Biological Forum – An International Journal **14(4a): 297-306(2022)**

ISSN No. (Print): 0975-1130
ISSN No. (Online): 2249-3239

Epidemiological Model for Potato Late Blight in the Northern Part of West Bengal

Vaidheki M.[1*], D.S. Gupta[2], S. Hembram[3], M.K. Debnath[4], T.K. Hath[5] and P. Basak[4]
[1]*Research Scholar, Department of Agricultural Statistics, UBKV (West Bengal), India.*
[2]*Professor, Department of Agricultural Statistics, UBKV (West Bengal), India.*
[3]*Assistant Professor, Department of Plant Pathology, UBKV (West Bengal), India.*
[4]*Assistant Professor, Department of Agricultural Statistics, UBKV (West Bengal), India.*
[5] *Professor, Department of Agricultural Entomology, UBKV (West Bengal), India.*

(Corresponding author: Vaidheki M.)*

(Received 11 September 2022, Accepted 12 November, 2022)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: *Phytophthora infestans* (Montagne) de Bary, the fungus that causes late blight in potatoes, can practically completely destroy all of the above-ground sections of sensitive cultivars in the presence of favourable environmental factors and in the absence of any preventative measures. Understanding and contrasting the four nonlinear models and empirical model for disease progressive curves of five year data are the main goals of the current study. Data on the progress of the late blight were investigated statistically. The area under the disease progress curve (AUDPC), disease rates, and disease progression curves were estimated. The estimation of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), R-square, MAE, MAPE, RMSE, standard error, and other regression parameters was done. The monomolecular model and the logistic model yielded the lowest standard errors and the highest R-square values. Additionally, the results demonstrated that, for each year, the monomolecular model and the logistic model with the lower AIC and BIC values provided a good fit for the disease progression curve. The area under the disease progression curve was calculated to determine the degree of response to the disease, and the monomolecular model and logistic allow computation of the disease progression rate. 2018 was the lowest prevalence of the *Phytophthora infestans* disease ever observed. A maximum area under the disease progress curve (AUDPC) value was determined in 2021. Breeding programmes targeted at creating varieties with improved resistance to *Phytophthora infestans* may benefit from year or varieties with low disease incidence. Empirical models showed the partial occurrence of the Late Blight Disease Incidence, so, we can conclude that all these model cannot fit for this region. Potato blight forecasting is important to protect the potato yield. If the favourable weather conditions can be forecast and communicated to the growers early with sufficient time for a control sprayed, the crop will be protected.

Keywords: *Phytophthora infestans*, non linear, disease rate, area under the disease progress curve.

INTRODUCTION

An epidemic of disease is the progress of the disease in time and space. An epidemic can be defined as a change in disease (incidence or severity) in a host population over time and space (Kranz, 1974). The fundamental way of depicting a plant disease epidemic is to plot disease level at several times or distances. The plot of disease versus time, the disease progress curve, summarizes the interaction of pathogen, host, and environment in disease development (Van der Plank, 1963; Kranz, 1974). Quantification of disease progress curves, as well as other biological phenomena, is done with the use of mathematical or statistical models. The value of a model is its "potential for bringing out relationships which are not obvious from the data alone" (Pruitt *et al.*, 1979). Although there are many different models that can be used to explain a disease progression curve, the one that is usually used has nonlinear features. The biological/statistical consideration of models and modeling activity is predominate in the field of growth curve analysis (Madden, 1992), a discipline that dates back, philosophically, to the work of Malthus (1986) and, more directly to that of Verhulst (1838); Gompertz (1825). One area of this study, with a much shorter history, focuses on the analysis of plant disease epidemics and their disease progression curves.

Potato is the world's major non-cereal food crop and the fourth largest crop after maize, rice and wheat, with production. India produced over 48 million tones of potato in 2019-20 with West Bengal accounting for 19.41 per cent of the produce. West Bengal, the second largest producer of potatoes in the country, is likely had a bumper crop this year 2020-2021. This state, which produces close to 110-115 lakh tones (2019) of the tuber each year, is estimated produce close to just 90 lakh tones 2020, (Potato PRO 2020) this year. Potato cultivation in Bengal is spread over close to 4.6 lakh hectares of land. Hooghly, Burdwan, Bankura, East Midnapore and west Midnapore are key growing areas.

Potato late blight (PLB) caused by *Phytophthora infestans* (Mont.) de Bary is amongst the most destructive diseases of potato crops , due to its fast reproductive cycle and aggressiveness, It can quickly result in the ultimate destruction of the crop, either in the field or in storage after harvest, if it is not handled. The disease was originally identified in West Bengal's Darjeeling district in 1883. The disease was initially identified in the plains during the Hooghly districts between 1898 and 1900. The disease is still present today in West Bengal's plains. Every year, it takes a mild to moderate form, but on rare instances, it takes a severe form and becomes an epidemic. Estimated yield losses in the plains range from 10 to 75 percent (Dutt, 1979).

Disease prediction models are used to explore the probability of disease outbreaks, providing significant new information for potato growers. This enables farmers to estimate risk, cost and benefit ratios, site selection, selection of propagative material and implementation of a timely disease management plan to protect the crop. Predictive models allow farmers for the pathogen to forecast when the environment is favorable for late blight infection (Morales and Hewitt 2004; Naerstad *et al.,* 2007).

