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Determination of critical weather parameters for the development of downy mildew disease of cucumber in the Terai region of West Bengal

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Cucumber downy mildew disease, caused by *Pseudoperonospora cubensis,* poses a serious threat to its cultivation in Terai region of West Bengal, India. The course and severity of this disease appear to be influenced by some weather parameters. The current study was conducted on farmers' fields of Pundibari, CoochBehar (Terai region), West Bengal, during 2022 - 24 cropping seasons. For both seasons, a total of twenty observations on PDI of the disease were recorded as well as the area under the disease progress curve (AUDPC) and rate of spread (ROS) of the disease were worked out at four-day interval. Weather parameters like maximum (MaxT) and minimum temperatures (MinT), maximum (MaxRH) and minimum relative humidity (MinRH), bright sunshine hour (BSH), evaporation (EVP) as independent variables were attempted to correlate with these three dependent variables. The results of the simple correlation study hinted a significant positive correlation of evaporation with both PDI (r=0.394*) and AUDPC (r= 0.594**); respective negative and positive correlations of MinRH and MinT with AUDPC and ROS. The result of regression analysis revealed that MinT, BSH had negative while EVP had positive contributions on the development of PDI (Y_{PDI}**=81.242-6.484MinT**-9.753BSH**+43.854EVP**) and AUDPC(Y_{AUDPC}**=-12734.075+471.461MaxT*-419.296MinT**+74.337MaxRH*-579.646BSH**+1667.0867 EVP**). Additionally, the maximum temperature had a demonstrable contribution to the increment of AUDPC. MaxT, MinRH and BSH were identified as critical weather parameters having significant positive influence on ROS (Y_{ROS}**=-0.867+0.018 MaxT*+0.007 MinRH**+0.025BSH*).

Keywords : Critical weather parameter, cucumber downy mildew, epidemiology, *Pseudoperonospora cubensis,* Terai region

INTRODUCTION

Plant disease epidemics are the manifestations of an ecological interaction process occurring at different spatiotemporal scales between the host and pathogen population under a conducive environment (Madden *et al*. 2007). The extent of the epidemic is often determined by the complex interactions of favourable weather conditions, virulence of the pathogen and susceptibility of the host during the growing season. An array of parameters from host, pathogen and environment are being used to develop the mathematical models that predict the risk of disease development, to aid the growers in decision-making for the timely adoption of efficient and effective disease management.

Cucurbit downy mildew, caused by *Pseudoperonospora cubensis* (Berk. & Curtis) Rostovzev, is one of the destructive diseases of cucurbits (McGrath 2004), affecting nearly 30% of cucurbit-growing areas globally and causing upto 60–100% yield losses under epidemic conditions (Govindasamy *et al*. 2021; Holmes *et al*. 2015). The fungus infects at least 9 of the 12 cultivated cucurbit genera under natural conditions and several semi-cultivated, wild, and weedy hosts of the family Cucurbitaceae accounting for approximately 60 species across 20 genera when artificial inoculation studies are included (Lebeda and Cohen 2011). Among the recorded host genera, *Cucumis* contains the

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highest number of host speciesof *Ps. cubensis,* including *C. sativus* L. (cucumber), two cultivated subspecies, and over 30 wild species (Thomas *et al*. 2017).The obligate nature of *P. cubensis* has developed in a strong host–pathogen relationship (Thines, 2014). Disease occurrence and spread are strongly influenced by weather parameters such as temperature, relative humidity, rainfall, leaf wetness duration, and night temperature (Hembram *et al.* 2014; Ghosh *et al.* 2015), which affect pathogen reproduction, survival, germination (Ojiambo *et al.* 2009), dispersal (Lebeda and Cohen 2011), spore deposition, and inoculum buildup. Several studies from India have reported significant correlations between these weather variables and cucumber downy mildew development (Ghosh *et al*. 2015; Daunde *et al*. 2017).

