Journal of Agrometeorology 17 (1) : 43-50 (June 2015)

Dependence of the weather on outbreak of cucumber downy mildew (*Pseudoperonospora cubensis*) in eastern India

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ABSTRACT

The present study critically examined the influence of weather parameters on the initiation and spread of the cucumber (*Cucumis sativus*) downy mildew disease and developed a suitable weather based disease forewarning models. The field experiment was laid out in the farm of Bidhan Chandra Krishi Viswavidyalaya, Kalyani, West Bengal during 2008-2011. Cucumber crops were sown during 33 times throughout the entire span of four years covering all the growing seasons of the years. High humidity (RH>94%) and average temperature (24-30^{0}C) along with leaf wetness not less than 8 hrs was found to trigger the initiation of downy mildew disease of cucumber. A model was produced using logistic regression analysis and cumulative value of night leaf wetness duration, average night temperature, night relative humidity (RH) and number of night hours having RH>95% from sowing time were a significant disease predictor. Among the weather parameters daily mean temperature during growth period had maximum degree of association (r = -0.50) with percent disease intensity (PDI). Disease progress curves were presented using logistic and Gompertz model. Weather based prediction model has been developed with different weather indices and disease severity using weekly average value and cumulative value from date of sowing. Cumulative values of weather variables could explain 95% variance of disease intensity, whereas average values of weather variable could explain only 33 % variance of disease intensity. These results will improve the timing and application of the fungicide spray for the control of cucurbit downy mildew.

Key word: Downy mildew, cucumber, logistic regression, forewarning model, PDI

Among the diseases that affect cucurbitaceous crops, downy mildew caused by the oomycete *Pseudoperonospora cubensis* is economically the most damaging (Lebeda and Cohen, 2011). Several cucurbit host types are infected by *P. cubensis*, of which cucumber (*Cucumis sativus*) is more susceptible to downy mildew than other cucurbits (Ojiambo *et al.,* 2010). The disease has a worldwide distribution and occurs wherever cucurbits are cultivated in temperate and tropical areas and in the semiarid areas in the Middle East. In these production regions, the disease is especially damaging in areas with warm and humid conditions which are conducive for disease development (Thomas, 1996).

The disease is an outcome of interaction among host, pathogen, and weather over a period of time. Disease forewarning will help in reducing excessive use of chemical pesticides, thus reduce the cost of cultivation as well as environment hazard. Monitoring the occurrence and movement of the pathogen enables the prediction of disease outbreaks in specific areas and the application of suitable control measures prior to infection (Holmes *et al.* 2004; Ojiambo *et al.*, 2009; Zhao *et al.* 2007).

The *P. cubensis* fungus is highly weather-sensitive. During periods of cool, wet, and overcast weather the disease can develop in greenhouses and/or fields and spread rapidly because of the polycyclic nature of the fungal pathogen. On the other hand when the weather becomes clear, dry, and hot, the epidemic usually slows considerably or stops completely. Hembram *et al.* (2014) recorded significant lower sporulation of *P. cubensis* during April-May period due to hot dry climate during that period. Two weather parameters temperature and leaf wetness greatly influenced the degree of infection of cucurbits downy mildew. Leaf wetness influenced the sporangia germination and allows for infection to occur, while temperature determines the extent of disease development (Arauz *et al.*, 2010).

Over recent years many epidemiological models and warning systems have been proposed for identifying the periods when conditions are favourable for disease development, and for scheduling fungicide applications (Madden *et al.*, 2000; Gobbin *et al.*, 2005). The advent of efficient data loggers, establishment of extensive networks of weather stations and development of new statistical tools has allowed for the development of next generation forecasting models. Many of these models have used nonparametric methods such as logistic regression to effectively predict the disease development. Most of these models are based on weather variables and do not require extensive sampling procedures, which makes them very attractive to the growers. Already forewarning system has been successful in an integrated programme for management of foliar diseases of carrot (Bounds *et al.*, 2006), reducing fungicide use by about 30% with no loss in carrot yield or quality. Similarly, use of a weather based forecasting model Tomcast prompted a 60% reduction in number of chlorothalonil sprays for purple spot of asparagus while maintaining quality and yield (Meyer *et al.*, 2000).

