

# Journal of Agrometeorology

ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 25 (4) : 577-582 (December - 2023)
https://doi.org/10.54386/jam.v25i4.2343
https://journal.agrimetassociation.org/index.php/jam


***Research Paper***

## Beta regression model for predicting development of powdery mildew in black gram


**S. KOKILAVANI[1*], V. GEETHALAKSHMI[2], R. PANGAYARSELVI[3], J. BHUVANESWARI[4], G. SUDHAKAR[5], S. SUBBULAKSHMI[6], P. PRIYANKA[1], TIMMANNA[7] and S.K. BAL[7]**

[1]*Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore 641003, Tamil Nadu, India*
[2]*Vice Chancellor, Tamil Nadu Agricultural University, Coimbatore 641003, Tamil Nadu, India*
[3]*Department of Physical Sciences and Information Technology, Tamil Nadu Agricultural University, Coimbatore 641003, Tamil Nadu, India*
[4]*Agricultural College and Research Institute, Killikulam, Tamil Nadu, India*
[5]*Agricultural Research Station, Vaigai Dam, Tamil Nadu, India*
[6] *Agricultural Research Station, Kovilpatti, Tamil Nadu, India*
[7]*AICRP on Agrometeorology, ICAR-Central Research Institute for Dryland Agriculture, Hyderabad – 500059, India*
**Corresponding Author:* kokilavani.s@tnau.ac.in



### ABSTRACT

Black gram is a widely grown pulse crop in Asia, prized for its nutritional value and compatibility with various cropping systems. However, the occurrence of powdery mildew, *Erysiphe polygoni* DC disease poses a significant challenge to black gram production, resulting in potential yield losses in Tamil Nadu. Over a six-year period, spanning from 2017-2018 to 2022-2023, field experiments were conducted during the rabi season at the black soil farm of the Agricultural Research Station in Kovilpatti, Tamil Nadu. The primary objective was to evaluate the incidence of powdery mildew in black gram and establish a statistical model by correlating it with weather variables. Notably, observations of disease index were most frequent during the flowering and pod development stages of the crop. Among the eleven weather parameters considered in the study, maximum temperature, afternoon relative humidity, and sunshine hours emerged as the key contributors to explaining the variation in the disease index. Further, a beta regression model was developed using these selected variables to predict powdery mildew incidence in black gram.



***Keywords*****:** Beta regression model, powdery mildew, black gram, prediction, weather


The shifting climate patterns observed over the years have had a significant impact on rainfed crops, particularly pulse crops. The primary reason for the inconsistent production of pulses is attributed to irregular weather conditions. Pulse crops are particularly susceptible to extreme weather events, with oilseeds and cereals also being affected to some extent (Gautam *et al*., 2013; Singh and Singh, 2016). Based on physiological characteristics, pulse crops are classified in terms of their ability to tolerate varying temperatures, with green gram being the most thermotolerant, followed by pigeon pea, black gram, chickpea, lentil, rajmash, and field pea (Singh *et al*., 2018). As per the recent reports, India's black gram production stands at approximately 24.5 lakh tonnes, cultivated across roughly 4.6 million hectares of land, with an average yield of 533 kg per hectare annually (Talasila *et al*., 2022).

Climate plays a crucial role in shaping the distribution and proliferation of insects, weeds, and pathogens. Temperature, light, and water are key factors that influence their growth and development. In a warmer climate, pests are expected to become more active and potentially expand their geographic range. This could lead to an increased use of pesticides and related inputs, which comes with health, ecological, and economic costs.

However, it's important to note that the relationship between pests and weather is complex and cannot be generalized. Different pest species respond differently to magnitude and periodicity of meteorological conditions (Bal and Minhas, 2017). Crop damage by pests and diseases is the result of intricate ecological interactions between multiple factors, thus making it challenging to predict their damage potential. For instance, dry conditions can hinder the growth of fungi, but they can also weaken crops, making them more susceptible to fungal infections (Milićević


***Article info - DOI*****:** https://doi.org/10.54386/jam.v25i4.2343
*Received: 8 September 2023; Accepted: 25 October 2023; Published online : 30 November, 2023*

*et al*., 2019). Some pathogens, like powdery mildews, thrive in hot and dry conditions, provided there is dew formation during night hours (Wadje *et al*., 2008).