In West Bengal, cucurbits especially cucumber comprised a great portion of total vegetable production. In 2022-23, West Bengal had about 25.010 thousand ha under cucumber cultivation, among which 900 ha was the share of Cooch Behar district alone, producing 15.600 thousand MT of cucumber (Annonymous, 2023) and had a significant impact on the farmers' economy of the district. The severe occurrence of downy mildew disease puts this crop in a dilapidated condition every year. Besides the variability in pathogenic virulence and host susceptibility (Lebeda and Cohen, 2011), the weather parameters may play a pivotal role for such condition of the crop. All the weather parameters may not be equally contributing the disease development and severity (Granke *et al*. 2014; Lebeda and Cohen, 2011; Son *et al.* 2025). So, the identification of those critical weather parameters is essential to determine the pattern of progress, rate of spread and prediction of severity of the disease. The present investigation was undertaken to identify the critical weather parameters and develop a prediction model for downy mildew progression in cucumber for this particular region.

MATERIALS AND METHODS

Site of the experiment

The investigation was carried out in Farmer's field at Rasher Kuthi village (26.212645',89.242136'), under Madhupur Gram Panchayet, in the Cooch Behar District of West Bengal during 2022-23 and 2023-24 seasons. The climate of the experiment site was characterized by subtropical, humid with an average rainfall of 3254.60 mm, mean annual maximum and minimum temperatures of 29.3(31)°C and 18.5(11) °C respectively. The district is located in the Sub Himalayan plains and belongs to the Terai agro-climatic zone of West Bengal. (data from the website of Cooch Behar KVK). The experiment was conducted during December to February of 2022-23 and 2023-24 with local cucumber variety 'kheera' in a field size of 50m × 50m (Fig.1A). 3 plots of size 4.0 m X 1.6 m were randomly selected. Each of the hills in the selected plots accommodated 3 plants. From each of the plots 3 hills were chosen arbitrarily. Thus, a total of 27 plants were evaluated to obtain the average PDI for each assessment date. Dates of sowing of cucumber seeds were 10th November, 2022 and 20th November, 2023 respectively. All the recommended packages and practices were adopted for raising the crop.

Recording of the data

Regular field monitoring was conducted to identify the onset of downy mildew disease. Once the disease was found to be initiated, observations on disease incidence were carried out. The effect of the weather parameters like temperature (maximum and minimum), relative humidity or RH (maximum and minimum), evaporation or EVP, bright sunshine hours or BSH on the development of downy mildew disease of cucumber was studied under field condition (as there was no rain during the period of experimentation, so this weather parameter was not taken under consideration during epidemiological studies). The weather data during the period of experimentation were collected from the adjoining meteorological station of the Uttar Banga Krishi Viswavidyalaya. The PDI of 9 plants was averaged to get the mean value of PDI for each assessment date at an interval of 4 days. The variable area under disease progress curve (AUDPC) was also worked out to obtain the cumulative area under diseases progression over time. Along with PDI and AUDPC, attempts were made further to retrieve information on the rate of spread (ROS) of the disease using the PDI values during the mentioned period. Recording of the data was continued upto when the PDI reached near the plateau stage for three consecutive observations. Each of the agro-meteorological indices of 4 days preceding the assessment date was taken as independent variables to evaluate their influence on 3 separate dependent variables, *i.e.* PDI, AUDPC and ROS through correlation studies and regression analyses. The severity of the downy mildew disease of cucumber was assessed according to the disease grading 0-9 scale proposed by (Yangan *et al.* 2007) (Table 1).

Downy mildew disease severity or percent disease index (PDI) of the affected cucumber plant was calculated based on the following formula proposed by (Wheeler, 1969).

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

AUDPC was calculated according to the trapezoidal method mentioned by (Madden *et al.* 2007), where the variable can be determined by discretization of the time variable along with the calculation of average disease intensity between each pair of adjacent time points.

$$\text{AUDPC} = \sum_{i=1}^{n} \frac{Y_i + Y_{i+1}}{2} \times (t_{i+1} - t_i)$$

Where Yi is an assessment of disease (percentage) at the ith observation, t_i is time (in days) at the ith observation and n is the total number of observations.

