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Nonlinear Logistic Model for Describing Downy Mildew Incidence in Grapes

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SUMMARY

Biological organism always tends to behave non-linearly contrary to linear growth as perceived in most of the data analysis procedure. In the present communication, a simple nonlinear logistic growth model has been developed to describe the population dynamics of incidence of downy mildew in grapes (cv. *Anab-E-Sahai*) so as to workout quantitative information about the biological parameters concerning intrinsic infection rate and maximum mildew severity over time-epoch. Statistical analysis of disease severity data over time period for three years (2004-05 to 2006-07) using non linear growth models revealed that 98% of the variability in disease progression over time-epoch was captured by nonlinear models. Nonlinear models developed were then used to construct area under disease progression over time period. Results showed that, in general, the rate of disease severity was maximum during fifth- sixth week after fore-pruning, calling for appropriate management strategies for controlling the disease within the period identified, thus avoiding crop loss. Before taking final conclusion about the model, the model-generated residuals were tested for their robustness using statistical techniques. SAS Programming codes were constructed to develop the nonlinear growth models.

Keywords: Coefficient of determination, Downy mildew, Gompertz model, Grapes, Logistic model, SAS programming, Weather factors.

1. INTRODUCTION

Grape (Vitis SPP.) is an important crop for the farmers for getting higher returns and with consumer for delicacy and as a medicinal fruit. Though, the crop suffers greatly because of the attack of different diseases, but among them downy mildew caused by *Plasmopara viticola* (Berk. and Curt.) De Toni is the most serious and involves more investment from the farmers for its management. In order to reduce cost of production, the farmers have to employ the control measures judiciously and need based. For this, the knowledge on the disease progression vis-à-vis amalgamated effect of climatic factors on disease incidence is very much important, for framing any successful management strategies.

Downy mildew is one of the most destructive vine diseases known. It occurs especially in regions that are warm and wet during the vegetative growth stage of the vine when control is poor and /or weather conditions are favorable, the disease may cause crop loss due to total or partial destruction of grape bunches, and also due to the secondary influence of foliage loss. While crop losses may range from 10 to 20%, if poor control is exercised, favorable weather conditions, especially during flowering, may even cause total (100%) crop loss (Magarey *et al.* 1994). In India downy mildew occur every year and hampers the production and quality of commercially grown grape varieties. Even complete failure of the crop has been reported (Reddy and Reddy 1983). For the management of the disease fungicidal usage is in vogue (Rawal 2008), which is

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very expensive and involves a lot of efforts. Farmers spray chemicals indiscriminately to contain the disease. Prevailing weather conditions influence the onset, initiation and progression of disease, besides others. Moreover, in grapes backward (May-June) and fore pruning (September-October) are the two pruning strategies adopted by researchers and farmers in the entire crop growth period. Rate of progression of disease over time epoch definitely plays a different role in both the pruning period studies. It was also known to the growers that managing the downy mildew in Fore pruning period is very difficult than in backward pruning period.

Furthermore, such a disease progression over time-epoch of a biological organism is rarely of linear nature. Accordingly, in this communication, suitable nonlinear growth models were employed and utilized to arrive at a decision to orient suitable management strategy for saving the crop.

2. MATERIALS AND METHODS

2.1 Database

Downey mildew disease initiation and further progression over time period for three years (2004-05 to 2006-07) recorded (Rawal *et al*. 2008) at the experimental plot of Indian Institute of Horticultural Research, Bangalore, were utilized for this study. Disease ratings were recorded at weekly interval by following 0 – 5 scale, where 0 = nil PDI; 1 = 0 > PDI ≤ 10; 2 = 11 ≥ PDI ≤ 25; 3 = 26 ≥ PDI ≤ 50; 4 = 51 ≥ PDI ≤ 75 and 5 = ≥ 76 Per cent Diseases Intensity (PDI). Data thus recorded were converted to Percent Disease Index by following Mcknney (1923). Role of weather factors on the incidence of downy mildew is reported by Rawal *et al.* 2008 and hence this communication address specifically about the application of non-linear models, which other-wise were not addressed earlier.