To describe how a disease spreads over time and how the majority of plant diseases change significantly after a specific amount of time, the disease progress curve is measured using statistical models. Models are frequently used to explain temporal disease epidemics and disease progression (Xu, 2006). Progress curve is well-fitted with nonlinear models (Lalancette and Hickey 1986; Contreras *et al.,* 2009) and these models are commonly used to describe temporal disease epidemics (Xu, 2006). One model may match a particular disease better than another based on the nature of the disease progress curves. All models may not fit well to specific diseases, and a given model may not fit to all plant diseases. The best fitted model for potato Late Blight disease can be used to estimate the area under the disease progress curve (AUDPC) and disease progress rate for determining the potato cultivars reaction to the potato Late Blight disease. However, no effort has been reported so far regarding the use of disease progress curve to select the best fitted model for Late Blight disease in potato. Hence, the present study was conducted to identify the goodness of fit of the nonlinear models (exponential, monomolecular, logistic and Gompertz models) and empirical (Beaumont, cook, hyre) to the potato Late Blight disease (*Phytophthora infestans* f.p. potato) disease.

Description of the study area. The experiment was conducted at Agricultural Farm, Pundibari, UBKV, West Bengal (26°39` N Latitude, 89° 39`E Longitude and 50 m amsl) during 2018-2022 crop seasons when there was severe incidence of late blight in the state. Five different date of planting was done for every year. The variety *viz.,* Kufri Jyoti received from Directorate of Farm, UBKV were used for this experiment. The crops are planted in randomized block design with 4 replications and 5 treatments at spacing of 60 cm × 30 cm in a plot size of 3 m × 3m.

Weather parameters were collected from the automatic weather station installed at AMFU, Cooch Behar Centre, UBKV, Pundibari, West Bengal and converted into the required format. Weather parameters (precipitation (mm), maximum temperature (°C), minimum temperature (°C), relative humidity (%), dew point (°C)) will be collected from the automatic weather station installed at AMFU, Cooch Behar Centre, UBKV, Pundibari, West Bengal

The nature of the spread of the disease was studied through visual observation from the initiation of the disease at seven days interval till after first appearance of symptoms. The disease was quantified using disease grading 0-9 scale suggested by McKinney (1923) where, 0 = Healthy Leaf, 1 =<1% area of leaf infected, 3= 1-10% area of leaf infected, 5=11-25% area of leaf infected, 7=26-50% area of leaf infected and 9=90% more than 50% area of leaf infected.

The percent disease intensity (PDI) was calculated as given below (Wheeler, 1969).

$$\mathrm{PDI} = \frac{\text{Total sum of numerical ratings}}{\text{number of leaves observed} \times \text{maximum disease ratings}} \times 100$$

For this purpose, five plants were selected randomly from each plot and observations were taken from late blight infected leaves up to after first appearance of symptoms at every 7 days interval.

1. Fitting disease progress curves using nonlinear models. The Potato Late Blight disease has a polycyclic disease cycle with multiple cycle of infection during the epidemic with populations of pathogens increase in a multiplicative rather than an additive way that allow the lesions data fitted well to nonlinear model (Arneson, 2011; Gilligan, 1985). There are several nonlinear model are used to described the Potato Late Blight disease progress such as exponential model, monomolecular model, logistic model and Gompertz model (Madden *et al.,* 1992). Table 1 described the disease progress curves and estimated model parameters for comparing epidemics.

Curve-fitting using Levenberg Marquardts algorithm. Curve fitting on the disease severity progress curve is done using R software. R package (Moddelr) fits nonlinear models by minimizing the error sum of squares. However, minimizing the residual sum of squares gave normal equations with nonlinear in the parameters which are not possible to solve nonlinear equations exactly. Therefore, the alternative is to obtain approximate analytic solutions by employing iterative procedure such as Levenberg-Marquardts algorithm (LM) Method.

Model selection using information criteria

Akaike's Information Criteria (AIC). The Akaike Information Criterion (AIC), a measure that is widely accepted for measuring the validity within a cohort of nonlinear models and frequently used for model selection (Burnham and Anderson 2003).

The general form for calculating AIC:

$AIC = -2.$ (likelihood) + $2K$

Where, ln is the natural logarithm, (likelihood) is the value of the likelihood and K is the number of parameters in the model.

AIC can also be calculated using residual sums of squares from regression:

$$AIC = n.\ln\left(\frac{RSS}{n}\right) + 2$$

Where n is the total number of observations (data points), and RSS stands for residual sums of squares.

Table 1: Summary of differential and integrated equations for common growth curve models used in plantdisease epidemiology.

