



Analysis of distribution pattern of peanut bud necrosis disease incidence in Pavagada district of Karnataka, India

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ABSTRACT

Peanut Bud Necrosis Disease (PBNB) is a major viral disease affecting the yield levels of groundnut infected by Peanut Bud Necrosis Virus (PBNV) and transmitted by principal vector *Thrips palmi*. The present study was attempted to assess the pattern of PBN disease incidence using continuous probability distributions for the secondary data collected from ARS, Pavagada, Tumkur for the period of 5 years (2015-2019). Descriptive statistics gave the summary of the data. One-way Analysis of Variance (ANOVA) was adapted to test the significant difference of mean disease incidence percentage among the study years during Kharif season and Duncan's Multiple Range Test (DMRT) was used to group the yearly mean incidence percentage. Specifically, Weibull, gamma, Exponentiated Exponential (EE), normal and lognormal distributions were examined to evaluate their suitability to represent the measured PBN disease incidence. Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) measures were used to test the accuracy of the above distributions. Kolmogorov-Smirnov goodness of fit test was used to evaluate the suitability of each of the above distributions.

Keywords : Analysis of variance (ANOVA), exponentiated exponential (EE) distribution, gamma distribution, lognormal distribution, normal distribution, Weibull distribution

Groundnut (*Arachis hypogaea* L.) is a legume plant widely grown in tropics and subtropics of the world with China being the world's largest producer with 173.33 lakh tonnes (37% contribution to global production), followed by India with 66.95 lakh tonnes (15% contribution to global production) and Nigeria with 28.87 lakh tonnes (6% contribution to global production) during 2019-2020 (Indiastat, 2021). Groundnut is India's most important oilseed crop, ranking first in area under the crop (55.60 lakh hectares) and second in terms of production (101 lakh tonnes) with a productivity of 1816 kg ha⁻¹ during 2020-2021. Karnataka, Gujarat, Andhra Pradesh, Tamil Nadu, Maharashtra, Rajasthan, Uttar Pradesh, Madhya Pradesh, and Orissa are major states growing groundnuts in India. Gujarat produced maximum groundnut (4645.52 thousand tonnes) followed by Rajasthan (1619.33 thousand tonnes), Tamilnadu (1033.00 thousand tonnes), Andhra Pradesh (848.79 thousand tonnes) and Karnataka (502.81 thousand tonnes) during 2019-2020 (Indiastat, 2021).

Despite its importance, the groundnut crop is associated with a vast number of diseases causing economic losses. Plant pathogens are thought to be responsible for up to 16 per cent of the global yield loss (Ficke *et al.*, 2018). More than 55 pathogens affect

groundnut (Kumar and Thirumalaisamy, 2016). Stem rot, collar rot, aflaroot, early and late leaf spot, bud necrosis and rust are among the major diseases that damage the crop in both *kharif* and *rabi* season. Peanut Bud Necrosis Disease (PBNB) is one of the most devastating virus diseases that affects groundnut spreading over a large area and causing a production loss ranging from 30 to 90 per cent. Reddy *et al.* (1968) first reported the presence of PBNB in India. Tospovirus causes PBNB and transmitted by principal vector *Thrips palmi*. The hotspot locations are Jamnagar in Gujarat, Jagtial in Telangana, Hyderabad in Andhra Pradesh, Latur in Maharashtra, Tikamgarh in Madhya Pradesh, Raichur in Karnataka and Mainpuri in Uttar Pradesh (Kumar and Thirumalaisamy, 2016).

Disease incidence is a huge setback to ideal output, since it varies from location to location and controlling it seems unattainable until it reaches a critical stage. As a result, it is necessary to examine the disease distribution pattern, which will aid in determining the manner in which disease occurs in the cropping area (Karale and Sharma, 2014; Bhavyashree and Bhattacharyya, 2019; Dutt *et al.*, 2016). Various studies related to distribution pattern of veterinary diseases using continuous probability distributions *viz.* Weibull,

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gamma, normal, lognormal etc. are available. In this article, an attempt has been made to determine the distribution pattern of incidence of plant disease.