Rate of disease spread of cucumber downy mildew was calculated as per the formula proposed by (Van der Plank, 1963) –

$$\text{Rate of spread (r)} = \frac{1}{T_2 - T_1}\left\{\left(\log_e \frac{X_2}{1-X_2}\right) - \left(\log_e \frac{X_1}{1-X_1}\right)\right\}$$

Where, $T_2 - T_1$ = time interval between two observations, X_1 = percent disease index at time T_1 and X_2 = percent disease index at time T_2

Statistical Analysis

Statistical analysis was carried out using IBM SPSS Software. The prediction models based on three dependent variables and weather parameters (independent variables) were generated using backward method multiple regression analysis for both 2022-23 and 2023-24 seasons, as in the form of pooled data. Simple correlation coefficients were worked out amongst any pair of the weather variables like max. temperature, min. temperature, max. relative humidity, min. relative humidity, bright sunshine hour, EVP with dependent variables PDI, AUDPC and ROS. Finally, the simple correlation coefficients were arranged in the form of a matrix. Multiple regression analysis for prediction of disease severity was done using the equation- Y = bo + b_1x_1 + b_2x_2 —— b_nx_n where Y = predicted disease severity, bo = intercept, b_1, b_2, b_3 —— b_n = regression coefficients and x_1, x_2, x_3 —— x_n = independent variables. However, a backward method of multiple regression analysis was also done to identify the most critical weather parameter(s) contributing much towards the disease severity.

RESULTS AND DISCUSSION

Development of the disease

Bright yellowish coloured, strictly angular, vein restricted scattered lesions were observed appearing on the upper leaf surface which created a mosaic pattern on the leaf (Fig. 1B). In the early morning hour white cottony growth was noticed on the corresponding lower surface. On aging, coalesced and formed large angular chlorotic zones on leaves, whereas in older and lower most leaves of the plant lesions converted the entire leaf blade to necrotic and rendered it to droop. The cottony growth turned to greyish or blackish on maturity (Fig. 1C).

Evaluation of the influence of different weather parameters on cucumber downy mildew

Initiation of the cucumber downy mildew disease in the field was recorded at 4th Dec in 2022, whereas in the 2023-24 season, the appearance of the first symptom was delayed to 12th Dec, 2023. The pooled data considering the mean values of the preceding 4 days' weather variables and the PDI of cucumber downy mildew for both the seasons 2022-23 and 2023-24 were worked out over twenty number of observation days. Similarly, the dependency of the other two variables *i.e.* AUDPC and ROS on the same weather parameters were also worked out summarizing the pooled value of two seasons. The pooled mean of these seven weather parameters along with the PDI, AUDPC and ROS of downy mildew disease were recorded and presented in (Table2).It can be easily comprehended that the weather variables during the assessment period for both the seasons appeared to follow similar trends. When pooled, the maximum and minimum temperature were found in the ranges of 21.72-27.71°C and 6.82-13.48°C respectively. Whereas, the maximum and minimum RH varied from 73-96 % and 41.25-71.62% respectively. During the observation period bright sunshine hours were recorded to vary from 2-6.67 hours and evaporation as 0.75-2.24mm / day whereas the downy mildew disease severity went as high as 77.78% from an initial severity of 5.92% over the 20 days of observation.

Simple correlation coefficients were worked out individually amongst any pair of the weather parameters as independent variables with three dependent variables separately and arranged those in the form of matrix. Finally, the simple correlation matrices of three dependent variables with the weather variables were compared, only the significant pairs were picked up and summarized (Table 3). It was apparent from the comparison that the evaporation was the only weather parameter being significantly positively correlated with both PDI (r=0.394*) and AUDPC (r= 0.594**). Apart from that, Min RH showed significant negative correlation with AUDPC (r=-0.358*), whereas the variable MinT was found to be positively correlated with ROS (r= 0.361*). None of the other pairs comprised independent and dependent variables showed any significant simple correlation.