Model	**The disease progress model, y**	**The rate of disease progress,** $\frac{dy}{dt}$	Estimated parameter
Exponential	$\frac{dy}{dt} = r * y_0$	$y(t) = y_0 \exp{(r*t)}$	y_0 is the initial disease intensity
Monomolecular	$\frac{dy}{dt} = r * (k - y)$	$y(t) = k - (k - y_0) \exp{(-r*t)}$	
Logistic	$\frac{dy}{dt} = r * y(1 - \frac{y}{k})$	$y(t) = k/(1 + \left(\frac{k}{y_0} - 1\right) \exp{(-r*t)}$	r, k are the rate parameter
Gompertz	$\frac{dy}{dt} = r * y(\ln(k) - \ln(y))$	$y(t) = k * exp(in\left(\frac{y_0}{k}\right) \exp{(-r*t)}$	

Bayesian Information Criterion (BIC): The Bayesian Information Criterion (BIC), which gives a higher penalty on the number of parameters (Schwarz, 1978) is given as follows:

The BIC is based on the residual sum of squares (RSS), which

BIC = n. $\ln(RSS/n) + K.\ln{(n)}$

k is the test's model's number of parameters. The model with the lowest BIC should always be chosen when choosing between various models. The BIC is both an increasing function of k and an increasing function of error variance two. In other words, the value of BIC rises as the number of explanatory variables and unexplained variability in the dependent variable rise. Therefore, a smaller BIC suggests either a better fit, fewer explanatory factors, or both.

2. Disease Rates (r): The progress curves have been used for estimating a rate of late blight. In this study r is the rate inherent in the production and spread of pathogen propagules (Van der Plank, 1963).

3. Area under Disease Progress Curves (AUDPC): The area under disease progress curves (AUDPC) was calculated using all data available. This calculation is the integral over time of the percentage of late blight on potato foliage as exemplified by Grunwald *et al.*, 2001; Campbell and Madden, 1990 and Van der Plank, 1963). The AUDPC has been used extensively in plant pathology research, particularly in the evaluation of crop loss and evaluation of partial or quantitative resistance.

$$\text{AUDPC}=\sum_{i=1}^{n}\left(\frac{y_i - y_{i+1}}{2}\right)(t_i - t)$$

Empirical model for late blight model: Three systems were selected to describe the occurrence of late blight epidemic by combination of weather conditions factors (Percent Disease Incidence). The first system was Beaumont (1947) system, which combines between minimum temperature 20°C and minimum RH 75% for at least 48 hours. The second system was Cook (1947) system (Moving 7-day), which combines between rainfall at least 3 mm and 7-day average daily temperature not less than 23.9°C. The third system was Hyre (1954) system (Moving graph), which combines between average 5-day temperature below 25.5°C, minimum temperature not less than 7.2°C and total rainfall over 10 day at least 3 mm.

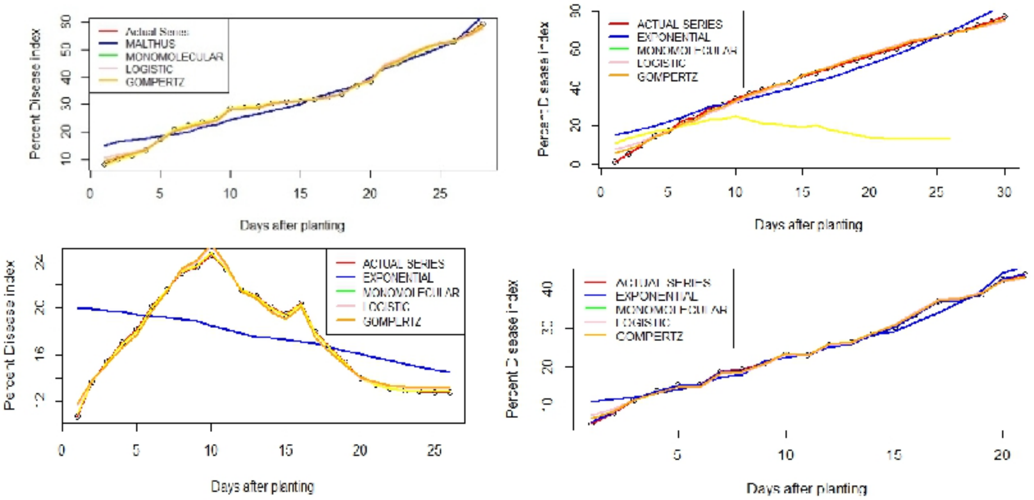

Fig. 1. Disease progress curve for the incidence of *Phytophthora infestans* disease on different years 2019-2022.

RESULTS AND DISCUSSION

Phytopthora infestations are a common and aggressive saprophyte in the soil, according to the disease's progression curve. It caused by the oomycete pathogen *Phytophthora infestans*, which resembles a fungus (Erwin and Ribeiro 1996). It can infect and destroy the leaves, stems, fruits, and tubers of potato and plants (Fehrmann and Dimond 1967). It survives in the soil debris as a mycelium and all spore types, but is most commonly recovered from the soil as chlamydospores. Potato Late Blight (*Phytophthora infestans*) is one of the most important potato leaf and tuber diseases that cause sudden death of plants and causing heavy economic losses. Several potato cultivars widely grown in potato cultivated areas do not possess high level of resistance to potato late blight disease. Contact fungicides will be the backbone of any late blight spray program because they are cost effective.