MATERIALS AND METHODS

Study area and sampling technique

The secondary data pertaining to incidence of PBNB in groundnut and related weather parameters such as Minimum Temperature (Tmin), Maximum Temperature (Tmax), Evening Relative Humidity (RHE), Morning Relative Humidity (RHM) and Rainfall (RF) were collected from Agricultural Research Station (ARS), Pavagada, Tumkur district for *kharif* season over the period of 5 years *i.e.*, from 2015 to 2019. The groundnut field was inspected in zig-zag manner to count the number of PBNB infected plants out of 10 randomly selected plants and then observations were recorded over monthly intervals after sowing *i.e.*, 30 Days After Sowing (DAS), 60 DAS, 90 DAS. Percentage Disease Incidence (PDI) was computed by the following formula:

$$PDI = \frac{\text{Number of infected plants}}{\text{Total number of plants examined}} \times 100 \quad (1)$$

Statistical analysis

Descriptive statistics was computed to summarize the given dataset. Further, ANOVA was applied to test the significant difference of mean disease incidence percentage among the study years during *kharif* season. Duncan's Multiple Range Test (DMRT) was used to group the yearly mean incidence percentage, which shows whether there is homogeneous incidence percentage or not.

To determine the pattern of disease incidence, five continuous probability distributions were used. Maximum Likelihood Estimation (MLE) method was used to estimate the parameters.

1. Weibull distribution

The probability density function (pdf) of Weibull distribution is given by Carrasco *et al.*, 2008, Tsutsui *et al.*, 2016 and Tojinbara *et al.* (2016):

$$f_W(x) = \alpha \lambda (x\lambda)^{\alpha-1} e^{-(x\lambda)^\alpha}; \quad \alpha, \lambda, x > 0 \quad (2)$$

where, α is the shape parameter, and λ is the scale parameter

2. Gamma distribution

The pdf of gamma distribution is given by Souza *et al.* (2019); Singer *et al.* (2001) and Schukken *et al.* (2010):

$$f_G(x) = \frac{\lambda^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\lambda x}; \quad \alpha, \lambda, x > 0 \quad (3)$$

where, α is the shape parameter, and λ is the scale parameter

3. Exponentiated Exponential distribution (EED)

The pdf of EE distribution is given by Gupta and Kundu (2001) :

$$f_E(x; \alpha, \lambda) = \alpha \lambda (1 - e^{-\lambda x})^{\alpha-1} e^{-\lambda x}; \quad \alpha, \lambda, x > 0 \quad (4)$$

where, ' α ' is the shape parameter and, ' λ ' is the scale parameter

4. Normal distribution

The pdf of normal distribution is represented by Nadarajah (2005) and Sathian *et al.* (2018):

$$f(x; \alpha, \lambda) = \frac{1}{\sqrt{2\pi} \lambda} e^{-\frac{1}{2} \left(\frac{x-\alpha}{\lambda}\right)^2}; \quad -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0 \quad (5)$$

where, α – Mean (shape parameter) and λ is Standard deviation (scale parameter)

5. Lognormal distribution

The pdf of Lognormal distribution is given by Antoniou *et al.* (2002); Mbete *et al.* (2019) and Yadav *et al.* (2019):

$$f(\log_e x; \alpha, \lambda) = \frac{1}{\sqrt{2\pi} \lambda} e^{-\frac{1}{2} \left(\frac{\log_e x - \alpha}{\lambda}\right)^2}; \quad 0 < x < \infty \quad (6)$$

where, α is Mean (shape parameter) and λ is Standard deviation (scale parameter)

Test for goodness of fit of the model

The non-parametric Kolmogorov-Smirnov test (K-S test) was used to test the goodness of fit of the model. It only applies to continuous distributions (Subrahmanyam *et al.*, 2013).

The test statistic is given by

$$D = \sup_x |F_0(x) - F_1(x)| \quad (7)$$

where, $F_0(x)$ = the cumulative distribution function (CDF) of hypothesized distribution, $F_1(x)$ = the empirical CDF of the observed data.

H_0 = The empirical CDF fits well with the theoretical CDF.

H_1 = The empirical CDF does not fit well with the theoretical CDF.

To test the accuracy of the model

Lower the value of these measures, better the fitted model (Kuha, 2004).