Among biotic stresses, diseases such as powdery mildew, Cercospora leaf spot, anthracnose, and mungbean yellow mosaic virus (MYMV) cause significant economic damage to the black gram crop. Of these, powdery mildew disease caused by *Erysiphe polygoni* DC is considered as major constraint to black gram production, resulting in both qualitative and quantitative grain losses, potentially reducing yields to the tune of 40 to 90% (Channaveeresh and Shripad Kulkarni, 2014). Powdery mildew is particularly problematic in late-sown kharif and rabi crops and can occur throughout the year under favourable conditions. Timely monitoring and early diagnosis are essential to minimize yield losses and maximize crop yields (Dutta *et al*., 2020). Kanzaria *et al.,* (2013) opined that maximum temperature (28.9 ºC) coupled with afternoon RH (40%) favoured powdery mildew intensity under natural conditions.

Principal component analysis (PCA) is a multivariate statistical method used to explore the correlations between multiple variables and understand the underlying structure of these variables through a few principal components. When applied to disease progress curves, multivariate analysis helps highlight the phases in which pathogens multiply most rapidly (Sankaran *et al*., 2010). Various models, including linear, Gompertz, exponential, Chapman Richards, logistic, and Weibull, have been employed to study the temporal patterns of disease development in plants (Campbell and Madden, 1990). Forecasting models based on the principal components of biometrical data have also been developed (Aneja and Chandrahas, 1984; Chandrahas and Narain, 1993; Jain *et al*., 1985). However, despite this knowledge, there is a lack of substantial analyses using field data to determine which weather factors and time periods are most suitable for forecasting.

In this context, an effort was made to establish a connection between weather variables and powdery mildew incidence through Principal Component Analysis. A Beta regression model was employed to capture the variability in disease index data. This newly developed powdery mildew forewarning model can assist the farming community in devising effective management strategies, particularly in the face of changing climatic conditions, to benefit black gram cultivation.

## MATERIALS AND METHODS

Field experiments were carried out at the Agricultural Research Station in Kovilpatti, which is situated at an elevation of 106 meters, with coordinates of approximately 9.19°N latitude and 77.88°E longitude. These experiments focused on the cultivation of black gram variety VBN-8 and spanned a period of six years, ranging from 2017-2018 to 2022-2023. The sowing of the crop took place within a variable timeframe, typically between the 41$^{st}$ and 43$^{rd}$ Standard Meteorological Week (SMW) (2$^{nd}$ week to 4$^{th}$ week of October), depending on the onset of the monsoon.

Meteorological data pertinent to various weather variables, including maximum temperature (Tmax), minimum temperature (Tmin), morning relative humidity (RH1), afternoon relative humidity (RH2), wind speed (WS), sunshine hours (SSH), morning cloud cover (CCM), afternoon cloud cover (CCA), morning dew point (DPM), afternoon dew point (DPA), and dew, were collected from the network centre of All India Coordinated Research Project (AICRP) on Agro-Meteorology, situated at the Agricultural Research Station in Kovilpatti, Tamil Nadu.

### *Disease incidence*

Regular observations of powdery mildew disease incidence were made at weekly intervals, starting from the time of sowing. From each plot, 20 plants were randomly selected, and their infection levels were assessed through visual observation. This data was then used to calculate the percent disease index. Notably, disease incidence was particularly monitored during the flowering and pod development stages, leading to an increased frequency of observations during these critical phases.

The leaf samples were graded based on the grade chart provided by Gawande and Patil in 2003 is given below.

| Grade | Description | Reaction |
|---|---|---|
| 0 | Plants free from infection on leaves, stems free from the disease | Free (F) |
| 1 | Plants showing traces to 10% infection on leaves, stems free from the disease | Highly Resistant (HR) |
| 2 | Slight infection with thin coating of powdery growth on leaves covering 10.1 – 25% leaf area, slight infection on stem and the pods usually free | Moderately Resistant (MR) |
| 3 | Dense powdery coating on leaves covering 25.1 – 50% leaf area, moderate infection on pods | Moderately Susceptible (MS) |
| 4 | Dense powdery coating covering 50.1 – 75% leaf area, stems heavily and pods moderately infected. Infected portion turns grayish | Susceptible (S) |
| 5 | Severe infection with dense powdery growth covering 75% area of the whole plant including pods, stems etc. resulting in premature defoliation and drying | Highly Susceptible (HS) |