2.2 Some Important Non-linear Growth Models

Nonlinear growth models which describe the growth behaviour over time are applied in many fields. In the area of population biology, growth occurs in plants, animals, organisms, etc. The type of model needed in a specific situation depends on the type of growth that occurs. In general, growth models are mechanistic in nature, rather than empirical. In the former, the parameters have meaningful biological interpretation; the latter is just like a ‘black-box’ where some input is given and some output is taken out. A mechanistic model usually arises as a result of making assumptions about the type of growth, writing down differential or difference equations that represent these assumptions, and then solving these equations to obtain a growth model. The utility of such models is that, on one hand, they help us to gain insight into the underlying mechanism of the system and on the other hand, they are of immense help in efficient management. We now discuss briefly some well-known nonlinear growth models (Prajneshu 2009).

If $N(t)$ denotes the population size or biomass at time t and r is the intrinsic growth rate, then the rate of growth of population size, due to Malthus law, is given by

$$\frac{dN}{dt} = rN. \tag{1}$$

Integrating, we get

$$N(t) = N_o \exp(rt), \tag{2}$$

where N_o denotes the population size at $t = 0$. Thus this law entails an exponential increases for $r > 0$. Furthermore, $N(t) \to \infty$ as $t \to \infty$ which cannot happen in reality.

Note. The parameter r is assumed to be positive in all models.

Logistic Model. This model is represented by the differential equation

$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right) \tag{3}$$

Integrating, we get

$$N(t) = \frac{K}{\left[1 + \left(\frac{K}{N_o} - 1\right)e^{-rt}\right]} \tag{4}$$

The graph of $N(t)$ versus t is elongated S-shaped and the curve is symmetrical about its point of inflexion.

The equation (4), may equivalently written as

$$Y_t = \frac{C}{(1 + be^{-at})} + e, \; b = \frac{C}{Y_o} - 1 \tag{5}$$

Gompertz Model. This is another model having a sigmoid type of behaviour and is found to be quite useful in biological work. However, unlike the logistic model, this is not symmetric about its point of inflexion.

The differential equation for Gompertz model is

$$\frac{dN}{dt} = rN \log_e\left(\frac{K}{N}\right) \quad (6)$$

Integration of this equation yields

$$N(t) = Ke^{\left[\log_e \frac{N_o}{K} e^{-rt}\right]} \quad (7)$$

The equation (7), may equivalently written as

$$Y_t = C * e^{(-b*e^{-at})} + e,\ b = \ln\left(\frac{c}{Y_o}\right) \quad (8)$$

where under all these models,

Y_t - percentage of disease incidence during the time t;

a, b, c and d are the parameters, e the error term.

a is the intrinsic growth rate.

b refers to the incremental relative rate of relative growth rate of the disease.

$Y_{(o)}$ corresponds to age of theoretical zero size, which also represents time when the growth curve crosses the t-axis

c represents the carrying capacity for each model.

In order to fit these non-linear growth models for the disease severity data, Levenberg-Marquardt technique (Ratkowsky 1990) was utilized and programming codes were developed using Statistical Analysis system (SAS) package available at IIHR, Bangalore. PROC NLIN subroutine was utilized to construct SAS codes (SAS-grapes-DM). Global convergence of the parameter estimates were ensured by trying different sets of initial values.

Measures of Model Adequacy

As a measure of goodness-of-fit, the value of coefficient of determination (R^2) (Kvalseth 1985) was calculated as below:

Coefficient of Determination (R^2)

$$R^2 = 1 - [\Sigma \hat{Y}_t - Y)^2 / \Sigma Y_t - \bar{Y})^2], \quad (9)$$

where Y_t represents the percent disease incidence during the period t.

Residual Analysis

Before taking any final decision about the statistical adequacy of the selected model, residual analysis was also carried out using the one sample run-test, for testing the randomness assumption and the normality assumption of residuals were tested using Shapiro-Wilk test (Siegel and Castellan 1988).

Area Under Disease Progressive Curve

Calculation of the area under the disease-progress curve (AUDPC) as a measure of quantitative disease resistance entails repeated disease assessments. For typical sigmoid disease-progress curves, repeated assessments may be unnecessary. A mathematical procedure is derived for estimating the AUDPC from two data points (Jeger and Viljanen-Rollinson 2001).