1. Akaike Information Criterion (AIC)

The formula for AIC is

$$AIC = 2K - 2 \ln(L)$$

where, K = Number of independent variables, and L = Log-likelihood estimate

2. Bayesian Information Criterion (BIC)

The formula for BIC is

$$BIC = K \ln(n) - 2 \ln(L(\theta))$$

where, n = sample size, K = Number of independent variables, θ – set of all the parameters, and $L(\theta)$ = Loglikelihood estimate

RESULTS AND DISCUSSION**Descriptive statistics for PBNB incidence for kharif season**

To understand the nature and behaviour of the data descriptive statistics for PBNB incidence such as mean, maximum, minimum, median, CV, skewness and kurtosis were computed for *kharif* season over five years separately at monthly intervals *i.e.*, 30 DAS, 60 DAS and 90 DAS to understand the pattern in dataset. The CV indicates the dispersion or variability in the data. If the data is positively skewed it indicates that most of the data is concentrated on the right tail while negatively skewed indicates that data is concentrated on the left tail. The descriptive statistics of PBNB incidence percentage for *kharif* season were computed at monthly intervals *i.e.*, 30 DAS, 60 DAS and 90 DAS and are presented in Table 1.

The average, minimum and maximum incidence percentages indicate an increasing disease incidence pattern across the fields over the cropping period in all the years. The variability in PBNB incidence per cent measured in terms of CV (%), indicates that an increase in average disease incidence per cent reduces the variability in disease incidence percentage among the fields over cropping period *i.e.*, from 30 DAS to 90 DAS, the same results are depicted in Table 1 and Fig. 1(a) to 1(d). The result clearly indicates that disease incidence was less at early stage *i.e.*, at 30 DAS and start spreading across the field at later stage to cover maximum incidence at 90 DAS.

Comparison of significance of mean incidence percentage of PBNB over different years

Table 2 reveals that at 30 DAS, incidence of PBNB was varied significantly among different years. The incidence was significantly less during 2017 (0.38%)

and it was on-par with 2015 (0.71%) and 2016 (0.42%). Significantly higher incidence of PBNB was observed in the year 2018 (7.19%) and it was on-par with 2019 (6.09%).

At 60 DAS, PBNB incidence varied significantly among different years. Significantly lower incidence was observed during 2016 (2.19%) and it was on-par with 2015 (3.00%). The incidence was significantly higher during 2018 (11.28%) followed by 2019 (9.81%) and 2017 (5.38%).

At 90 DAS, incidence of PBNB was varied significantly among different years. The incidence was significantly lower during 2016 (4.66%) and was on-par with 2015 (5.85%). The incidence was significantly higher during 2018 (15.57%) and it was on-par with 2019 (14.04%) followed by 2017 (8.23%).

Analysis of distribution pattern of PBNB incidence for kharif season**Kharif – 2015**

For PBNB incidence in *kharif* – 2015, computed parameters estimate, AIC, BIC and K-S test statistic values for Weibull, gamma, EE, normal and lognormal distributions are tabulated in Table 3. The computed values of K-S test statistic (D) for the Weibull, gamma, EE and normal distributions were non-significant ($p \geq 0.05$) whereas lognormal distribution was significant ($p \leq 0.05$). Among the selected models, Weibull distribution has the lowest K-S test statistic value. The lowest AIC and BIC values for Weibull distribution indicates that the Weibull distribution was the best fitted model for the *kharif*–2015. Fig. 2 depicts a CDF plot of the Weibull distribution demonstrating better agreement between theoretical and empirical CDFs which indicates PBNB incidence pattern follows the Weibull distribution.

Kharif – 2016

For PBNB incidence in *kharif* – 2016, calculated parameters estimate, AIC, BIC and K-S test statistic values for Weibull, gamma, EE, normal and lognormal distributions are presented in Table 3. The computed values for K-S test statistic (D) for the EE and gamma distributions were non-significant whereas Weibull, normal and lognormal distributions were significant. Among the selected models, EE and gamma distribution has the lowest K-S test statistic value. The EE distribution was the best fitted model for *kharif* – 2016 based on the lowest AIC and BIC values. Fig. 3 depicts a CDF plot of the EE distribution, demonstrating a better