West Bengal state in India produces highest quantity of vegetables. Also high humidity of the region creates a conducive weather for disease development of the region. The annual losses from cucurbits downy mildew diseases have not been estimated in West Bengal but are believed to be substantial. High level of variability of Pathogen along with weather sensitivity and frequent climate change aggravate the downy mildew disease situation. Besides exploitation of genetic resistance, weather based disease forewarning system and need based application of selective fungicide at right time is the best management strategy, farmers can adopt for effective management of the disease. Hence, the present investigation was carried out to develop a disease forecasting model of cucumber downy mildew disease based on logistic regression using weather variables and to predict the spread of the disease using weather variables for West Bengal.

MATERIALS AND METHODS

Site of experiments

The field experiments were carried out at Research Farm of Bidhan Chandra Krishi Viswavidyalaya (BCKV) at Kalyani, Nadia, West Bengal (22.9^{0}N latitude, 89^{0}E longitude with an elevation of 9.75 meter above the mean sea level). The climate of the site is subtropical humid type and receives an average annual rainfall of 1480 mm and experiences mean annual minimum and maximum temperatures of 12.5 and 36.2°C, respectively. Mean weekly meteorological parameters recorded during 2008-2011 at BCKV meteorological observatory are presented in Fig. 1. The experiment site was under new alluvial zone of Indo-Gangetic plain, sandy loam in texture with low in soil organic carbon and available nitrogen. The seeds of cucumber were sown on 33 different dates in three different seasons Autumn-Winter (September-January); Spring-Summer (February-April); Summer-Rainy season (May-August) during 2008 to 2011 (Table 1).

Raising of the crop

To conduct the experiment, the field was prepared by deep ploughing and prepared into a fine tilth before seed sowing. Seeds of popular local cucumber variety 'Maa Tara' were sown in the plots of 5 m x 2 m in size following pit sowing with 100 cm x 50 cm spacing with three replications. The recommended dose of fertilizers @ 80: 40: 40 (N: P_2O_5: K_2O) kg ha^{-1} and FYM 15-20 t ha^{-1} were applied. N, P and K were supplied through urea, single super phosphate and muriate of potash, respectively. Half of the nitrogen was applied at the time of sowing as basal dose and the rest half was equally split at vine development stage and at flower initiation stage. The full doses of both phosphorus and potassium were given at the time of final land preparation. Hand weeding and irrigations were provided as required and usual crop husbandry measures were undertaken.

Recording of data

Regular monitoring for the date of disease onset and subsequent symptom development of downy mildew was recorded during early morning. Once the initial downy mildew symptoms were observed on the plant in the field, the lesion colour changed from light yellow to dark yellow to light brown to dark brown/necrotic with the progress of the disease. The nature of the spread of the disease was studied through visual observation from the initiation of the disease at seven days interval till final harvest or death of the plant. The disease was quantified using disease grading 0-9 scale (Yangn *et al.*, 2007) where, 0 = Healthy Leaf, 1 = 1%- 5%, 3 = 6%- 10%, 5 = 11%- 25%, 7 = 26%-55%, and 9 = 56% - 100% of infected leaf.

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

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

For this purpose, five plants were selected randomly from each plot and observations were taken from downy mildew infected leaves.

Recording of standard weather data

Since 2008 a complete automatic weather station has been deployed just beside the experimental field for measurement of air temperature (°C) relative humidity (RH) (%), and leaf wetness (0/1, leaf wetness 0 = no, 1 = yes). Leaf wetness sensor was installed at the top of the experimental field at 0.3 m above the ground deployed with an angle of 45° to horizontal and facing southwest (model 237, Campbell Sci., Logan, UT). All the sensors were connected to a data logger (Delta-T devices DL2, Burwell, Cambridge, UK) and data were recorded every 10 minutes. The weather data was presented with two temporal scales 6 a.m. to 6 p.m. as day and 6 p.m. to 6 a.m. as night. Daily rainfall (mm) and bright sunshine hour was recorded another meteorological observatory installed 500 m away from the experiment site. The weather parameters used in the study were average daily temperature ($T_{average}$) (°C), Average day temperature (T_{day}) (°C), average night temperature (T_{night}) (°C), daily maximum temperature (T_{max}) (°C), daily minimum temperature (T_{min}) (°C), average day relative humidity (RH_{day}) (%), average night relative humidity (RH_{night}) (%), number of day hours having RH> 95% ($RH_{dayhr95}$), number of night hour having RH >95% ($RH_{nighthr95}$), day leaf wetness duration (LWD_{day}) (hour), night leaf wetness duration (LWD_{night}) (hours), bright sun shine hour (SSH) and rainfall. The growing degree day (GDD) was calculated by subtracting base temperature (10°C) from average daily temperature. Heliotermal unit (HTU) was derived by multiplying GDD with bright sunshine hours. Cumulative value of weather parameters were calculated by adding everyday value since the date of sowing.