The AUDPCs were calculated directly from data and estimated from the described equation.

$$AUDPC = \frac{\sum_{i=2}^{h} d(N_I - N_{i-1})}{2} \quad (10)$$

where,

N_I denotes estimated disease severity at time I

h is the number of data

d is the interval between two data points

In this study, *AUDPC* values were calculated separately for all the three years to know the severity of disease progression. For all the data sets, weekly growth of downy mildew was evaluated by computing the values of the derivative $\frac{dX}{dt}$, for different values

Table 1. Results of Nonlinear Regression Analysis

Fore pruning	Logistic				Gompertz			
	2004-05	2005-06	2006-07	Pooled	2004-05	2005-06	2006-07	Pooled
a	0.64	0.57	0.40	0.54	0.41	0.35	0.25	0.33
b	347.42	136.6	69.5	150.75	27.1	14.2	9.8	15.12
c	91.37	92.3	89.4	89.8	93.4	94.85	93.93	92.84
R^2 (%)	99	98	98	99	99	99	99	99
MSE	8.01	16.1	26.3	15.1	8.01	16	10.3	10.01
Run test (*Z*)	2.52 ^{NS}	1.2*	1.5*	0.98*	1.7*	2.1	2.2	2.4^{NS}
SW stat	0.96*	0.97*	0.87*	0.96*	0.91*	0.97*	0.92*	0.97*
AUDPC	86.37	85.48	78.19	-	65.77	63.85	61.33	-

* indicates significance at 5% level.

of t, for both Logistic and Gompertz models. Furthermore, it can be seen that time (t) for which the downy mildew severity growth was maximum, is given by $t = Ln\frac{b}{a}$. AUDPC were calculated for each data set and the results are reported in Table 1.

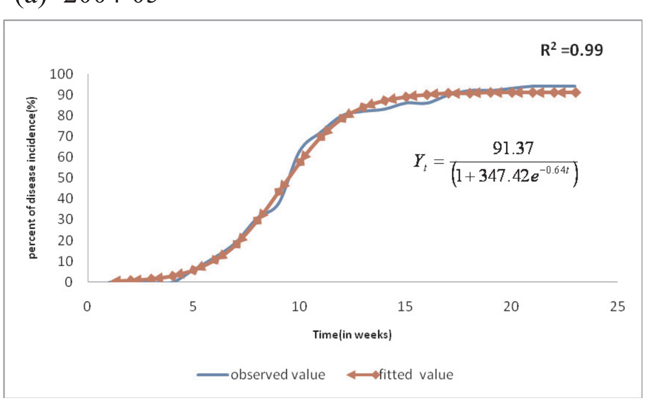
A perusal indicates that the values obtained by logistic and Gompertz are ranged from 48 to 84 and 25 to 65 respectively for backward pruning data. However, for the fore pruning data the results showed that AUDPC values were higher as it ranged from 78 to 86 and 61 to 65 respectively.These results indicate that the downy mildew rate of progression in Fore pruning is much severe than in backward pruning. The graphs for the rate of disease growth for the nonlinear models for backward and fore pruning data sets are also presented.

3. RESULTS AND DISCUSSION

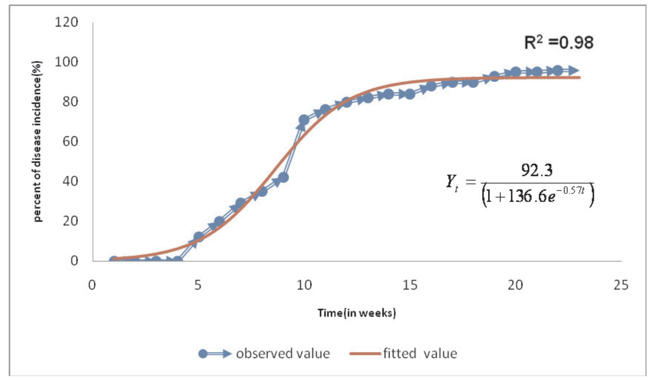
3.1 Nonlinear Statistical Modeling (Fore Pruning, 2004-05)

Results of data pertaining to Fore pruning (2004-05) are presented in Table 1. Parameter estimates of fitted models, measures of goodness of fit of these models (R^2 and MSE) along with the tested, measures of model adequacy were also presented. Results showed that downy mildew severity over time (Fore pruning 1 year data) is explained by Logistic and Gompertz fit to the extent of 99%. Mean square error values were equal (8.01) in both the case of Gompertz fit and Logistic fit. Further, examination of assumptions about residuals show that errors are randomly distributed as the run test statistics value (1.7) is well within the critical region of 1.96, for Gompertz model only. However, both the tests of normality (Shaprio Wilk test), resulted in significant values for both the models. This further