The per cent disease index (PDI) of powdery mildew was determined using the following formula, as outlined by Wheeler (1969)

$$PDI = \frac{Sum\ of\ all\ numerical\ ratings}{Number\ of\ observations\ \times Maximum\ disease\ grade} \times 100$$

### *Principal component analysis (PCA)*

Principal Component Analysis (PCA) is a statistical technique that transforms a set of original variables into a new dataset of uncorrelated derived variables. These derived variables, known as principal components, are the outcomes of linear combinations of the original variables. In PCA, the total variances of the original and derived variables are equal. The PCA was performed using the R statistical package (version, R-4.3.1). The first principal component (PC1) captures the most significant portion of the data's variance, followed by the second principal component (PC2), which accounts for the next-largest amount of variance, and so on for subsequent PCs. The values of PC1 and PC2 can be calculated using the equations provided below, respectively. Typically, in a PCA analysis, most of the variation in data matrices that describe the original observations is explained by the first few principal components. This allows for a reduction in the dimensionality of the original dataset by retaining only the most informative dimensions.

$$PC1 = \sum_{j=1}^{k} a_{1j}x_j = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1k}x_k$$

$$PC2 = \sum_{j=1}^{k} a_{2j}x_j = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2k}x_k$$

Where $a_{ij}$ stands for the eigenvectors and $x_1,x_2,\ldots,x_k$ stands for the original variables in the data matrix.

***Beta regression***

In typical linear regression modelling, we explore the relationship and impact of selected explanatory variables on a response variable that follows a normal distribution. However, this approach is not suitable when the response variable is confined to the interval (0, 1) and is related to other variables through a regression structure. In such cases, beta regression is a well-known statistical model. Beta regression is particularly useful when the response variable takes the form of fractions or percentages. It employs a beta probability density function, which offers flexibility by allowing for various shapes in parameter estimation. These shapes can range from left-skewed to symmetric to right-skewed (Cribari-Neto and Zeileis, 2010). Beta regression utilizes two gamma distributions, one bounded at zero and the other bounded at one, to estimate the coefficients of the structural model through iterative calculations (Douma and Weedon, 2019). The beta regression model is based on the work of Ferrari and Cribari-Neto (2004) and Kieschnick and McCullough (2003). It provides a valuable framework for modelling when the response variable has specific constraints and characteristics.

$$E \times \frac{Y}{1-Y} = e^{\eta} \qquad logit\ lin$$

$$\eta = \sum^{n} \beta_i x_i \qquad linear\ predict$$

$$Y \sim Beta\ (\alpha, \beta) \qquad beta\ err$$

Where,

Y is the response variable as a percentage,

$x_i$ is an explanatory variable,

βi is vector or scalar parameter, and

i = 0…n indexes the list of explanatory variables.

$\beta_0$ is an intercept, with units of odds.

$\beta_i$ is a list of slopes and contrasts, with units of odds/units of $x_i$.

The intercept on the data scale is $e^{\beta 0}$ with units of the response variable, %. The list of parameters on the data scale is $e^{\beta i}$ with units of % unit of $x_i$. $\alpha$ and $\beta$ are shape parameters of the beta distribution. In this parameterization of beta regression, the mean $\mu$ of the response given covariates X is assumed to be linear on the logit-transformed scale. In an alternate parametrization~Beta (μ,ϕ) where $\mu = \alpha/(\alpha + \beta)$, and is a precision parameter $\varphi = \alpha + \beta$.

## RESULTS AND DISCUSSION

***Field conditions observed during the crop period***

The crop was cultivated in rainfed vertisol, and over a seven-year period, an analysis of the average soil pH, electrical conductivity (E.C.), and organic carbon content at a depth of 0-15 cm yielded values of 8.0, 0.12, and 0.31 respectively. The proliferation of pathogens was also facilitated by the microclimate created by the dense crop canopy (Hiremath, 1996). In the current study, data were collected during the flowering and pod formation stage, clearly demonstrating that the severity and progression of the disease depend on factors such as location, crop stage, cultural practices, and the susceptibility of the cultivated varieties. Wherever black soil was present, crop growth was more pronounced, and the denser crop canopy contributed to the development of a microclimate, fostering the accumulation of pathogens.