Model development

First student's t- test was run to compare the means of two independent populations viz. population with no disease and population with disease for all meteorological characters under study, may be responsible for disease initiation. Logistic equation was derived to identify indicator variabes responsible for disease initiation. Binary logistic regression was used to create a dichotomous model that would predict either the presence (= 1) or absence (= 0) of downy mildew disease. Logistic regression was chosen due to the fact that logistic regression does not assume that multivariate observations are distributed normally (Johnson, 1998). The logistic regression formulas are stated in terms of the probability (P) of occurrence of disease and can be written as

$$\ln\left(\frac{P}{1 - P}\right) = \beta_o + \beta_1 X$$

The 'ln' symbol refers to a natural logarithm and β_o and β_1 are constant and X is explanatory variables, in this case any weather parameter. The probability of occurrence of disease 'P' can be computed theoretically and the expected probability (P) of disease for a given value of X is

$$P = \frac{\exp(\beta_o + \beta_1 X)}{1 + \exp(\beta_o + \beta_1 X)}$$

If there are multiple explanatory variables, then the above expression $\beta o+\beta_1 X$ can be revised $\beta_o+\beta_1 X_1 +\beta_2 X_2+\ldots\beta_m X_m$ where βo and $\beta_1,\beta_2\ldots\beta_m$ are constant and X_1, X_2, ... X_m are different explanatory variables and in present study it is different weather parameters. Linear multiple regression equation was developed for prediction of intensity of disease (PDI) with different weather variables. Logistic and multiple regressions were carried out using SPSS software (SPSS, 2006).

Plant disease progress with time was expressed using following logistic and Gompertz equation (Berger, 1981):

$$Y = 1/(1 + b \times \exp(-rt))$$

Where Y = disease proportion in the range 0<Y<1, r = rate parameter also called apparent infection rate, and t time (days after sowing, DAS) and b = constant. Similarly Gompertz disease progress model was expressed as $Y = \exp(-b \times \exp(-kt))$. The k parameter of Gompertz model is the rate parameter, which corresponds to the apparent infection rate (r) of the logistic equation. The nonlinear equation was solved in Statistica software (Statistica, 1993).

RESULTS AND DISCUSSIONS

Disease initiation

Downy mildew disease appeared in all three growing seasons spread over 33 different sowing dates and disease started as early as second week of September for autumn-winter crop and second week of February in case of spring –summer crop and fourth week of May in case of summer-rainy season crop. Four years data (2008-2011) indicated that more time required for initiation of disease in case of spring-summer season crops (February-April) (average 33 days after sowing (DAS) in compare to autumn-winter season crop (September-January) (Average 16 DAS) and summery-rainy season (May-August) (average 28 DAS)

Table 1: Date of sowing of cucumber during 2008-2011 for downy mildew disease study.

2008	2009	2010	2011
12th September	10th March	14th March	1st January
22nd September	17th September	17th April	18th January
2nd October	27th September	19th May	31st January
12th October	7th October	19th June	17th February
22nd October	17th October	19th July	
2nd November	27th October	19th August	
12th November	6th November	17th September	
7th December	16th November	17th October	
	10th December	1st November	
		17th November	
		2nd December	
		17th December	

(Fig. 2). Disease appeared in all 33 times of sowing indicated that inoculums were present every season. On an average it took 20 days time after sowing for incidence of downy mildew disease and in all three seasons of sowing for entire four years of experiment. The downy mildew disease appeared minimum time of 9 days when it was sown in the month of January whereas it took maximum time of 41 days when it was sown during March.