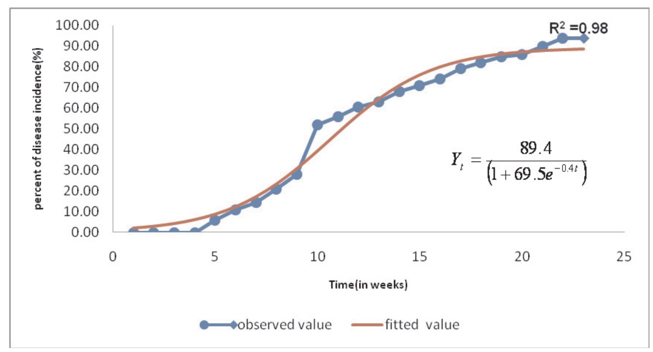
(a) 2004-05



(b) 2005-06



(c) 2006-07



(d) 2004-07 (pooled)

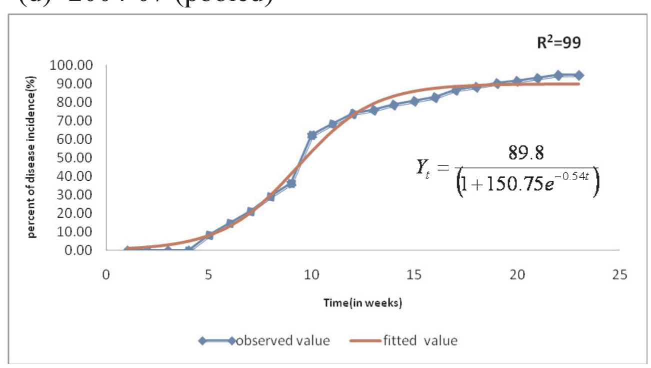


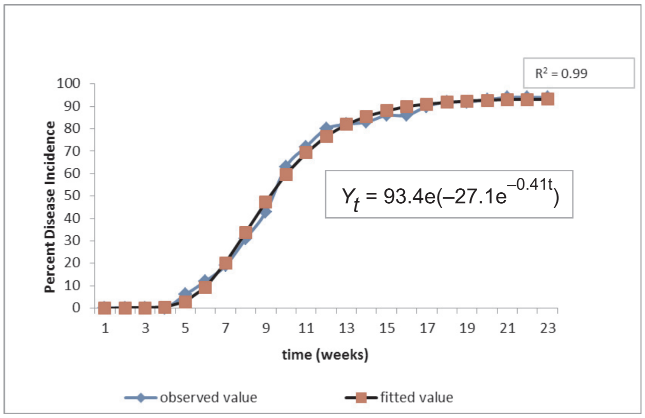
Fig. 1a. Graphical Representation of Logistic Model Fore Pruning data sets

strengthens the statistical adequacy of the fitted models. A graphical representation of fitted models is also depicted (Fig. 1a and 1b).

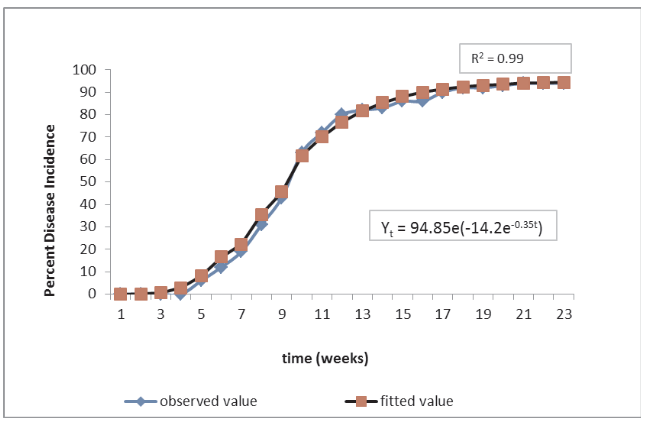
3.2 Nonlinear Statistical Modeling (Fore Pruning, 2005-06)

Results of data pertaining to Fore pruning (second year 2005-06) are presented in Table 1. Parameter estimates of fitted models, measures of goodness of fit (R^2 and MSE) along with the tested measures of model adequacy were also presented. Results showed that downy mildew severity over time (Fore pruning 2 year data 2005-06) is explained by Logistic fit to the extent