In order to identify critical weather parameter(s) contributing much towards the increment of PDI, AUDPC and ROS, the backward method of multiple regression analyses was also performed. Considering these dependent variables, a total of 4, 2 and 4 regression equations were obtained in each case respectively. Among the equations obtained, three best-fit equations considering the three different dependent variables were presented collectively in (Table 4).

Results of the backward method of multiple regression analyses for prediction of the downy mildew disease severity (PDI) and its coefficients of multiple determination (R^2) value revealed that a combined effect of minimum temperature (MinT), bright sunshine hour (BSH) and EVP explained 64.1% of the total variation of PDI. The combined effect of these three parameters, identified as critical, contributed much towards the PDI increment. Out of these parameters, the minimum temperature and bright sunshine hour (BSH) contributed negatively while EVP contributed positively towards the PDI increment. The representative multiple regression equation for the prediction of cucumber downy mildew disease severity was – Y_{PDI}**=81.242-6.484MinT**-9.753BSH**+43.854EVP**(where coefficients of multiple determination R^2 = 0.641, adjusted coefficients of multiple determination R^2 = 0.582 and multiple R = 0.801 and standard error of estimate = 16.02). Whereas, the combined effects of Max RH and Max T were also found to be accountable along with minimum temperature (MinT), bright sunshine hour (BSH) and EVP for explaining the 78% of the total variation of AUDPC. The representative multiple regression equation obtained, Y_{AUDPC}**=-12734.075+471.461MaxT*-419.296MinT**+74.337 Max RH*-579.646BSH** +1667.860EVP** (where the coefficients of multiple determination R^2 = 0.780, adjusted coefficients of multiple determination R^2 = 0.712 and multiple R = 0.883 and standard error of estimate = 658.436). Contradictorily, the variables MaxT, MinRH and BSH were found to be responsible for the increment of ROS when the similar backward method of multiple regression analyses was performed. Collectively, these three variables can explain 44.2% of the total variation in the rate of spread of the pathogen**.** All of these variables showed significant positive correlations. The representative multiple regression equation obtained, Y_{ROS}**=-0.867+0.018 MaxT*+0.007 Min RH**+0.025BSH* (where coefficients of multiple determination R^2 = 0.442 adjusted coefficients of multiple determination R^2 = 0.344 and multiple R = 0.665 and standard error of estimate = 0.053).

Table 1: 0 – 9 scale along with the description of disease severity used for scoring the severity of cucumber downy mildew.

Grades under scales	Description of disease severity under each grade
0	Healthy leaf
1	1%-5% leaf area infected
3	6%-10% leaf area infected
5	11%-25% leaf area infected
7	26%-55% leaf area infected
9	56%-100% leaf area infected

As per Yangan *et al.* 2007

Fig. 1 : A- View of experimental plot. **B-** Symptom of downy mildew on the adaxial and C- abaxial surface of cucumber leaf

All the three best-fit multiple regression equations considering three dependent variables were compared and the weather parameter(s) critically influencing more than one dependable variable were tried to be identified (Table 5).

Considering the dependent variables PDI and AUDPC, it could be easily interpreted from the pooled result of multiple regression models that the variables MinT, BSH and EVP had a collective and inevitable effect on the development of the downy mildew disease. While MinT and BSH imposed a negative correlation, EVP exhibited a positive correlation in both cases. Whereas, the variable MaxT exhibited positive influence on both the AUDPC and ROS. The variables MaxRH and Min RH were found to be positively correlated with AUDPC and ROS respectively.