The weekly average weather value during disease initiation indicated that high night relative humidity (> 93%) more than 8 hours night leaf wetness duration and night relative humidity and slightly lower temperature trigger the initiation of downy mildew disease of cucumber (Table 2). Student's t-test for comparing two independent populations viz. with no disease and with disease for weather parameters indicated that temperature related parameters like average night temperature, minimum temperature, average day temperature, daily mean temperature, growing degree days value were statistically significant at $p<0.05$. There was very high relative humidity (>93%) throughout the growing season in the study region. Along with high RH when the temperature dropped by 1-2°C, the weather was conducive for downy mildew in the region. The importance of temperature and leaf wetness for degree of infection of cucurbits downy mildew was also mentioned by Neufeld and Ojiambo (2012). Leaf wetness influences the sporangia germination and allows for infection to occur, while temperature determines the extent of disease development.

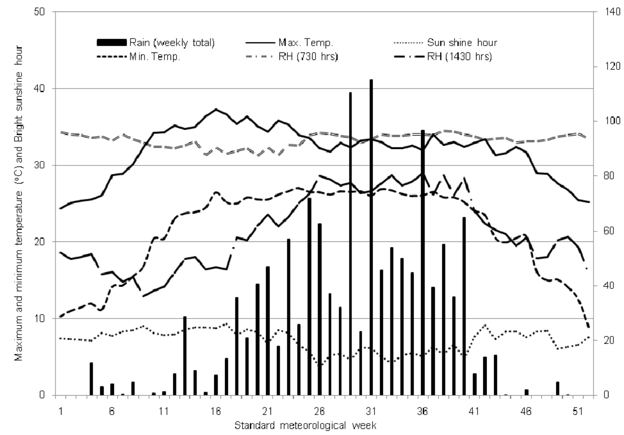

Fig. 1: Weekly average weather parameters at experiment site during 2008-2011

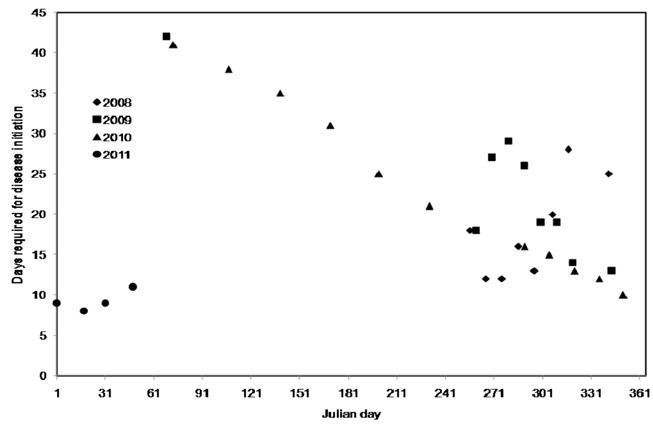

Fig. 2: Effect of date of sowing on cucumber downy mildew disease initiation during 2008-2011

Logistic regression model for disease initiation

To find out the key variable(s) responsible for disease initiation considering categorical value '0' to express non-occurrence of disease and '1' to express occurrence of disease was fitted with weekly average value of all weather parameters as independent variables. But none of the weather parameter gave reasonably good coefficient of determinant as expressed by Nagelkerke R^2 (<0.05). Then binary logistic regression was run using cumulative value of weather parameters and three weather parameters i.e., LWD_{night}, $RH_{nighthr95}$ and RH_{night} recorded Nagelkerke $R^2 > 0.3$ (Table 3). A predicted probability curve was produced for LWD_{night}, $RH_{nighthr95}$ and RH_{night} using logistic regression formula for each weather parameters (Fig. 3). It was estimated that probability of disease initiation >0.5 when the cumulative LWD_{night} was 250 hours, and cumulative $RH_{nighthr95}$ was 265 hours where as for RH_{night} it was 2950. Also logistic regression was run using different combination of weather parameters

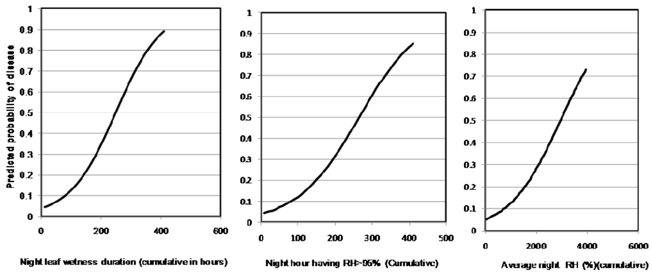

Fig. 3: Predicted probability of cucumber downy mildew for defferent weather parameter estimated through logistic regression equation.