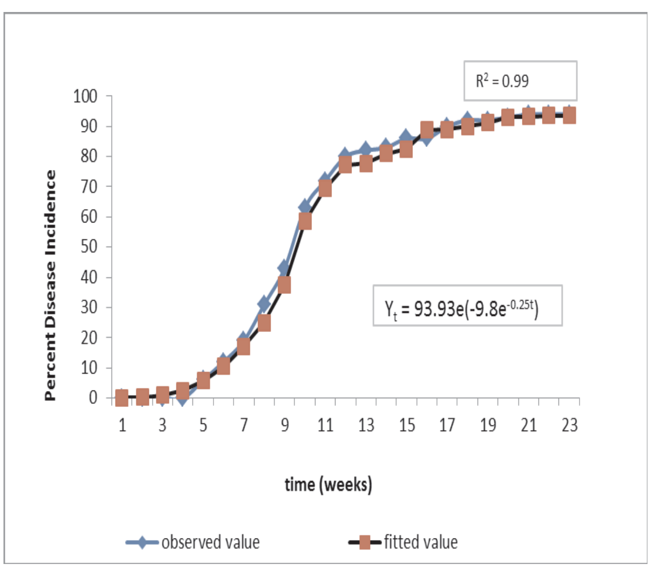
(a) 2004-05



(b) 2005-06



(c) 2006-07



(d) 2004-07 (Pooled)

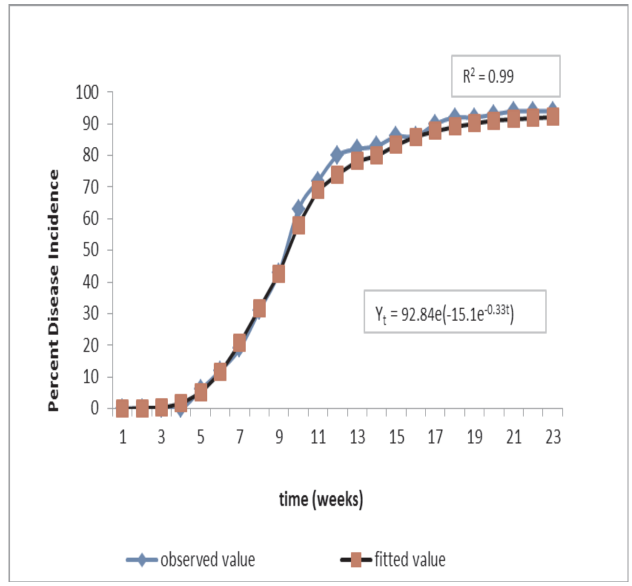


Fig 1b. Graphical Representation of Gompertz Model Fore Pruning data sets

of 98% and by Gompertz fit to the extent of 99%. Mean square error values were lesser (16.0) in the case of Gompertz fit than Logistic fit (16.01). Further, examination of assumptions about residuals show that errors are randomly distributed as the run test statistics value (1.2) is well within the critical region of 1.96, for Logistic model only. However, both the tests of normality (Shaprio Wilk test), resulted in significant values for both the models. This further strengthens the statistical adequacy of the fitted models. A graphical representation of fitted models is also depicted (Fig. 1a and 1b).

3.3 Nonlinear Statistical Modeling (Fore Pruning, 2006-07)

Results of data pertaining to Fore pruning (3 year 2006-07) are presented in Table 1. A parameter estimate of fitted models measures of goodness of fit of these models (R^2 and MSE) along with the tested measures of model adequacy was also presented. Results showed that downy mildew severity over time (Fore pruning third year data 2006-07) is explained by Logistic fit to the extent of 98% and by Gompertz fit to the extent of 99%. Mean square error values were lesser (10.3) in the case of Gompertz fit than Logistic fit (26.3). Further, examination of assumptions about residuals show that errors are randomly distributed as the run test statistics value (1.5) is well within the critical region of 1.96, for Logistic model only. However, both the tests of normality, resulted in significant values for both the models. This further strengthens the statistical adequacy of the fitted models. A graphical representation of fitted models is depicted (Fig. 1a and 1b).

