Effect of meteorological factors on progression of Alternaria leaf blight of mustard and comparison of logistic and Gompertz growth models in predicting disease severity

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ABSTRACT: The step down multiple regression analysis (MRA) was carried out to determine the meteorological parameters influencing variation in disease severity of Alternaria leaf blight (Alternaria brassicae and A. brassicicola) of mustard. Disease severity estimates (Y) was considered as dependent variable, whereas other weather parameters like maximum (T_{max}) and minimum temperature (T_{min}); maximum (RH_{max}) and minimum relative humidity (RH_{min}); total rainfall (RT); wind velocity evening (WV_{evening}) and morning (WV_{morning}); vapour pressure noon (VP_{noon}) and morning (VP_{morning}); and bright sunshine hour (BSH) were used as independent variables. The weather variables were found to influence the disease severity differently when crops were shown at different dates of five sowing time for the two consecutive years. The Gompertz equation was best linearized with the disease progress data followed by the logistic and the untransformed data sets. The linear prediction equations are (1) Y = 3.203 - 0.356 (T_{min}) + 0.015 (RH_{min}) for 20th October sowing; (2) Y = -1.929 + 1.634 (WV_{morning}) + 0.067 (RT) for 5th November sowing; (3) Y = -121.91 + 1.57 (T_{min}) + 1.083 (RH_{max}) + 0.29 (RH_{min}) - 2.27(VP_{noon}) - 0.61(VP_{morning}) - 17.17(WV_{evening}) + 17.83(WV_{morning}) + 1.65(BSH) + 0.113(RT) for 20th November sowing; (4) Y = -5.131 + 0.25 (VP_{noon}) + 0.256 (BSH) + 0.057 (RT) for 5th December sowing; (5) Y = -3.19 + 0.235(T_{min}) for 20th December sowing. Gompertz transformation is best for linerizing and prediction of disease severity in all dates of sowing and in early sowing Tmin, RH_{min} and WV_{morning} influenced the disease progression.

Key words: Alternaria leaf blight, epidemiological models, mustard, prediction equation, weather parameter

Leaf blight of Indian mustard incited by Alternaria brassicae and A. brassicicola is a major threat of mustard cultivation in India causing huge reduction of yield and loss of seed viability. The yield loss caused by this disease has been estimated up to 47% (Kolte, 1985) as no proven sources of resistance against this disease has been identified. Various predisposal factors such as age of plant, soil reactions, environmental factors and host nutrients have shown to effect disease severity. The relation of leaf blight disease with environmental factors and chemical treatment have been shown critically previously (Godika et al., 2001; Sinha et al., 1992; Awasthi and Kolte, 1994). A multiple regression model has been developed based on study of epidemic leaf blight in relation to different meteorological factors (Chattopadhay et al., 2005; Singh et al., 2008; Sangeetha and Siddharamaiah, 2007). In the present study effort has been made to identify and develop a prediction model using comparative functional model equations for the prediction of disease severity of Alternaria leaf blight of mustard before the appearance of the disease at different dates of sowing.

MATERIALS AND METHODS

A mustard cultivar Binoy was collected from Department of Agronomy, Bidhan Chandra Krishi Viswavidyalaya (BCKV), Mohanpur and sown at expermetal farm of BCKV, Mohanpur in 5 x 5 m² plot with 15-20 cm plant to plant and 80 cm row to row distance with three replications at five different dates of sowing, 20th October, 5th November, 20th November, 5th December and 20th December for two consecutive years. Recommended agronomic practices and intercultural operations were adopted and natural epiphytotic development was allowed in field condition. The onset of time for disease was monitored, first appearance of lesion and disease severity were recorded every 10 days interval. Disease rating were done by using this scale 0-5 (Sharma and Kolte, 1994), where, 0 = no visible symptoms; 1= 1-10% disease severity; 2= 11-25% disease severity; 3 = 26-50% disease severity; 4 = 51-75%; 5 =>75% disease severity. Number of 10 plants per replication were selected randomly to record the disease severity and tagged, and whole plants were assessed till to date of 15 days before harvesting. The disease severity was calculated using standard methods (Dhingra and Sinclair, 1993). The plants in border rows were not considered for disease assessment. The data obtained were subjected to both the Gompertz (Kranz, 1974; Berger, 1981) and the logistic transformation (Vanderplank, 1963) using following equations;

Logistic equation= Logit (Y) = \ln \left[ \frac{Y}{1-Y} \right];

Gompertz equation: Gompertz = gompit (y) = - \ln [-\ln(y)],

Where Y = proportion of diseased tissue.

The weather parameters were maximum (T_{max}) and minimum temperature (T_{min}); maximum (RH_{max}) and
minimum relative humidity ($\text{RH}_{\text{min}}$); total rainfall (RT); wind velocity (km/h) evening (WV$_{\text{evening}}$) and morning (WV$_{\text{morning}}$); vapour pressure (millibar) noon (VP$_{\text{noon}}$) and morning (VP$_{\text{morning}}$); and bright sunshine hour (BSH) were continuously recorded at the adjacent meteorological observatory. The averages of 10 days data of these variables, except for 10 days cumulative rainfall for the specific period of disease prediction were worked out for statistical analysis. The step wise multiple regression analysis was carried out and the prediction equation used was following:

$$v = b_0 + b_1x_1 + b_2x_2 \cdots \cdots \cdots + b_nx_n$$

Where $v$ = predicted disease severity; $b_0$ = intercept; $b_1, b_2, \ldots, b_n$ = regression co-efficient; $x_1, x_2, \ldots, x_n$ = independent variables.