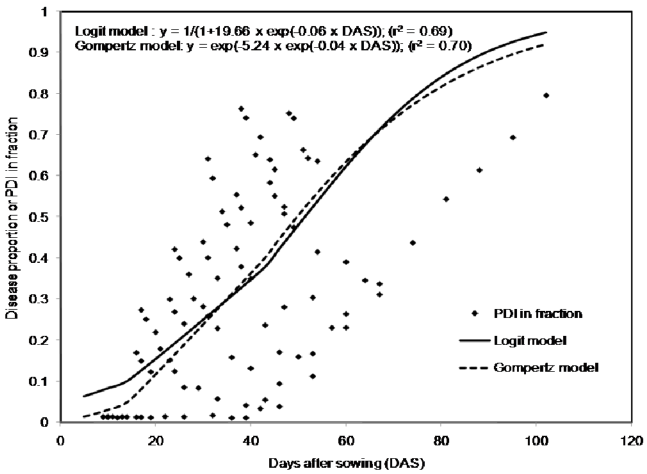

Fig. 4: Observed PDI along with disease progress curve estimated using Logit and Gompertz model

as covariates and highest R^2 (Nagelkerke $R^2 = 0.469$) was recorded when cumulative LWD_{night}, cumulative RH_{night} and cumulative T_{night} was taken together as dependent variables. The binary logistic model with LWD_{night}, RH_{night} and T_{night} had 45.5% sensitivity, 93.3% specificity. The positive likelihood ratio (LR+), which means accurately predicting disease occurrence and is calculated as the ratio between the sensitivity and 1 - specificity (Yuen and Mila, 2004) was 6.79. The negative likelihood ratio (LR–), which means erroneously predicting disease occurrence and is calculated as the ratio between 1 - sensitivity and specificity, was 0.58. Models are considered to have good predictive capabilities when LR+ is >1 and LR– is <1 (Biggerstaff, 2000). These results indicate that in-season weather variables could be used to predict downy mildew incidence of cucumber. Similar type of disease forecasting model was also developed using logistic regression analysis for predicting risk of white mold incidence on dry bean in north Dakota using weather variables like rainfall, average minimum temperature and number of rainy days as predictors (Harikrishnan and del

Table 2: Weekly weather parameters during 2008-2011 in West Bengal at the time of cucumber downy mildew disease initiation in three growing seasons

Weather parameters	Autumn-winter (Sep.-Jan.)	(Feb.-April)	Spring-Summer (May-Aug)		Summer-rainy season		Pooled data	
	Disease	No disease	Disease	No disease	Disease	No disease	Disease	No disease
Day temperature (ºC) (T_{day})	25.8	27.1	31.6	31.5	30.3	30.7	26.9	28.5
Night temperature(ºC) (T_{night})	19.9	21.8	24.5	25.2	26.9	27.2	21.2	23.4
Day relative humidity (RH) (%) (RH_{day})	75.5	79.5	60.7	63.1	91.5	89.3	76.1	78.9
Night relative humidity (%) (RH_{night})	99.0	99.0	94.1	92.7	99.0	99.0	99.0	99.0
Day leaf wetness duration (hour) (LWD_{day})	3.0	3.1	2.0	2.7	3.2	3.2	2.9	3.0
Night leaf wetness duration (hour) (LWD_{night})	11.6	11.5	8.3	8.6	11.1	11.4	11.3	10.8
Number of day hours having RH>95% ($RH_{dayhr95}$)	3.2	3.7	1.6	1.9	5.4	4.9	3.3	3.7
Number of night hour having RH>95% ($RH_{nighthr95}$)	11.3	11.7	7.9	7.2	11.7	10.5	11.1	10.8
Maximum temperature (T_{max}) (ºC)	29.9	30.9	35.5	35.3	34.1	34.1	30.9	32.2
Minimum temperature (T_{min}) (ºC)	18.4	20.4	22.4	22.8	26.6	26.4	19.8	21.9
Mean temperature ($T_{average}$) (ºC)	24.2	25.7	28.9	29.0	30.3	30.3	25.4	27.1
Growing degree days (ºC)	14.2	15.7	18.9	19.0	20.3	20.3	15.4	17.1
Bright sunshine hour	7.4	7.0	9.2	8.5	5.2	6.1	7.3	7.1
Heliothermal unit	103.4	109.6	172.7	162.9	105.9	125.7	110.0	120.9
Weekly total rain (mm)	21.0	15.5	0.1	4.3	17.4	32.3	18.7	17.0

