit by comparing the data to the cut-off value. However, the predicted condition doesn't necessarily match the true condition as always. There could be four possible outcomes true positive, true negative, false positive, and false negative.

ROC curve plots the true positive rate or sensitivity against the false positive rate (1-Specificity) (Fig. 3) for all possible cut-off values. It is essentially a trade-off between true positive and false positive. The ROC curve gives a visual representation of how well the forecast model performs across all false-positive rates.

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 diagonal line serves as a reference line since it is the ROC curve of the analytical test that arbitrarily classifies the condition. The area under the ROC curve provides a numeric depiction of the overall performance of the forecasting model and it is 0.924 for the model developed hereby means, it is carrying a pretty good impression for determining the disease risk situation.

Disease forecasts based on mathematical models support the growers in time application of fungicides only when the weather conditions are conducive for plant infections by fungal pathogens (Campbell and Madden, 1990). Therefore, it has been proved that the model developed through the experiment to predict the disease severity of collar rot in chickpea is highly acceptable and would be an imperious tool in the future study of plant disease forecasting and epidemiology to envisage the disease appearance precisely.

Forecast system developed by several scientists viz program for *anthracnose* by Sahoo *et al*., (2012), *phytophthora* blight programs by Do *et al*., (2012) and early blight by Saha and Das, (2013). The anthracnose infection model estimates a collective infection risk (IR) value every hour based on the hourly temperature and moisture characteristics (Kang *et al*., 2010). The Phytophthora model (Do *et al*., 2012) estimates the date of the first outburst, based on the daily soil temperature and water content, and acclaims fungicide application before disease establishment which is pertinent for any soil-borne disease. Each of these programs has a critical model for guiding the proper time for up-taking control measures.

## CONCLUSION

The present study demonstrates that soil moisture is the critical factor for the development of collar rot of chickpea in field conditions in contrast to soil temperature. Literature also supports the endurance of *Sclerotium rolfsii* in a wide range of soil temperatures 27-35$^0$C (Tarafder *et al*., 2018). The accuracy of this model has been tested based on field data along with predicted disease situations which showed up to 80 per cent precision in forecasting. Moreover, the threshold value determined from the realized data showed almost match with the predicted situation depicted through the model and area under ROC covered 92.4 per cent conveyed that the developed model would ably forecast the disease risk situation at any cut off value by nullifying 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 at a juvenile stage of crop growth with the soil-borne pathogen, the situation becomes more menace for the stakeholder to have a good crop stand. 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 would be a milestone to provide an insight to the future researchers to develop a computer-simulated forecast model for collar rot of chickpea.

***Conflict of Interest Statement:*** The author(s) declare(s) that there is no conflict of interest.

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