In the absence of the oospore stage, *P. infestans* survives between potato crops as mycelium in infected tubers or potato fruit. If infected tubers are left behind at harvest or dumped at the edges of fields, sporangia may be produced on the infected tubers or new volunteer sprouts that appear the following spring. Sporangia are transported to healthy potato foliage by air currents. Freshly cut seed tuber surfaces are particularly vulnerable to infections from airborne spores in contaminated storage facilities, which can lead to stem sores that can kill the plant. Local infection may happen if infected seed is planted. The pathogen moves through the tissues of infected tubers, and clonal lineages frequently reproduce asexually (Xu, 2006).

Comparison between non-linear models. Statistical significance of the parameters of the non-linear model was determined by the evaluating the 95% confidence intervals of the estimated parameter. The null hypothesis H_0: (all the parameters = 0) was rejected when 95% confidence intervals of the estimated parameters does not include zero.

Next, the models were diagnosed using error analysis. The error analysis is performed to analyze difference between the error values and the estimated values of observation. This analysis is able to investigate the goodness of fit of the nonlinear models graphically and some of the plots are illustrated in the figures of this chapter Fry (1975).

The scatter plot of the error is important in deciding whether the residual values are uniformly distributed, there is no systematic trend of the residual values or the variance is constant or not. If the error plot showed that the errors have a homogenous variance then the models are adequate to model the data.

Table 2: Parameter estimates of the Logistic, Gompertz, Monomolecular and exponential growth models for late blight of potato data for the year 2018.

Model	Parameter	Estimation	Asymptotic standard Error	95% confidence inter	
				Lower Bound	Upper bound
Exponential	y_0	6.253	0.476	5.336	7.306
	r	0.026	0.001	0.024	0.029
Monomolecular	k	94.239	22.794	89.136	99.953
	y_0	-60.320	19.008	-71.108	-57.746
	r	0.015	0.006	0.003	0.026
Logistic	k	54.772	2.292	50.908	60.994
	y_0	0.850	0.231	0.476	1.473
	r	0.074	0.006	0.062	0.086
Gompertz	k	43.230	6.472	40.299	49.976
	y_0	0.000	0.000	4.588	5.251
	r	0.094	0.116	0.031	0.129

Table 3: Parameter estimates of the Logistic, Gompertz, Monomolecular and Exponential growth models for late blight of potato data for the year 2019.

Model	Parameter	Estimation	Asymptotic standard Error	95% confidence inter	
				Lower Bound	Upper bound
Exponential	y_0	9.947	0.459	9.048	10.910
	r	0.019	0.001	0.018	0.020
Monomolecular	k	186.731	131.489	179.987	190.654
	y_0	-10.545	4.660	-15.62	-9.986
	r	0.004	0.004	0.002	0.143
Logistic	k	64.709	6.332	65.913	71.921
	y_0	5.134	0.867	3.442	7.290
	r	0.041	0.005	0.031	0.052
Gompertz	k	78.462	11.769	61.786	81.296
	y_0	2.524	0.978	1.881	2.950
	r	0.023	0.004	0.014	0.032

Table 4: Parameter estimates of the Logistic, Gompertz, Monomolecular and Exponential growth models for late blight of potato data for the year 2020.

Model	Parameter	Estimation	Asymptotic standard Error	95% confidence inter	
				Lower Bound	Upper bound
Exponential	y_0	5.699	0.412	4.894	6.617
	r	0.030	0.001	0.028	0.032
Monomolecular	k	322.325	787.123	312.466	335.893
	y_0	-37.754	24.189	-41.785	-30.056
	r	0.004	0.010	-0.0034	0.008
Logitic	k	384.000	1098.000	374.663	389.528
	y_0	5.094	1.905	3.990	8.683
	r	0.033	0.011	0.011	0.060
Gompertz	k	131.804	73.685	127.471	139.562
	y_0	0.533	0.900	3.098	6.262
	r	0.024	0.011	0.006	0.0305

Table 5: Parameter estimates of the Logistic, Gompertz, Monomolecular and Exponential growth models for late blight of potato data for the year 2021.

Model	Parameter	Estimation	Asymptotic standard Error	95% confidence inter	
				Lower Bound	Upper bound
Exponential	y_0	7.179	5.068	1.258	2.057
	r	4.610	9.541	0.046	0.053
Monomolecular	k	77.688	5.122	69.200	91.813
	y_0	-10.541	2.266	-15.525	-6.124
	r	0.014	0.001	0.010	0.018
Logistic	k	55.799	1.317	53.363	58.991
	y_0	6.751	0.455	5.843	7.7424
	r	0.050	0.002	0.045	0.055
Gompertz	k	61.497	2.001	57.888	66.438
	y_0	3.617	0.530	2.601	4.801
	r	0.032	0.002	0.028	0.036

Table 6: Parameter estimates of the Logistic, Gompertz, Monomolecular and Exponential growth models for late blight of potato data for the year 2022.

Model	Parameter	Estimation	Asymptotic standard Error	95% confidence interval	
				Lower Bound	Upper bound
Exponential	y_0	5.699	0.412	4.894	6.617
	r	0.030	0.001	0.028	0.032
Monomolecular	k	322.325	787.123	320.484	328.654
	y_0	-37.754	24.189	-41.092	-23.986
	r	0.004	0.010	0.001	0.054
Logistic	k	384.000	1098.000	366.190	389.664
	y_0	5.094	1.905	3.924	7.597
	r	0.033	0.011	0.021	0.069
Gompertz	k	131.804	73.685	127.413	135.607
	y_0	0.533	0.900	0.334	1.436
	r	0.024	0.011	0.002	0.034

Table 7: Fitted R^2 value, Mean absolute percentage error (MAPE), Mean absolute error (MAE), Root Mean Square Error (RMSE) of different models for late blight of potato in the different year.