Table 1 indicates that during the six-year period, station received average rainfall amounted to 290.2 mm, the lowest (85.5 mm) recorded in 2018-19 and the highest (509.9 mm) recorded in 2021-22. The mean maximum temperature was 31.5 °C, with the lowest was 30.8°C and the highest was 32.0 °C. The mean minimum temperature was 21.1 °C, ranging from a low of 17.5 °C to a high of 22.5 °C. Morning relative humidity averaged 93.3%, while afternoon relative humidity was at 61.1%. The mean wind speed was 2.0 kmph, and daily sunshine hours averaged 5.0 hrs. Morning and afternoon cloud cover both averaged 4 Octa. The morning dew point temperature was 22.3 °C, and the afternoon dew point was 21.6°C, with a mean dew deposition of 3.0 mm during the crop growth period. The mean disease incidence ranged from 38.6% to 51.7% during this period (Table 1).

Disease incidence (DI), maximum temperature (Tmax), minimum temperature (Tmin), morning relative humidity (RH1), afternoon relative humidity (RH2), wind speed (WS), sunshine hours (SSH), morning cloud cover (CCM), afternoon cloud cover (CCA), morning dew point (DPM), afternoon dew point (DPA)

Considering the crop's vulnerability, especially during flowering to pod initiation, the weather parameters were quantified to assess the disease incidence. When the maximum temperature was around 31.0 °C, the minimum temperature was approximately 20.8 °C, morning relative humidity reached 93.2%, afternoon relative humidity was at 61.1%, wind speed measured 1.9 kmph, daily sunshine hours were 5, morning and afternoon cloud cover was 4 Octa, morning dew point temperature was about 21.9 °C, afternoon dew point temperature was 21.6 °C, and dew recorded at 1.1 mm, the disease incidence percentage was higher. During the

**Table 1:** Incidence of powdery mildew in black gram and weather parameters (2017-18 to 2022-23)

| Powdery mildew disease and prevailed weather parameters during the overall crop growth period | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | DI | RF | Tmax | Tmin | RH1 | RH2 | WS | SSH | CCM | CCA | DPM | DPA | Dew |
| 2017-18 | 39.7 | 331.3 | 32.0 | 22.0 | 90.5 | 56.3 | 2.5 | 5.9 | 3 | 4 | 22.2 | 21.0 | 2.5 |
| 2018-19 | 40.3 | 85.5 | 32.1 | 20.5 | 92.7 | 54.2 | 2.4 | 5.2 | 5 | 4 | 21.8 | 20.3 | 0.6 |
| 2019-20 | 51.7 | 206.2 | 31.1 | 22.3 | 93.6 | 65.1 | 2.0 | 4.8 | 4 | 4 | 22.7 | 22.6 | 1.0 |
| 2020-21 | 43.3 | 466.8 | 30.8 | 17.5 | 95.9 | 67.8 | 1.8 | 4.7 | 4 | 4 | 22.5 | 22.3 | 8.1 |
| 2021-22 | 38.6 | 509.9 | 31.3 | 22.5 | 96.2 | 66.5 | 1.9 | 4.6 | 4 | 4 | 22.4 | 21.6 | 1.5 |
| 2022-23 | 46.1 | 141.5 | 31.8 | 21.5 | 90.9 | 56.8 | 1.3 | 5.0 | 3 | 3 | 22.4 | 21.7 | 4.1 |
| Mean | 43.3 | 290.2 | 31.5 | 21.1 | 93.3 | 61.1 | 2.0 | 5.0 | 4 | 4 | 22.3 | 21.6 | 3.0 |
| Weather parameters prevailed during the vulnerable stages (flowering to pod development stage) | | | | | | | | | | | | | |
| Year | DI | RF | Tmax | Tmin | RH1 | RH2 | WS | SSH | CCM | CCA | DPM | DPA | Dew |
| 2017-18 | 61.5 | 28.6 | 31.2 | 21.6 | 92.6 | 58.1 | 2.1 | 6.1 | 3.5 | 4.4 | 22.0 | 21.4 | 1.20 |
| 2018-19 | 60.1 | 0.8 | 32.8 | 20.8 | 91.0 | 46.9 | 2.6 | 6.0 | 4.5 | 4.1 | 21.2 | 19.2 | 0.29 |
| 2019-20 | 64.4 | 38.3 | 29.7 | 22.0 | 92.3 | 68.9 | 1.9 | 3.3 | 3.7 | 4.0 | 21.9 | 22.3 | 0.16 |
| 2020-21 | 58.9 | 132.3 | 29.5 | 16.6 | 97.3 | 71.2 | 1.5 | 3.6 | 4.7 | 3.6 | 22.2 | 22.3 | 3.39 |
| 2021-22 | 59.5 | 36.0 | 31.2 | 22.6 | 95.7 | 63.7 | 1.3 | 6.1 | 3.7 | 3.9 | 22.2 | 22.3 | 0.55 |
| 2022-23 | 63.6 | 17.5 | 31.4 | 21.3 | 90.3 | 58.0 | 1.7 | 4.9 | 2.5 | 4.1 | 21.9 | 21.8 | 1.13 |
| Mean | 61.3 | 42.3 | 31.0 | 20.8 | 93.2 | 61.1 | 1.9 | 5.0 | 4.0 | 4.0 | 21.9 | 21.6 | 1.10 |