Plant disease epidemic is a dynamic process consisted of three major wings *i.e.* host, pathogen, and environment. The synchronous interaction between host, pathogen, and environment governs the development of the disease. If the host is susceptible, pathogen is virulent then the weather parameters individually or collectively may regulate the course, direction and intensity of epidemic, revealing the undoubted importance of it. To conceptualize the dynamics of these complex interactions in terms of temporal progress, pioneer epidemiologists like van der Plank, Zadok had brought analytical mathematics to the scenario during the late sixties. Generally, the amount of disease present in a population of plants is assessed several times over the observation to measure the temporal disease development. These data can be presented collectively in the form of disease progress curve, essentially depicting the dynamics of disease development with time. This simple temporal progress curve exhibits representative outcomes of complex interactions between host, pathogen, environments and crop husbandry. Till date, mostly 2 types of epidemiological experiments are applied, *i.e.* holistic experiment and meristic experiment. A holistic model is comprised of as many as possible variables from host, pathogen and environment; whereas a meristic model includes the study of a few key variables to explain most of the effects governing an epidemic (Kranz

Table 2 : Mean values of weather variables and PDI, AUDPC and ROS (Pooled values of season 2022-23 and 2023-24)

Number of observation	Temperature (°C)		Relative Humidity (%)		BSH	EVP	PDI	AUDPC	ROS
	Max.	Min	Max	Min	(Hr.)				
1st	26.31	13.49	85.13	61.13	4.49	1.28	5.92	46.44	0.16
2nd	25.78	12.59	83.50	58.00	3.48	0.91	10.95	96.93	0.07
3rd	24.80	10.18	87.50	55.00	4.76	1.04	14.30	170.40	0.15
4th	26.48	9.04	73.00	46.13	6.68	1.83	22.44	274.36	0.10
5th	25.15	8.93	78.88	50.00	6.05	1.33	29.54	405.18	0.07
6th	24.70	9.96	83.63	50.13	4.54	1.13	35.87	556.07	0.04
7th	25.68	9.55	82.13	53.25	6.21	1.50	39.58	718.96	0.03
8th	25.90	10.40	79.00	50.25	4.61	1.54	41.87	897.00	0.05
9th	22.43	12.69	94.38	75.63	2.00	0.75	47.15	1093.56	0.04
10th	22.60	9.51	96.00	64.13	2.31	1.18	51.13	1307.77	0.05
11th	22.96	9.49	84.63	64.50	3.28	1.18	55.98	1538.27	0.03
12th	23.30	9.83	85.00	65.63	2.84	0.89	59.28	1783.88	0.05
13th	22.24	8.28	94.88	51.13	3.59	1.45	63.53	2042.92	0.03
14th	21.73	6.83	94.63	55.38	3.60	1.39	65.99	2313.42	0.04
15th	23.56	8.98	81.63	53.25	4.24	1.46	69.51	2595.37	0.04
16th	25.09	8.60	84.88	49.50	5.41	2.09	72.16	2888.92	0.04
17th	26.29	10.48	86.63	44.25	4.93	1.71	75.06	3192.34	0.02
18th	27.54	10.44	76.38	41.25	5.43	2.19	76.66	3499.62	0.00
19th	27.00	10.44	73.50	42.63	5.88	2.43	76.99	3809.16	0.01
20th	27.71	12.28	77.25	50.50	5.68	2.11	77.79	4049.06	

Max.=maximum, Min.= minimum, BSH=bright sunshine hour, Hr=hour, EVP= evaporation, PDI=percent disease index, AUDPC=Area under disease progress curve, ROS=Rate of spread

and Rotem, 2012). The complexity and requirements of large research facilities have prioritized the need of meristic models over holistic ones. Reviewing the numerous instances citing the higher degree of dependency of downy mildew pathogens on the climatic factors for disease development, meristic approach was selected in the current study to construct the models comprised of weather factors in a particular spatio-temporal scale.