	Model	R^2	MAPE	MAE	RMSE	AIC	BIC
2018	Exponential	0.9699	0.0367	1.1629	1.3872	79.342	82.476
	Monomolecular	0.9926	0.0192	0.5504	0.6860	51.768	55.946
	Logistic	**0.9942**	**0.0169**	**0.4801**	**0.6069**	**46.621**	**50.800**
	Gompertz	0.6990	0.1795	4.9350	5.9247	142.319	146.497
2019	Exponential	0.9711	0.0548	1.3807	1.6701	118.045	122.147
	Monomolecular	**0.9879**	**0.0274**	**0.8545**	**1.0789**	**94.702**	**100.172**
	Logistic	0.9833	0.0353	1.0350	1.2716	104.236	109.705
	Gompertz	0.9856	0.0315	0.9500	1.1791	99.856	105.325
2020	Exponential	0.9781	0.0374	1.1841	1.3772	80.939	85.117
	Monomolecular	0.9729	0.0352	1.3452	1.5302	85.461	89.639
	Logistic	**0.9782**	**0.0373**	**1.2024**	**1.3740**	**79.037**	**82.171**
	Gompertz	0.9756	0.0356	1.2940	1.4572	83.409	87.588
2021	Exponential	0.5500	7.1765	3.4213	1.8737	18779.750	18783.960
	Monomolecular	**0.9971**	**0.0114**	**0.3656**	**0.4197**	**41.050**	**46.655**
	Logistic	0.9959	0.0135	0.4279	0.4991	51.435	57.040
	Gompertz	0.9966	0.0121	0.3840	0.4537	45.720	51.325
2022	Exponential	0.9755	0.0440	1.2423	1.4778	78.380	81.367
	Monomolecular	**0.9919**	**0.0228**	**0.7215**	**0.8519**	**58.347**	**62.330**
	Logistic	0.9892	0.0283	0.8462	0.9790	63.910	67.893
	Gompertz	0.8285	0.1387	4.0580	4.5272	125.162	129.145

Estimated parameter is significantly contributed to the fitted nonlinear models by validated that 95% confidence interval results showed that almost all of the estimated parameters are significantly contributed to the fitted nonlinear models at 5% significant level.

From the above table it can be concluded that for potato late blight in 5 year data, all the models have given good fit and their R^2 values are more or less approximately similar. R^2 values gives best fit of monomolecular model for 2019, 2021, 2022 and logistic model for 2018 and 2020. From the above table we can say that for potato data, monomolecular model gives the lower AIC and BIC values for 2019, 2021, 2022 followed by Logistic model gives the lower AIC and BIC value for 2014, 2018 and 2020.

It is well known that R^2 is inappropriate when used for demonstrating the performance or validity of a certain nonlinear model. We have supplemented it with other methods such as AIC, BIC, EMS, MAE, MAPE etc. Monomolecular model produces a smaller Mean absolute percentage error (0.0274, 0.0114, 0.0228 in the year of 2019, 2021, 2022) and Logistic model model 0.0169, 0.0373 in the year 2018, 2020). From the above table of RMSE value, we can see that lowest value found for monomolecular model (1.0789, 0.4197, 0.8519 in the year 2019, 2021, 2022) and Logistic model produces smallest value for (0.6069 and 1.3740 in the year 2018, 2020)

In addition, the monomolecular and logistic model was best fitted for the disease progression from the rest of models when tested with the two tests (Akaike Information Criterion and the Bayesian Information Criterion) for each year of the potato late blight.

Disease progress rate of potato Late Blight. Monomolecular and Logistic model was well fitted for the disease progress of each potato Late Blight year and hence, disease progress rate was obtained by regressing the Late Blight incidence overtime after data was fitted to the Monomolecular and Logistic model. For Monomolecular model for the year 2017, 2019, 2021, 2022 the highest disease progress rate was calculated from the year 2022 (Table 8) (Van der Plank, 1963).

Table 8: Disease progress rate of potato Late Blight disease on Monomolecular Model.

Model	year	Disease growth rate	Percent disease growth rate
Monomolecular model	**2019**	0.023	2.263
	2021	0.020	2.017
	2022	**0.032**	**3.168**
Logistic model	**2014**	0.056	5.606
	2018	**0.077**	**7.677**
	2020	0.046	4.616

Area under disease progress curve (AUDPC). The highest AUDPC value was recorded from year 2021 (**1900.682% - day**). However, the lowest value was recorded from the year 2018 (1451.462% - day) (Table 1). This result indicated that the lowest disease epidemic was calculated from the year 2018. This might be due to the fact the year posse a resistance gene (R) to Potato Late Blight disease. Because, once Late blight is established in the area, the use of resistant varieties or management practice is the most effective means to manage this disease (Grunwald *et al.*, 2001).

Table 9: AUDPC of Late Blight disease on Potato in the year 2017-2021.