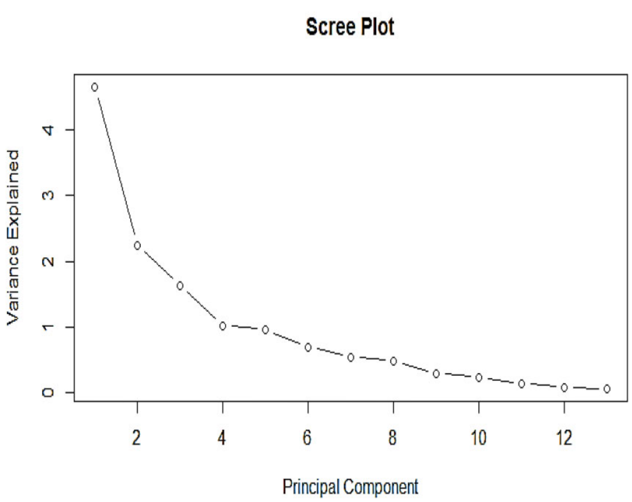


**Fig 1.** Scree plot between the number of principal components and variance explained

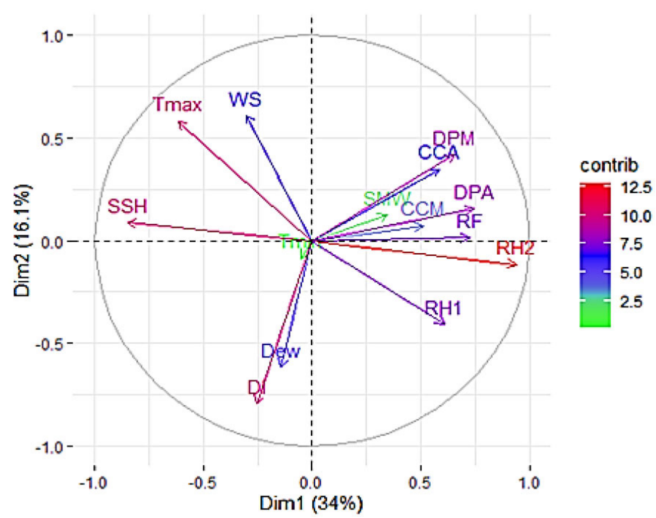


**Fig 2**: Factors contribution to disease index

flowering to pod initiation stage, the mean disease incidence ranged from 58.9% to 64.4% (Table 1). Interestingly, the disease incidence value exceeded 40% as the crop progressed from the 50% flowering stage to pod initiation.

### *Principal component analysis on weather variables*

Principal component analysis (PCA) was employed to identify the most significant weather variables among the various ones examined. Fig. 1 presents a screen plot that helps determine how many principal components are needed to account for the data's variability. In this screen plot, a notable change in direction occurs at the 5th principal component, indicating that the first four components are the primary variables that contribute significantly to explaining the maximum variability in the dataset. In contrast, the contribution of the remaining components is comparatively minor in explaining this variability.

Table 2 presents the values obtained from the PCA. Notably, the eigenvalues for the first four principal components exceed one, specifically PC1 - 4.664, PC2 - 2.248, PC3 - 1.627, and PC4 - 1.021. This suggests that these initial four principal components play a significant role in explaining the variation within the data. By examining Table 2. and Fig. 2, it becomes evident that among the eleven parameters considered, maximum temperature, afternoon relative humidity, and sunshine hours have the most substantial influence on explaining the variation in the percent disease index. In Fig. 2, the dark colour signifies their pronounced impact on the disease percent disease index. Further, these three factors have been selected for the formulation of a model.