Table 3: Logistic regression model summary for cucumber downy mildew disease initiation (LWD_{night} = Night leaf wetness duration (hours), $RH_{nighthr95}$ = Number of night hours having RH>95%, RH_{night} = Night relative humidity (%), T_{night} = night temperature (°C); C in equation indicates cumulative value of the weather parameter from date of sowing)

Weather parameter	Logistic regression equation; expected probability of disease (P)	Nagelkerke R^2
$CLWD_{night}$	$P = \frac{\exp(0.013CLWD_{night} - 3.23)}{1 + \exp(0.013CLWD_{night} - 3.23)}$	0.332
$CRH_{nighthr95}$	$P = \frac{\exp(0.012CRH_{nighthr95} - 3.17)}{1 + \exp(0.012CRH_{nighthr95} - 3.17)}$	0.332
CRH_{night}	$P = \frac{\exp(0.001CRH_{night} - 2.95)}{1 + \exp(0.001CRH_{night} - 2.95)}$	0.301
CT_{night}, $CLWD_{night}$, CRH_{night}	$P = \frac{\exp(0.018CLWD_{night} + 0.003CRH_{night} - 0.013CCT_{night} - 4.23)}{1 + \exp(0.018CLWD_{night} + 0.003CRH_{night} - 0.013C\,CT_{night} - 4.23)}$	0.469

Classification table between observed and predicted cucumber downy mildew disease initiation using logistic regression model taken T_{night}, LWD_{night}, RH_{night} as covariates

Predicted	Observed		Total
	Diseased	Not diseased	
Diseased	15	7	22
Not diseased	18	97	115
Total	33	104	137

True positive fraction = 15/33 =0.455, represents the model's sensitivity,

True negative fraction = 97/104 = 0.933 represents the model's specificity,

The positive likelihood ratio (LR+) = sensitivity/(1-specificity) = 6.79,

The negative likelihood ratio (LR-) = (1- sensitivity)/ specificity =0.584

Rio, 2008). In our study along with night temperature, and humidity, leaf wetness duration (LWD) has a strong relationship with the development and outbreak of plant diseases because many important pathogens require a layer of free water to move on the surface of plant organs and start their infective processes. The main problem in using LWD is that it is not widely measured parameter and not considered a true agrometeorological variable. We also derived a relationship between night hour having RH>95% ($RH_{nighthr95}$) and night leaf wetness duration (LWD_{night}) (LWD_{night} = 0.66RHnighthr95 + 3.82; r^2 = 0.492) so that the binary model could be used more flexible way. Sentelhas *et al.*, (2008) also used RH>90% for estimating LWD. When the logistic regression was run using cumulative value of T_{night}, $RH_{nighthr95}$ and RH_{night} the coefficient of determinant produced as Nagelkerke R^2 = 0.449.

Downy mildew disease spread and its relationship with weather variables

Successive values of PDI from initiation of downy mildew disease of cucumber until harvest showed that the values of PDI increased linearly up to harvest. Dynamics of downy mildew progress (PDI in fraction) curves were presented through logistic and Gompertz equations. The PDI value of 2008 and 2009 PDI with days after sowing (DAS) was used for generating coefficients of the model and the PDI of 2010 and 2011 were used for validation (Fig. 4). Though none of the model fitted well, the Gompertz model represented slightly better the disease progress than Logit model as was seen lower residual sum of square, lower Standard error and higher R^2 in case of Gompertz model than Logit model. The downy mildew disease progress curves are

Table 4: Pearson's correlation coefficient between percent disease intensity (PDI) and weekly average weather parameters

Weather parameter	PDI
T_{day}	-0.41**
T_{night}	-0.42**
RH_{day}	-0.15*
RH_{night}	0.12
LWD_{day}	0.02
LWD_{night}	0.05
$RH_{dayhr95}$	-0.09
$RH_{nighthr95}$	0.11
T_{max}	-0.49**
T_{min}	-0.49**
$T_{average}$	-0.50**
GDD	-0.50**
SSH	-0.03
HTU	-0.40**
Rain	-0.26**

** Correlation is significant at the 0.01 level (2-tailed), *correlation is significant at the 0.05 level (2-tailed).

characterized by steep slopes when disease proportion (Y) < 0.2, linearization for the range 0.2<Y<0.7 and values that fall below the general slope when Y> 0.7. Ojiambo *et al*. (2003) also noted that disease progress curves of *Alternaria sesame* of sesame were better described using the Gompertz rather than the logit model.