Year	AUDPC	rAUDPC
2018	**1451.462**	**18.85016**
2019	1888.036	22.21219
2020	1456.485	19.68223
2021	**1900.682**	**25.6849**
2022	1494.304	18.4482

Empirical models for Late Blight of potato. The basic feature of the forecasting method described in this models is that the predictions are made from charts of the temperature, relative humidity and rainfall instead of from field surveys for the presence of the disease or a general impression of the weather. The presence of the disease in fields where the environmental conditions are especially favorable for late blight does not necessarily mean that an epiphytotic is starting, and yet it may be so alarming that general spraying or dusting would be advised

The purpose of the present study was to find the most reliable method of forecasting the disease for northern parts of West Bengal. Three systems were selected to describe the occurrence of late blight epidemic by combination of weather conditions factors (Percent disease Incidence).

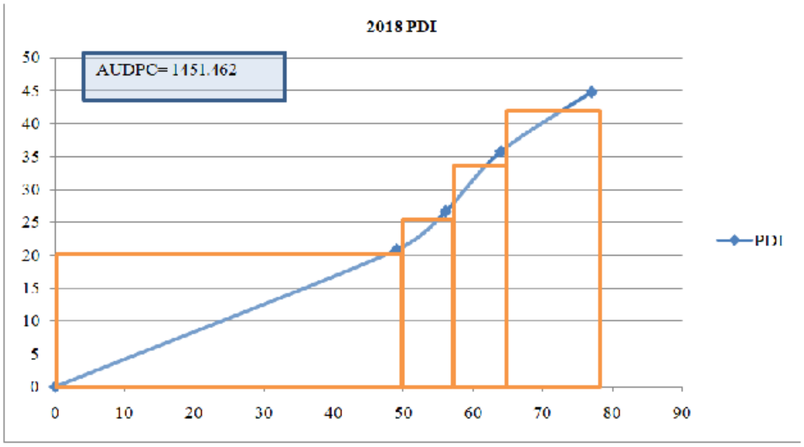

Fig. 2. AUDPC of Late Blight disease on Potato in the year 2018.

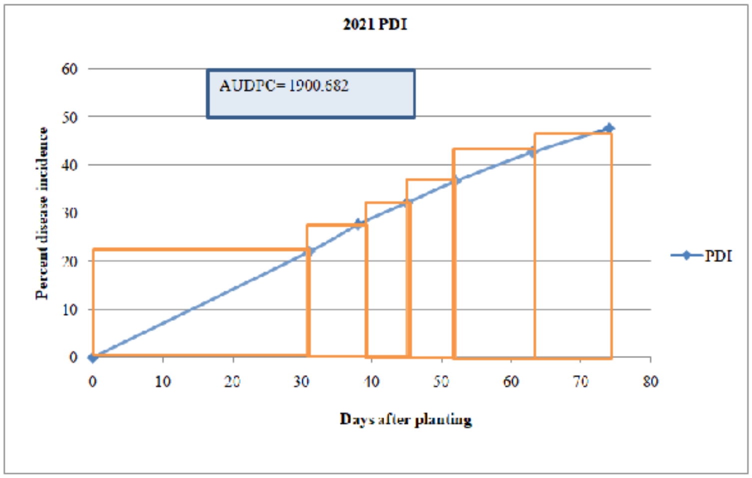

Fig. 3. AUDPC of Late Blight disease on Potato in the year 2021.

Beaumont System. The first system was Beaumont (1947) system, which combines between minimum temperature 10°C and minimum RH 75% for at least 48 hours.

Table 10: Beaumont system of Potato late blight model in the year 2018-2022.

	Beaumont System				
Year	**Observed DAP**	**Predicted DAP**	**R^2**	**Adjusted R^2**	**RMSE**
2018	January 10	January 14	0.747351	0.717628	4.27829
2019	January 11	January 19	0.793275	0.777373	6.95996
2020	January 20	February 5	0.447069	0.385632	6.249096
2021	January 2	January 15	0.07125	0.002454	12.29116
2022	January 25	February 13	0.476006	0.41436	6.639451

Cook system. The second system was Cook (1947) system (Moving 7-day), which combines between rainfall at least 3 mm and 7-day average daily temperature not more than 23.9°C.

Table 11: Cook system of Potato late blight model in the year 2018-2022.

Cook System					
YEAR	**Observed DAP**	**Predicted DAP**	**R^2**	**Adjusted R^2**	**RMSE**
2018	January 10	January 19	0.64181	0.566355	5.094113
2019	January 11	January 15	0.834091	0.821328	6.235129
2020	January 20	February 3	0.703846	0.67094	4.573418
2021	January 2	January 21	0.027594	-0.04285	12.57672
2022	January 25	February 11	0.487841	0.427587	6.564042

HYRE System. The third system was Hyre and Hyre & Bonds's system (Hyre, 1954). This method involved "moving" graphs, as developed by Hyre. An initial outbreak of blight would be forecast by 10 consecutive days favorable for blight and a forecast of continuing blight-favorable weather.

Table 12: Hyre system of Potato late blight model in the year 2018-2022.