**Table 2:** Principal component analysis of per cent disease index with weather variables

| Variables | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 | PC8 | PC9 | PC10 | PC11 | PC12 | PC13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rainfall (mm) | -0.338 | 0.002 | 0.001 | 0.09 | -0.222 | -0.427 | 0.651 | -0.155 | 0.227 | -0.331 | 0.163 | -0.024 | -0.101 |
| Maximum temperature(°C) | 0.291 | 0.378 | 0.394 | -0.215 | -0.275 | -0.013 | 0.021 | 0.130 | 0.286 | -0.073 | -0.536 | -0.150 | -0.430 |
| Minimum temperature(°C) | 0.001 | -0.032 | -0.247 | -0.896 | 0.227 | -0.043 | 0.184 | 0.012 | -0.130 | 0.021 | 0.138 | -0.076 | -0.066 |
| Relative Humidity 1 (%) | -0.021 | -0.257 | -0.008 | -0.239 | -0.438 | -0.342 | -0.336 | -0.154 | 0.226 | 0.395 | -0.157 | 0.323 | 0.087 |
| Relative Humidity 2 (%) | 0.436 | -0.070 | 0.413 | 0.057 | 0.027 | 0.120 | -0.020 | -0.071 | 0.041 | 0.389 | -0.032 | -0.778 | -0.134 |
| Wind Speed (KMPH) | 0.137 | 0.416 | -0.328 | 0.011 | -0.343 | 0.165 | 0.232 | -0.510 | 0.366 | 0.290 | -0.067 | 0.036 | 0.108 |
| Sun Shine Hours (hours /day) | 0.393 | 0.050 | 0.436 | -0.104 | -0.257 | 0.109 | -0.160 | -0.224 | 0.446 | -0.007 | 0.627 | -0.217 | 0.117 |
| Cloud Cover Morning (Octa) | -0.241 | 0.065 | 0.151 | -0.014 | -0.489 | 0.160 | -0.323 | 0.333 | -0.180 | -0.410 | 0.172 | -0.104 | -0.156 |
| Cloud Cover Afternoon (Octa) | -0.269 | 0.243 | -0.369 | 0.018 | 0.200 | 0.445 | 0.116 | 0.096 | 0.617 | 0.106 | -0.064 | 0.243 | 0.113 |
| Dew Point Morning(°C) | -0.299 | 0.276 | 0.041 | -0.234 | -0.074 | 0.137 | -0.082 | -0.067 | -0.076 | -0.324 | -0.177 | -0.096 | 0.648 |
| Dew Point Afternoon(°C) | -0.339 | 0.097 | 0.220 | -0.079 | 0.077 | 0.334 | -0.123 | -0.343 | -0.131 | -0.073 | 0.220 | 0.324 | -0.534 |
| Dew (mm) | 0.066 | -0.420 | 0.248 | -0.073 | -0.391 | 0.478 | 0.453 | 0.325 | -0.093 | 0.183 | 0.000 | 0.103 | 0.065 |
| Disease Incidence | 0.116 | -0.531 | -0.204 | -0.021 | 0.014 | 0.245 | -0.050 | -0.519 | 0.131 | -0.409 | -0.358 | -0.121 | -0.014 |
| Eigen Values | 4.664 | 2.248 | 1.627 | 1.021 | 0.951 | 0.692 | 0.536 | 0.470 | 0.289 | 0.232 | 0.137 | 0.073 | 0.052 |
| Variance explained | 0.359 | 0.172 | 0.125 | 0.078 | 0.073 | 0.053 | 0.041 | 0.036 | 0.022 | 0.178 | 0.010 | 0.005 | 0.004 |

**Table 3:** Fitted beta regression model for powdery mildew

| Coefficient means with logit link | | | | |
|---|---|---|---|---|
| | Estimate | Std. error | z value | Pr(>\|z\|) |
| Intercept | 22.188 | 3.384 | 6.555 | <0.001** |
| Tmax | 0.711 | 0.099 | -7.130 | <0.001** |
| RH2 | -0.032 | 0.013 | -2.384 | 0.017* |
| SSH | 0.311 | 0.083 | 3.722 | <0.001** |
| Phi coefficients (precision model with identity link): | | | | |
| (phi) | 8.078 | 1.406 | 5.747 | <0.001** |

Note: level of significance (* 5%, ** 1%)

***Developing a model for powdery mildew***

A beta regression model was utilized to examine the connection between disease occurrence and key influential factors, namely maximum temperature, afternoon relative humidity, and sunshine hours. To assess the autocorrelation in the residuals, the Box-Pierce test was applied. The p-value obtained from the Box-Pierce test exceeded 0.05, indicating a lack of statistical significance. This suggests that the model was a good fit. The outcomes of the beta regression can be found in Table 3.