The goodness of fit of multiple regression model was evaluated by co-efficient of determination ($R^2$), adjusted co-efficient of determination ($R^2_a$), standard error (SE), and residual sum of squares (RSS) (Madden, 1986; Cornell and Berger, 1987).

**RESULTS AND DISCUSSION**

Pooled data of two years from mustard nurseries sowing at five different dates were analysed. There were only six observations of blight severity 45 days prior to the data predicted and to use the entire set of observation, a value of 0.0001 were given to zero disease severity data and 1.0 was given to maximum disease severity data recorded. The biological rational for adding a value to zero data was on believe that an intensive observations of the crop nursery would revealed that weather variables had profound influence on development and spread of Alternaria leaf blight on mustard during the rabi seasons in all the dates of sowing. The association between the weather parameter and disease severity vary with the season to season and year to year and thus drawing any conclusion is misleading. Hence multiple regression analysis was done with combined and pooled data analysis, effort was made to draw conclusion. Of the ten variables weather parameter used in present the analysis, in 5th November sowing, the prediction equation was $Y = -1.929 + 1.634 \text{WV (morning)} + 0.067 \text{RT}$ in cooperation transformation equation. It was observed that WV (morning hours, 1.634 units) and total rainfall (RT, 0.67 units) were in combination influenced by disease progression to reach 50-90% disease severity. Here, the predicted and actual disease severity showed no correlation with untransformed data, and on the other hand predicted value through Gompertz transformation matched well with actual data at least for final two observations (65 and 85 DAS). Among the three models, Gompertz model was best fitted and it confirmed with high $R^2$ (0.37 for logit and 0.64 for gompit), low SE (1.91 for logit and 0.14 for gompit) and RSS (3.64 for logit and 0.02 for gompit) values (Table 1).

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In 20th November sowing, three different equations were formulated and it showed that out of ten variables nine variables were significantly correlated either positively or negatively. The untransformed, logit and gompit transformation equations showed high co-efficient of determination value ($R^2$) from 0.95 to 0.98 and it indicated that the three equations were good for predicting the disease severity, and 95-98% change in disease severity was due to the nine variables out of ten variables. However, the predicted and actual disease severity showed that the untransformed and gompit transformation provided good correlation on last two dates of observations (65 and 85 DAS). Among the three models, Gompertz transformation model provided the best fitting model during three dates of sowing and the model was $Y = -121.91 + 1.57 \text{(T}_{\text{min}}) + 1.083 \text{(RH}_{\text{min}}) + 0.29 \text{(RH}_{\text{min}}) - 2.27 \text{(VP}_{\text{noon}}) - 0.61 \text{(VP}_{\text{morning}}) - 17.17 \text{(WV}_{\text{evening}}) + 17.83 \text{(WV}_{\text{morning}}) + 1.65 \text{(BSH)} + 0.113(\text{RT})$. Although, the $R^2$ was high for both the Logistic (0.98) and Gompertz (0.97), the low SE (0.55 for logit and 0.28 for gompit) and RSS (0.31 for logit and 0.078 for gompit) values later made it a better choice (Table 1).

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Table 1. Prediction equations of two different growth models and untransformed data and their comparable factors at five different dates of sowing