3.4 Nonlinear Statistical Modeling (Fore Pruning, Pooled Data of 2004-05 to 2006-07)

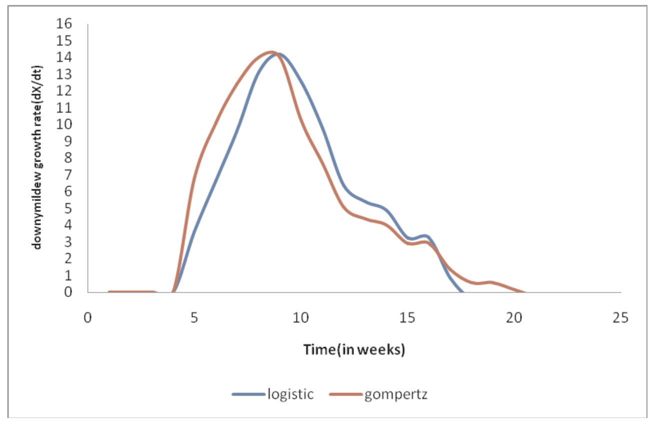
Results of data pertaining to Fore pruning of pooled data (2004-2007) are presented in Table 1. Parameter estimates of fitted models measures of goodness of fit of these models (R^2 and MSE) along with the tested measures of model adequacy were also presented. Results showed that downy mildew severity over time (Fore pruning of polled 2004-2007) is explained by Logistic and Gompertz fit to the extent of 99%. Mean square error values were lesser (10.01) in the case of Gompertz fit than Logistic fit (15.1). Further, examination of assumptions about residuals show that errors are randomly distributed as the run test statistics value (0.98) is well within the critical region of 1.96, for Logistic model only. However, both the tests of normality (Shaprio Wilk test), resulted in significant values for both the models. This further strengthens the statistical adequacy of the fitted models. A graphical representation of fitted models is depicted in Fig. 1.

Under all the models, the intrinsic disease growth rate (the rate at which the disease period over time-epoch) was computed to be 0.40 to 0.64 (for logistic fit) and 0.25 to 0.41 (for gompertz fit). The carrying capacity (maximum disease severity) which can be attainable was also computed to be 89.4 to 92.3 (for logistic fit) and 92.84 to 94.85 (for gompertz fit).

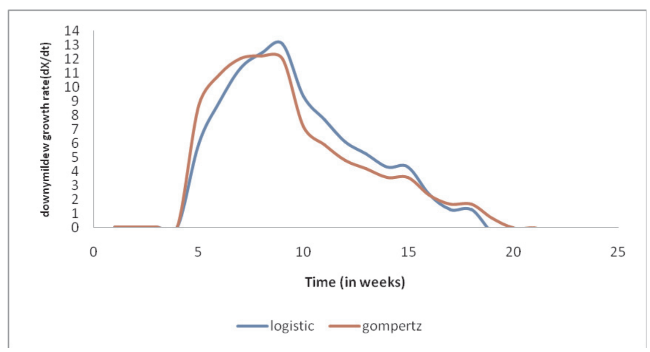
To know how the disease progressed over time epoch for three different years, area under disease progression is captured by a curve. The results are also presented in Table 1.

Perusal of results showed that the disease progression was more during the first year 2004-05 both in logistic and Gompertz (86.37, 65.77 respectively) as compared to second and third year of fore pruning. To study further, how the rate of disease growth had occurred over time epoch, the graphs for the rate of disease growth for the nonlinear models are also depicted in Fig. 2. Perusal of the graphs for fore pruning data of first second and third year of logistic model fit showed that rate of disease severity was maximum during the sixth, sixth and fifth week respectively. Perusal of the graphs for fore pruning data of first second and third year of Gompertz models fit showed that rate of disease severity was maximum during the fifth, fourth, fourth week respectively. Hence, appropriate management strategies for controlling the

(a) 2004-05



(b) 2005-06



(c) 2006-07

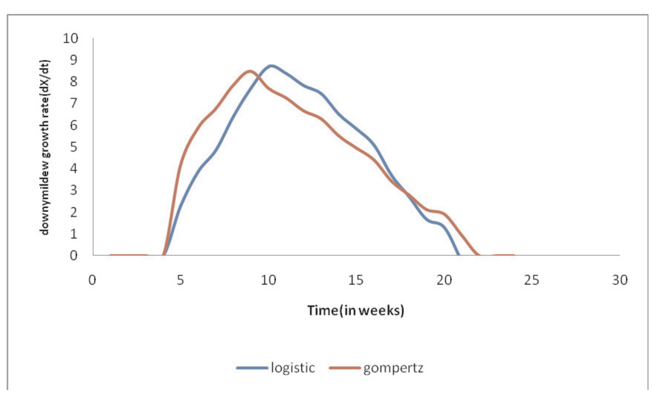


Fig. 2. Graphical Representation of AUDPC for Fore Pruning data sets

disease should be oriented within the period identified in the investigation separately for backward and fore pruning, as envisaged by the rate of disease growth. The message arising out of this present investigation is that proper prophylactic measures, if taken by considering the model resulted results along with knowledge about disease progression over time as depicted by nonlinear models, not only results in an efficient and economic management strategies for controlling downy mildew incidence in grapes (cv *Anab-E-Shai*) but also considerably reduce crop yield loss thereby providing better return to the farmers. This methodology can be very well utilized for developing disease forecasting models for other crops also.

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