Among the three principal component variables, maximum temperature and sunshine hours exhibit a positive relationship with disease incidence. Conversely, afternoon relative humidity demonstrates a negative association with disease incidence. Specifically, as maximum temperature rises, disease incidence increases by 71%, and an increase in sunshine hours is associated with a 31% rise in disease incidence. This aligns with the findings of Mishra and Shirsole (2017), who reported a positive correlation between disease severity and both maximum temperature and sunshine hours. On the other hand, when afternoon relative humidity increases, disease incidence decreases by 3%, which corresponds with Nayak (2007), findings in which disease incidence showed a negative correlation with minimum temperature, relative humidity, and total rainfall. Additionally, Nag and Khare (2017) also observed a positive correlation between powdery mildew severity and temperature and wind velocity, with a negative correlation with relative humidity. Bana *et al*., (2020) affirmed that temperature (maximum and average) and evaporation showed positive relationship with incidence and severity of powdery mildew.

## CONCLUSION

The findings indicate that powdery mildew disease was most noticeable during the flowering and pod development stages of the crop. Furthermore, the research highlights that the disease occurrence is primarily influenced by maximum temperature, afternoon relative humidity, and sunshine hours when compared to other weather factors under scrutiny. As demonstrated by the beta regression model developed in this study, there exists a positive correlation between disease incidence and maximum temperature as well as sunshine hours, while a negative correlation is observed with afternoon relative humidity.

## ACKNOWLEDGEMENTS

The authors wish to acknowledge the data support from the Agricultural Research Station, Kovilpatti, Tamil Nadu Agricultural University and technical support from AICRPAM, ICAR-CRIDA, Hyderabad.

***Funding:*** The authors acknowledge the financial support from AICRPAM, ICAR-CRIDA Hyderabad to carry out the field experiment and necessary observations.

***Data availability:*** The authors confirm that the data supporting the findings of this study are available within the article

***Conflict of Interests***: The authors declare that there is no conflict of interest related to this article.

***Authors contribution:*** **S. Kokilavani**: Conceptualization, conducted experiments, writing, reviewing, editing; **V. Geethalakshmi**: Conceptualization, guidance, reviewing and editing; **R. Pangayarselvi**: Data Analysis; **J. Bhuvaneswari**: conducted experiments, writing; **G. Sudhakar**: conducted experiments, writing; **S. Subbulakshmi**: conducted experiments, writing; **P. Priyanka**: review and writing; **Timmanna**: reviewing and editing; **S.K. Bal**: guidance, reviewing and editing.

***Disclaimer***: The contents, opinions, and views expressed in the research article published in the Journal of Agrometeorology are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

***Publisher's Note***: The periodical remains neutral with regard to jurisdictional claims in published maps and institutional affiliations

## REFERENCES


Aneja, K.G. and Chandrahas (1984). Preharvest crop yield forecast based on plant biometrical characters. Silver jubilee souvenir, IASRI, New Delhi.

Bal, S.K. and Minhas, P.S. (2017). Atmospheric Stressors: Challenges and Coping Strategies. In: P.S. Minhas *et al.* (eds) Abiotic Stress Management for Resilient Agriculture. Springer Nature Singapore Pte. Ltd., 9-50. https://doi.org/10.1007/978-981-10-5744-1_2

Bana, J.K. Jaipal, S., Choudhary, P.D., Ghoghari, Hemant Sharma, Sushil Kumar and Patil, S.J. (2020). Influence of weather parameters on powdery mildew of mango inflorescence in humid tropics of South Gujarat. *J. Agrometeorol.,* 22(4): 488-493. https://doi.org/10.54386/jam.v22i4.473

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

Chandrahas and Narain, P. (1993). Pilot studies on preharvest forecasting of apple yield on the basis of data on biometrical characters, weather factors and crop inputs in Shimla District (H.P.) during 1984-86. IASRI, New Delhi.