Relationship between advancement of downy mildew disease of cucumber (PDI) and various weather indices were summarized in the form of Pearson's correlation coefficient and presented in Table 4. PDI was positively correlated with humidity related weather parameters like, RH_{night}, LWD_{day}, LWD_{night}, $RH_{nighthr95}$ and negatively correlated with temperature related weather parameters like T_{day}, T_{night}, T_{max}, T_{min}, $T_{average}$, GDD, SSH and HTU. The results showed that temperature related weather variables contributed more towards intensification of downy mildew disease as compared to humidity and wetness related variables. Rainfall also negatively correlated with downy mildew disease severity.

Multiple linear regression equations were developed for fitting the progressive increase of PDI as a function of various weather parameters. It was observed that combined weekly weather variables pertaining to various growth stages of cucumber could explain only up to 33% of the variability of the disease intensity. Multiple regressions were also run with cumulative weather parameters from date of sowing. Accumulated values of weather variables could explain 95% variance of disease intensity. The multiple regression equation is

$$PDI = 0.03CT_{day} - 0.01CT_{night} + 0.03CRH_{day}^{**} - 0.02CRH_{night}^{**} - 0.07CLWD_{day} - 0.01CLWD_{night}^{**} - 0.12CRH_{dayhr95}^{**} + 0.01CRH_{nighthr95}^{**} + 0.21CT_{max}^{**} + 0.09CT_{min} - 0.39CGDD^{**} - 0.14CSSH^{**} + 0.03CRain + 4.99$$

($R^2 = 0.955$; Standard error = 6.48; ** parameters significant at the 0.01 level (2-tailed); C in equation indicates cumulative value of the weather parameter from date of sowing).

As in many weather-based prediction systems, the accuracy of any model will greatly depend on the availability, resolution, and reliability of the weather data. Thus, the use of this predictive model could help growers with informed decision- making about fungicide spraying and likely reduce the number of unwarranted fungicide applications.

CONCLUSION

Outbreaks of cucumber downy mildew cased by *Pseudoperonospora cubensis* are depends on the weather. Quantitative analysis of cucumber downy mildew disease intensity were successfully constructed using large number of weather variables. The parameters like night leaf wetness duration, average night temperature, night relative humidity and number of night hours having RH>95% from sowing time were key weather parameters for predicting disease initiation. It is important to note that, presently, no advisory system is available to determine the risk of the disease development during the growing season. Such a system is useful to guide within–season fungicide application after initial infection and should improve fungicide efficiency compared with the current calendar-based application schedule.

ACKNOWLEDGEMENT

The first author is grateful to Bidhan Chandra Krishi Viswavidyalaya, Kalyani, West Bengal for providing fellowship as well as all the facilities to run this experiment during his Ph.D. programme.

REFERENCES

Arauz, L.F., Neufeld, K.N., Lloyd. A.L. and Ojiambo, P.S. (2010). Quantitative models for germination and infection of *Pseudoperonospora cubensis* in response ot temperature and duriation of leaf wetness.

Phytopathology, 100: 959-967.

Berger, R. D. (1981). Comparison of the Gompertz and logistic equation to describe plant disease progress. *Phytopathology,* 71: 716-719.

Biggerstaff, B. J. (2000). Comparing diagnostic tests: A simple graphic using likelihood ratios. Stat. *Med J.* van Boekel, S., Stein, A. and van Bruggen, A.H.C. eds. Wageningen UR Frontis Series, Wageningen, The Netherlands.

Bounds, R.S., Hausbeck, M.K. and Podolsky, R.H. (2006). Comparing disease forecasters for timing fungicide sprays to control foliar blight on carrot. *Plant Dis.,* 90: 264–268.

Gobbin, D., Jermini, M., Loskill, B., Pertot, I., Raynal, M. and Gessler, C. (2005). Importance of secondary inoculum of *Plasmopara viticola* to epidemics of grapevine downy mildew. *Plant Pathology*, 54: 522–534.