HYRE System					
Year	**Observed DAP**	**Predicted DAP**	**R^2**	**Adjusted R^2**	**RMSE**
2018	January 10	January 12	0.710197	0.642313	4.788862
2019	January 11	January 15	0.902035	0.894499	4.791223
2020	January 20	February 3	0.67767	0.641855	4.771253
2021	January 2	January 19	0.000428	-0.07099	12.75118
2022	January 25	February 9	0.436105	0.369765	6.8876

The forecasts are for epiphytotics that affect the whole areas and do not apply to minor or local outbreaks of the disease. Even when most of an area is entirely free of the disease, local outbreaks may occur in individual fields if they are on low land, surrounded by high windbreaks or have been in the path of a succession of local showers.

All these models showed the partial occurrence of the Late Blight Disease Incidence, so, we can conclude that all these model cannot fit for this region.

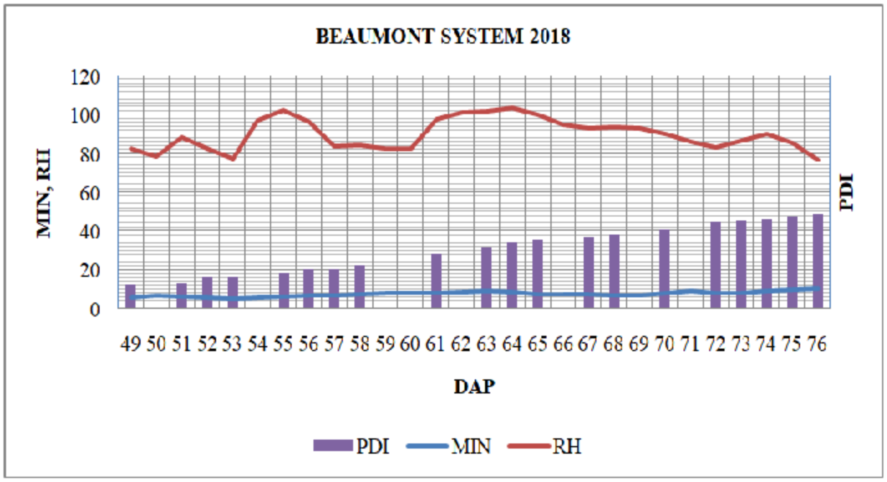

Fig. 4. Beamount system of Late blight model in the year 2018.

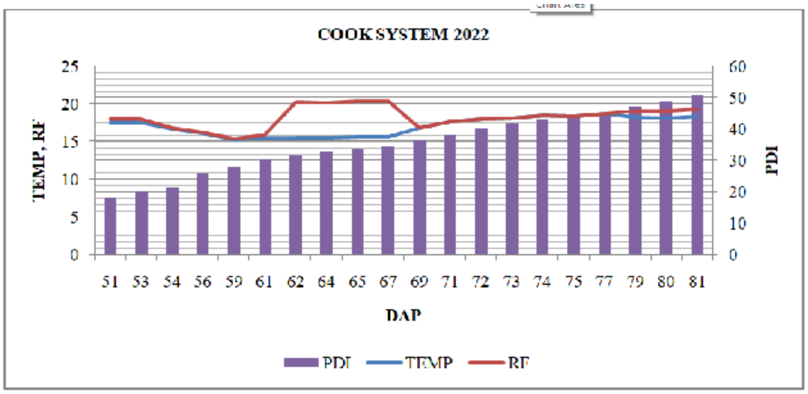

Fig. 5. Cook system of Late blight model in the year 2022.

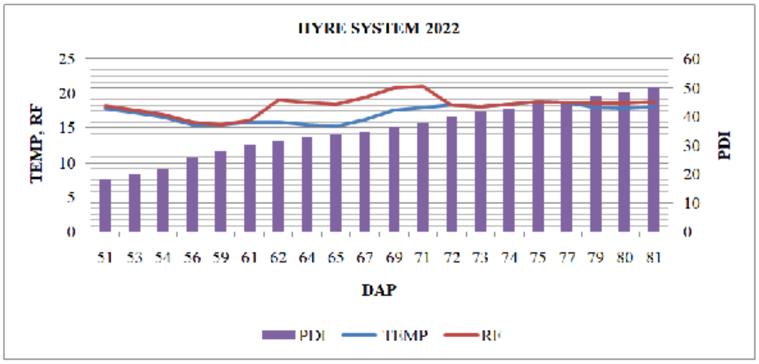

Fig. 6. Hyre and Bond's system of Late blight model in the year 2022.

CONCLUSION

The relatively cool nights during December and January within potato growing area makes a big drop for blight occurrence. There was a big problem in these seasons. With the moving-graph method blight would always have been forecast before it occurred, although in some cases it was first observed quite a while after the first favorable period. Based on the results non linear regression models were the most appropriate for description the disease progress data. Late Blight was expected to appear within 7-10 days after ten consecutive disease incidence by the Beamount, Cook and Hyre & Bond's system.

FUTURE SCOPE

The research being done aims to model the progression of a disease over time in a particular setting. Here, we would propose that comparing the incidence of late blight on several sites or different types of potatoes provides higher precision than comparing it on a single place. The most accurate data are obtained from a weather observatory installed in a field of potatoes.