Channaveeresh, T.S. and Shripad Kulkarni. (2014). Biochemical parameters in relation to powdery mildew resistance in black gram. *Int. J. Agric. Sci.*, 5(2): 145–149.

Cribari-Neto, F. and Zeileis, A. (2010). Beta regression in R. *J. Stat. Softw.,* 34: 1-24.

Douma, J.C. and Weedon, J.T. (2019). Analysing continuous proportions in ecology and evolution: A practical introduction to beta and Dirichlet regression. *Methods Ecol. Evol.,* 10(9): 1412-1430.

Dutta, J., Dutta, J. and Gogoi, S. (2020). Smart farming: An opportunity for efficient monitoring and detection of pests and diseases. *J. Entomol. Zool. Stud.*, *8*: 2352-59.

Ferrari, S., and Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *J. Appl. Stat.,* 31(7): 799-815.

Gautam, H.R., Bhardwaj, M.L. and Kumar, R. (2013). Climate change and its impact on plant diseases. *Curr. Sci.,* 105(12): 1685-1691.

Gawande, V.L. and Patil, J.V. (2003) Genetics of powdery mildew (*Erysiphe polygoni* DC.) resistance in mungbean (*Vigna radiata* (L.) Wilezck). *Crop Protect.,* 22: 567-571.

Hiremath, S.S. (1996). Studies on powdery mildew of Bhendi caused by *Erysiphe cichoracearum* DC. Ex. Merat. *M. Sc. (Agri.) Thesis*, Univ. of Agril. Sci, Dharwad (India).

Jain, R.C., Jha, M.P. and Agrawal, R. (1985). Use of growth indices in yield forecast. *Biom. J.,* 27(4): 435-439.

Kanzaria, K.K., Dhruj, I.U. and Sahu, D.D. (2013). Influence of weather parameters on powdery mildew disease of mustard under North Saurashtra agroclimatic zone. *J. Agrometeorol.,* 15(1): 86-88. https://doi.org/10.54386/jam.v15i1.1450

Kieschnick, R. and McCullough, B.D. (2003). Regression analysis of variates observed on (0, 1): percentages, proportions and fractions. *Stat. Model.*, 3(3): 193-213.

Milićević, D., Petronijević, R., Petrović, Z., Đjinović-Stojanović, J., Jovanović, J., Baltić, T., and Janković, S. (2019). Impact of climate change on aflatoxin M1 contamination of raw milk with special focus on climate conditions in Serbia. *J. Sci. Food Agric.,* 99(11): 5202-5210.

Mishra, T. and Shirsole, S.S. (2017). Epidemiological Studies on Powdery Mildew of Pea. *Int. J. Curr. Microbiol. Appl. Sci.,* 6: 3276-3279

Nag, U.K. and Khare, C.P. (2017). Epidemiological studies on powdery mildew of vegetable pea. *Plant Arch.*17: 171-176.

Nayak, S. (2007). Studies on powdery mildew (*Erysiphe polygoni* DC) of black gram. M.Sc. (Agri.) Thesis, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh.

Sankaran, S., Mishra, A., Ehsani, R. and Davis, C. (2010). A review of advanced techniques for detecting plant diseases. *Comput. Electron. Agric.*, 72(1): 1-13.

Singh, A.K. and Singh, Y.P. (2016). Impact of weather abnormalities and mitigation techniques for pulse production in Central India. In *81st annual Convention of ISSS and special symposiums on "Sustainable pulse production from less for more" held at RVSKVV, Gwalior. SOUVENIR* (pp. 1-13).

Singh, S., Singh, Y.P. and Tomar, S.S. (2018). Review on climatic abnormalities impact on area, productivity of central India and strategies of mitigating technology on yield and benefits of black gram. *J. Pharmacogn. Phytochem.*, 7(3): 1048-1056.

Talasila, S., Rawal, K., Sethi, G. and Sanjay, M.S.S. (2022). Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms. *Data Brief*, 45: 108725.

Wadje, A.G., Suryawanshi, A.P., Gawade, D.B., Kadam, T.S. and Pawar, A.K. (2008). Influence of sowing dates and varieties on incidence of powdery mildew of mungbean. *J. Plant Dis. Sci.*, 3(1): 34-36.

Wheeler, B.E.J. (1969). An introduction to plant disease. John Wiley and Sons Ltd., London, 301.