Harikrishnan, R. and del Rio, L.E. (2008). A logistic regression model for predicting risk of white mold incidence on dry bean in North Dakota. *Plant Dis.*, 92(1): 42-46.

Hembram, S., Dutta, S., Bhattacharya, I., Saha, A. and Majumder, D. (2014). Influence of weather variables on morphological structures of *Pseudoperonospora cubensis* in cucumber. *J. Agrometeorol.*, 16(2): 219-221.

Holmes, G.J., Main, C.E., and Keever, Z.T., III. (2004). Cucurbit downy mildew: a unique pathosystem for disease forecasting. In P.T.N. Spencer-Phillips & M. Jeger (Eds.), Advances in downy mildew research, vol. 2 (pp. 69–80). Dordrecht: Kluwer Academic Publishers.

Johnson, D.E. (1998). Applied Multivariate Methods for Data Analysts. Duxbury Press, Pacific Grove, CA.

Lebeda, A. and Cohen, Y. (2011). Cucurbit downy mildew (*Pseudoperonospora cubensis*)—biology, ecology, epidemiology, host-pathogen interaction and control. *European J. Plant Pathol.,* 129: 157-192.

Madden, L.V., Ellis, M.A., Lalancette, N., Hughes, G. and Wilson, L.L. (2000). Evaluation of a disease warning system for downy mildew of grapes. *Plant Dis.,* 84: 549–554.

Meyer, M.P., Hausbeck, M.K. and Podolsky, R. (2000). Optimal fungicide management of purple spot of asparagus and impact on yield. *Plant Dis.,* 84: 525–530.

Neufeld, K.N. and Ojiambo, P.S. (2012). Interactive effects of temperature and leaf wetness duration on sporangia germination and infection of cucurbit hosts by *Pseudoperonospora cubensis. Plant Dis.,* 96 (8): 345-353.

Ojiambo, P.S., Paul, P.A., and Holmes, G.J. (2010). A quantitative review of fungicide efficacy for managing downy mildew in cucurbits. *Phytopathology,* 100:1066-1076.

Ojiambo, P., Kanetis, L. and Holmes, G. (2009). Forecasting long distance movement of *Pseudoperonospora cubensis* and the Cucurbit ipmPIPE. *Phytopathology*, 99: S171.

Ojiambo, P.S. Mibey, R.K. Narla, R.D. and Ayiecho, P.O. (2003). Field transmission efficiency of Alternaria sesami in sesame from infected seed. *Crop Protection,* 22: 1107-1115.

Sentelhas, P.C., Dalla Marta, A., Orlandini, S., Santos, E.A., Gilespie, T.J. and Gleason, M.L. (2008). Suitability of relative humidity as an estimator of leaf wetness duration. *Agril. Forest Meteorol.,* 148: 392-400.

SPSS (2006). SPSS 15.0 Command Syntax Reference 2006, SPSS Inc., Chicago.

Statistica (1993). Statistica for Windows 4.5. StatSoft, Inc.

Thomas, C. E. (1996). Downy mildew. In T.A. Zitter, D.L. Hopkins, & C.E. Thomas (Eds.), Compendium of cucurbit diseases (pp. 25–27). American Phytopathological Society Press, St. Paul, MN.

Wheeler, B.E.J. (1969). An Introduction to Plant Disease, pp 172–7. John Wiley, London. p 301.

Yangn, X.L.I. M., Zhao, C., Zhang, Z. and Hou, Y. (2007). Early warning model for cucumber downy mildew in unheated greenhouse. *New Zealand J. Agric. Res.,* 50: 1261-1268.

Yuen, J. and Mila, A. (2004). Are Bayesian approaches useful in plant pathology? Pages 95-103 in: Bayesian Statistics and Quality Modeling in the Agro-Food Production Chain, Vol. 3. M. A. epidemic system as a basis for cucumber downy mildew warning in greenhouse. Progress of Information Technology in Agriculture, pp. 527–532.

Zhao, C.J., Li, M., Han, X., Zhang, Z., & Wang, Y. (2007). Analysis and monitoring for epidemic system as a basis for cucumber downy mildew warning in greenhouse. Progress of Information Technology in Agriculture, pp. 527–532.

Received : June 2014 ; Accepted : March 2015