Table 3 : Summary table of three simple correlation matrices considering the different weather parameters as independent variables and PDI, AUDPC and ROS as dependent variables

	Weather Parameter(s)					
	MaxT	MinT	MaxRH	MinRH	BSH	EVP
PDI						(+)*
AUDPC				(-)*		(+)**
ROS		(+)*				

** = Highly Significant (at P<0.01), *= Significant (at P<0.05)

Table 4 : Backward methods of determination of multiple regression equations for prediction of PDI, AUDPC and ROS

Dependent variable	Model	R	R square	Adjusted R square	Standard error of estimate	Significance
PDI	Y_{PDI}**=81.242-6.484MinT**-9.753BSH**+43.854EVP**	.801[d]	.641	.582	16.022	.000[e]
AUDPC	Y_{AUDPC}**=-12734.075 +471.461MaxT*-419.296MinT**+74.337MaxRH *-579.646BSH**+1677.860EVP**	.883[b]	.780	.712	658.436	.000[c]
ROS	Y4**=0.867+0.018MaxT* +0.007MinRH**+0.025BSH*	.665[d]	.442	.344	.0537	.017[e]

** = Highly Significant (P<0.01), *= Significant (P<0.05)

Table 5: Summary table for multiple regression analyses representing the most critical weather variables responsible for the increment of PDI, AUDPC and ROS

	Weather Parameter(s)					
	MaxT	MinT	MaxRH	MinRH	BSH	EVP
PDI		(-)**			(-)**	(+)**
AUDPC	(+)*	(-)**	(+)*		(-)**	(+)**
ROS	(+)*			(+)**	(+)**	

** = Highly Significant (P<0.01), *= Significant (P<0.05)

The pooled mean of seven weather parameters along with the PDI, AUDPC and ROS of downy mildew disease were recorded in the current study. It can be easily comprehended that the weather variables during the assessment period for both the seasons appeared to follow similar trends. Within the observation period the downy mildew disease severity went as high as 77.78% from an initial severity of 5.92%. This scenario supports the idea that in field conditions weather factors impose an inescapable effect on the course of development of downy mildew disease severity.

Considering the variable PDI and AUDPC, three independent variable MinT, BSH and EVP were found to impose collective and inevitable effect on the development of the downy mildew disease. As the variable AUDPC is a cumulative summary of PDI over the time, so, the identification of similar weather variables as critical for both the dependent parameters is explicable. Respective negative and positive contribution of MinT and EVP on cucumber downy mildew disease severity from our study showed partial resemblance with the findings of (Daunde *et al*. 2017; Ghosh *et al.* 2015), where both of them demonstrated the negative effect of minimum temperature on the development of cucumber downy mildew. But, according to (Daunde *et al.* 2017), 63% of the variation of the PDI of cucumber downy mildew was influenced by the negative correlations of both MinT and evaporation which is contradictory to the current finding. This conflict can be justified by the findings of (Rawal *et al.* 2008) wherein they analyzed the severity of grapevine downy mildew along with the weather variables separately in two different stages (*i.e.* at severity less than 10% and severity exceeding 40%) because development of a single prediction model correlating the wide range of disease severity with weather variables might be misleading in the identification of all the weather variables as critical. This became true when they developed two different models for the prediction of disease severity for two separate range of severity. They noted that the parameter EVP exhibited a negative contribution in explaining the disease severity of less than 10% level. But, the same parameter was found to be significantly positively correlated when the best-fit prediction model was evaluated for the later stage of crop showing greater than 40% disease severity. In the present experiment, out of 20 observations, 7 and 13 (*i.e.* 65%) observations fell below and above 40% respectively, indicating major disease severity data were at higher range. It could be hypothesized that the EVP might have positive contribution to the disease severity at higher range and the present finding proves the hypothesis true.