Acknowledgement. I would like to acknowledge and give my warmest thanks to my chairman, Dr. D.S. Gupta, Professor, Head of the Department, Department of Agricultural Statistics, Faculty of Agriculture, Uttar Banga Krishi Viswavidywlaya, cooch behar, West Bengal, who made this work possible. His guidance and advice carried me through all the stages of writing my project. I would also like to thank my committee members for letting my defense be an enjoyable moment, and for your brilliant comments and suggestions, thanks to you.

REFERENCES

Anderson, R. M. and May, R. M. (1979). Population biology of infectious diseases: Part I. *Nature*, *280*(5721), 361-367.

Burnham, K. P., & Anderson, D. R. (2002). Model selection and multi model inference: a practical information-theoretic approach 2nd edition Springer-Verlag. *New York, New York*.

Beaumont, A. (1947). The dependence on the weather of the dates of outbreak of potato blight epidemics. *Transactions of the British Mycological Society*, *31*(1-2), 45-53.

Contreras-Cornejo, H. A., Macías-Rodríguez, L., Cortés-Penagos, C. and López-Bucio, J. (2009). Trichoderma virens, a plant beneficial fungus, enhances biomass production and promotes lateral root growth through an auxin-dependent mechanism in Arabidopsis. *Plant physiology*, *149*(3), 1579-1592.

Cook, H. T. (1947). Forecasting tomato late blight. *Food Packer*. *Apr*, 69-70.

Campbell, C. L., & Madden, L. V. (1990). *Introduction to plant disease epidemiology*. John Wiley & Sons.

Dutt, B. L. (1979). Bacterial and fungal diseases of potato [in India].

Erwin, D. C. and Ribeiro, O. K. (1996). *Phytophthora* diseases worldwide, St. Paul, Minnesota, *American Phytopathological Society* (APS Press). P. 21.

Fehrmann, H. and Dimond, A. E. (1967). Peroxidase activity and *Phytophthora* resistance in different organs of potato plant. *J. Phytopathol*., *57*, 69-75.

Fry, W. E. (1975). Integrated effects of polygenic resistance and a protective fungicide on development of potato late blight.

Gompertz, B. (1825). XXIV. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. In a letter to Francis Baily, Esq. FRS &c. *Philosophical transactions of the Royal Society of London*, *115*, 513-583.

Gilligan, C. A. (1985). Mathematical modelling of crop disease. In: Gilligan CA (ed) Advances in Plant Pathology, Vol. *3* (p 255) Academic Press, Inc, New York

Grunwald, N. J., Flier, W. G., Sturbaum, A. K., Garay-Serrano, E., van den Bosch, T. B., Smart, C. D. and Fry, W. E. (2001). Population structure of Phytophthora infestans in the Toluca valley region of central Mexico. *Phytopathology*, *91*(9), 882-890.

Hyre, R. A. (1954). Progress in forecasting late blight of potato and tomato. *Plant Disease Reporter*, *38*(4), 245-253.

Kranz, J. (1974). Comparison of epidemics. *Annual Review of Phytopathology*, *12*(1), 355-374.

Lalancette, N. and Hickey, K. D. (1986). An apple powdery mildew model based on plant growth, primary inoculum, and fungicide concentration. *Phytopathology*, *76*(11), 1176-1182.

Madden, L. V. (1992). Rainfall and the dispersal of fungal spores. *Advances in Plant Pathology*, *8*, 39-79.

McKinney, H. (1923). Influence of Soil Temperature and Moisture on infection of Wheat Seedlings by Helmin. *Journal of agricultural research*, *26*, 195.

Morales, M. F. and Hewitt, J. (2004). Toward epoch of reionization measurements with wide-field radio observations. *The Astrophysical Journal*, *615*(1), 7.

Naerstad, R., Hermansen, A. and Bjor, T. (2007). Exploiting host resistance to reduce the use of fungicides to control potato late blight. *Plant Pathology*, *56*(1), 156-166.

Pruitt Jr, B. A. (1979). The burn patient: II. Later care and complications of thermal injury. *Current problems in surgery*, *16*(5), 1-95.

Schwarz, G. (1978). Estimating the dimension of a model. *Ann. Stat.*, 6, pp. 461-464.

Van Everdingen, E. (1926). Het verband tusschen de weersgesteldheid en de aardappelziekte (*Phytophthora infestans*). *Tijdschrift over plantenziekten*, *32*(5), 129-139.

Van der Plank, J. E. (1963). Plant disease: epidemic and control. Academic Press, New York.

Verhulst, P. F. (1838). Notice on the law that the population follows in its growth. *Corresp Math Phys*, *10*, 113-126.

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International journal of remote sensing*, *27*(14), 3025-3033.

Xu, X. (2006). Modelling and interpreting disease progress in time. *In: The epidemiology of plant disease*. Cooke, B.M., Gareth Jones, D. and Kaye, B. (eds) Springer, Dordrecht, The Netherlands, pp. 215 238.

How to cite this article: Vaidheki M., D.S. Gupta, S. Hembram, M.K. Debnath, T.K. Hath and P. Basak (2022). Epidemiological Model for Potato Late Blight in the Northern Part of West Bengal. *Biological Forum – An International Journal*, *14*(4a): 297-306.