<table>
<thead>
<tr>
<th>Date of Sowing</th>
<th>Equation 1 (PDI)</th>
<th>Equation 2 (PDI(Logit))</th>
<th>Equation 3 (PDI(Gompit))</th>
<th>R²</th>
<th>Adj.R²</th>
<th>SE(est.)</th>
<th>RSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st date of sowing</td>
<td>PDI (%) = 1.089 – 0.063 Temp(min)**</td>
<td>PDI(Logit)=12.46 – 1.637 VP (noon)** + 0.074RH (min)*</td>
<td>PDI(Gompit)= 3.203 – 0.356 Temp(min)** + 0.015RH (min)*</td>
<td>0.67</td>
<td>0.64</td>
<td>0.13</td>
<td>0.016</td>
</tr>
<tr>
<td>2nd date of sowing</td>
<td>PDI (%) = -0.118 + 0.41 WV (morning)** + 0.019 RT*</td>
<td>PDI(Logit)= -5.319 + 4.248 WV (morning)*</td>
<td>PDI(Gompit)= -1.929 + 1.634 WV (morning)** + 0.067 RT*</td>
<td>0.61</td>
<td>0.54</td>
<td>0.58</td>
<td>0.33</td>
</tr>
<tr>
<td>3rd date of sowing</td>
<td>PDI (%) = -28.757 + 0.412T (min)** + 0.250RH (max) + 0.075RH (min)** - 0.564VP (noon)** - 0.157VP (morning)** - 0.3754 WV (evening) + 0.3963WV (morning) + 0.451 BSH** + 0.030 TR**</td>
<td>PDI(Logit)= -315.514 + 0.361T (max) + 3.487T (min) + 2.833RH (max)** + 0.707RH (min)** - 5.83VP (noon)** - 0.49VP (morning)** - 4.431WV (evening)** + 4.541WV (morning)** + 3.802BSH** + 0.288TR**</td>
<td>PDI(Gompit)= -121.91 + 1.57T (min)** + 1.083RH (max)** + 0.29RH (min)** - 2.27VP (noon)** - 0.61VP (morning) - 17.17WV (evening)** + 17.83WV (morning)** + 1.65BSH** + 0.113TR*</td>
<td>0.95</td>
<td>0.83</td>
<td>0.099</td>
<td>0.009</td>
</tr>
<tr>
<td>4th date of sowing</td>
<td>PDI (%) = -1.272 + 0.079 VP (noon)** + 0.084BSH** + 0.018 TR*</td>
<td>PDI(Logit)= -5.698 + 0.402 VP (noon)**</td>
<td>PDI(Gompit)= -5.131 + 0.25 VP (noon)** + 0.256 BSH** + 0.057 TR*</td>
<td>0.83</td>
<td>0.78</td>
<td>0.11</td>
<td>0.012</td>
</tr>
<tr>
<td>5th date of sowing</td>
<td>PDI (%) = -0.653 + 0.075T (min)**</td>
<td>PDI(Logit)= -5.827 + 0.376T (min)**</td>
<td>PDI(Gompit)= -3.19 + 0.235T (min)**</td>
<td>0.73</td>
<td>0.71</td>
<td>0.41</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Abbreviation of PDI= (Percent Disease Index), R²=Coefficient of determination Adj.R²=Adjusted coefficient of determination, SE(est.)=Standard Error(estimate). RSS=Residual sum of square

The investigation on 5th December sowing showed that VPnoon, BSH and RT were positively and significantly correlated in Alternaria leaf blight disease progression for untransformed, logit and gompit transformation models. It indicated that these three variables had high influence in changing the disease severity 66-75%. Here among the three models, untransformed and gompit models were fitted for disease prediction, whereas logit model was poorly fitted, that was confirmed with high R² (0.66 for logit and 0.73 for gompit and untransformed), low SE (0.41 for logit and 0.13 for gompit) and RSS (0.17 for untransformed and 0.017 for gompit). The predicted model was Y = - 3.19 + 0.235(Tmin).

Further, the predicted actual disease severity data also showed here that Gompertz transformation provided the best correlation for three observations (Table 2). On the basis of the predictability of the disease severity data subjected to Gompertz transformation and MRA analysis provided the best fitting model for all the dates of sowing. It was, therefore, concluded that Gompertz transformation is the best fit in linearised the disease progress curve in all the dates of sowing. Similar observations have been reported earlier for other pathosystems such as wheat leaf rust (Hau and Kranz, 1977), apple scab (Analytis, 1979) and groundnut rust (Das and Raj, 2000).

In the present investigations, it was found that the ten selected independent variables taken into consideration to develop prediction model, either positive, untransformed data, and on the other hand predicted value through Gompertz transformation matched well with actual data at least for final two observations (65 and 85 DAS). Among the three models, Gompertz model was best fitted and it confirmed with high R² (0.37 for logit and 0.64 for gompit), low SE (1.91 for logit and 0.14 for gompit) and RSS (3.64 for logit and 0.02 for gompit) values (Table 1).
negative, poor and no correlation with the disease severity was observed. For proper prediction of disease severity, it is necessary to identify all those meteorological parameters along with biological parameters including host (susceptible or resistant or tolerant) and pathogen factors like (fungus virulence, fungal growth and sporulation) which have definite interaction with disease epidemic of Alternaria blight of mustard. This model needs to be tested on multi-locational trial for its best suitability using different cultivars so that the measurement of disease is predicted before the onset of the epidemic.

REFERENCES


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Table 2. Regression function in different transformation models with predicted disease severity in different dates of sowing

<table>
<thead>
<tr>
<th>Date of sowing</th>
<th>Untransformed</th>
<th>Logit transformation</th>
<th>Gompertz transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>II</td>
<td>III</td>
</tr>
<tr>
<td>20th October</td>
<td>0.10</td>
<td>0.38</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.19)</td>
<td>(0.53)</td>
</tr>
<tr>
<td>5th November</td>
<td>0.22</td>
<td>0.23</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.22)</td>
<td>(0.58)</td>
</tr>
<tr>
<td>20th November</td>
<td>0.24</td>
<td>0.25</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.28)</td>
<td>(0.61)</td>
</tr>
<tr>
<td>5th December</td>
<td>0.09</td>
<td>0.24</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.23)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>20th December</td>
<td>0.07</td>
<td>0.25</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.26)</td>
<td>(0.65)</td>
</tr>
</tbody>
</table>

Figures in the parenthesis are actual disease severity and its logit and Gompertz transformation, I = data taken 45 days after sowing (DAS) II = 65 DAS, II = 85 DAS