The negative impact of BSH on the disease development can be supported by several literatures. (Granke *et al*. 2014) demonstrated the negative association of solar radiation with the occurrence of cucumber downy mildew disease, which is found in same line with the current study as the increase in amount of bright sunshine hours is likely to cause the increase of solar radiation. Also, considering the ecology and epidemiology of the cucurbit downy mildew pathogen a number of supporting evidences can be discussed. Lebeda and Cohen, (2011) mentioned about the inhibition of sporangial production of *P. cubensis* in the presence of light and the procedure was strongly temperature-dependent. Increased inhibition was observed with higher temperatures. Subsequently, the maximal production of sporangia at night was observed (Lebeda and Cohen, 2011) and different night weather parameters like average night temperature, night relative humidity (RH) and number of night hours having RH>95% were estimated as the significant predictors of cucurbit downy mildew (Ghosh *et al*. 2015). Even the detached sporangia of the pathogen were also shown to survive better in cloudy than in sunny days or solar radiation had been identified as the primary physical variable negatively affecting spore survival in atmosphere (Ojiambo et al. 2009), which in turn indicated about the better chances of disease progression in cloudy days. It is evident from all of these findings that the day light or the effective bright sunshine hours is not congenial for disease development, which also found true to the result of the current study. Regarding the positive correlation of Max RH on AUDPC, studies by (Ahmed and El-Hassawy, 2021; Ghosh *et al*. 2015) found the similar trend. In both cases the abundance of high relative humidity was found critical for predicting the disease epidemic, which ultimately interpreted the positive influence of the parameter over the AUDPC.

Considering the rate of spread of the pathogen (ROS) MaxT, MinRH and BSH were found to express significant positive correlations. These findings are partially supported by the studies of earlier workers, where the low humidity and dry leaf surface were mentioned as optimal for the dispersion of sporangia, though temperature and light exhibited low influence on dispersal. However, the dispersed sporangia were demonstrated to withstand high temperatures if the low relative humidity condition prevails These results can justify the positive impact of MaxT and MinRH collectively over the rate of the disease progress. Even, in an recent observation (Cohen *et al.* 2020) recorded an astonishing rapid revival of *P. cubensis* population in Israel after an extremely hot and dry wave of 6 days having maximum temperature of 46.5 °C and minimum relative humidity reaching 10% and 45 hours with temperature of 40 °C, which in turn indicated that global warming might not only adversely affect crop yields with its direct negative effect on plant physiology but might also enhance the tolerance of the pathogens to heat. Contradiction to the various pieces of literature citing the effect of MinT on downy mildew as most relevant can be justified by this particular study supporting the effect of high temperature as well and it also opens a vast road of studying the details of region-specific epidemiology under climate-changing conditions as well as the population biology of the *P. cubensis*. Also, considering the airborne sporangia concentrations as one of the most important biotic factors for determining the disease onset, several pioneer studies can be cited. In a large-scale field study over 2 seasons (Granke et al. 2014) were able to trap sporangium of *P. cubensis*with a spore trapper at 0.5m upper the ground level and demonstrated the correlation of hourly weather parameters with the number of sporangia trapped. In their study, the hourly temperature in 1-h periods was positively correlated with the number of airborne sporangia detected for the entire dataset combined and when separated by disease severity, except at low disease severity. Also, the number of airborne sporangia averaged for 1-h periods was positively correlated with RH only in the early morning hours but the correlation was not significant for the entire day. This can also partially explain the current study result representing the positive impact of temperature and relative humidity on the rate of spread of the disease. But, regarding the positive influence of bright sunshine hour over the rate of spread of the pathogen no supporting evidences are found, which may support the idea of recording more precise environmental data at hourly intervals to identify a more accurate scenario.

Therefore, three best-fit equations were obtained by considering three different disease progression parameters as dependent variables, *viz.*

1. Y_{PDI}**=81.242-6.484MinT**-9.753BSH**+43.854EVP**(PDI as dependent variable)

2. Y_{AUDPC}**=-12734.075+471.461MaxT*-419.296MinT**+74.337MaxRH*-579.646BSH**+1667.0867EVP** (AUDPC as dependent variable)

3. Y_{ROS}**=-0.867+0.018MaxT*+0.007MinRH**+0.025BSH* (ROS as dependent variable)

These regression equations can be efficiently utilized to develop weather-based prediction models, which will ultimately help the farmers involved in cucumber cultivation of this particular region to schedule effective management strategies at the correct point of time or the course of the downy mildew disease progression, leading to significant reduction of cost of cultivation.

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DECLARATION

Conflict of Interest. Authors declare no conflict of interest.

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