Table 1: Descriptive statistics for PBND incidence during *kharif*-2015 to 2019

Summary statistics	PBND Incidence (%)														
	2015			2016			2017			2018			2019		
	30	60	90	30	60	90	30	60	90	30	60	90	30	60	90
Mean	0.71	3.00	5.86	0.42	2.19	4.67	0.38	5.39	8.24	7.19	11.29	15.57	6.10	9.81	14.05
Median	1.00	3.00	6.00	0.00	2.00	4.00	0.00	5.00	9.00	8.00	11.00	16.00	7.00	10.00	14.00
Maximum	2.00	5.00	9.00	2.00	5.00	8.00	3.00	9.00	11.00	13.00	16.00	21.00	11.00	15.00	19.00
Minimum	0.00	1.00	2.00	0.00	1.00	2.00	0.00	1.00	5.00	0.00	6.00	9.00	0.00	6.00	7.00
CV	109.0	38.00	28.00	157.0	55.00	46.00	255.0	44.00	23.00	62.00	27.00	22.00	52.00	22.00	22.00
Skewness	0.57	-0.22	-0.55	1.35	0.91	0.60	2.34	-0.25	-0.23	-0.48	-0.33	-0.30	-0.72	0.07	-0.21
Kurtosis	-1.07	-1.03	0.55	0.75	-0.05	-1.14	4.11	-0.42	-1.03	-0.93	-1.01	-0.61	-0.57	0.63	0.03

agreement between theoretical and empirical CDFs which indicates PBND incidence pattern follows EE distribution.

Kharif – 2017

For PBND incidence in *kharif* – 2017, computed parameters estimate, AIC, BIC and K-S test statistic values for Weibull, gamma, EE, normal and lognormal distributions are reported in Table 3. The calculated values for K-S test statistic for normal distribution were non-significant ($p \geq 0.05$) whereas Weibull, gamma, EE and lognormal distributions were significant ($p \leq 0.05$). Among the selected models, normal distribution has the lowest K-S test statistic value. Although, other models possess lowest AIC and BIC values than normal distribution, they fail to satisfy the condition of K-S test. Hence, the normal distribution was considered to be best fitted model for *kharif* – 2017. Fig. 4 depicts a CDF plot of the normal distribution, demonstrating a better agreement between theoretical and empirical CDFs which indicates PBND incidence pattern follows normal distribution.

Kharif – 2018

For PBND incidence in *kharif* – 2018, calculated parameters estimate, AIC, BIC and K-S test statistic values for Weibull, gamma, EE, normal and lognormal distributions are tabulated in Table 3. The computed values for K-S test statistic for Weibull and normal distributions were non-significant ($p \geq 0.05$) whereas gamma, EE and lognormal distributions were significant ($p \leq 0.05$). Among the selected models, normal distribution has the lowest K-S test statistic value. Based on the lowest AIC and BIC values, the normal distribution was the best fitted model for *kharif* – 2018. Fig. 5 depicts a CDF plot of the normal distribution, demonstrating a better agreement between theoretical and empirical CDFs which indicates PBND incidence pattern follows normal distribution.

Kharif – 2019

For PBND incidence in *kharif* – 2019, calculated parameters estimate, AIC, BIC and K-S test statistic values for Weibull, gamma, EE, normal and lognormal distributions are presented in Table 3. The computed values for K-S test statistic for Weibull and normal distributions were non-significant ($p \geq 0.05$) whereas gamma, EE and lognormal distributions were significant ($p \geq 0.05$). Among the selected models, normal distribution has the lowest K-S test statistic value. The normal distribution was found to be best fitted model for *kharif* – 2019 based on the lowest AIC and BIC values. Fig. 6 depicts a CDF plot of the normal

Table 2: Comparison of means of PBNB incidence per cent over different years for *kharif* season

Year	30 DAS	60 DAS	90 DAS
2015	0.71 ^a	3.00 ^a	5.85 ^a
2016	0.42 ^a	2.19 ^a	4.66 ^a
2017	0.38 ^a	5.38 ^b	8.23 ^b
2018	7.19 ^b	11.28 ^d	15.57 ^c
2019	6.09 ^b	9.81 ^c	14.04 ^c

Means followed by the same letter in a column indicates no significant difference in disease incidence percent over different years

Table 3: Parameter estimates, AIC, BIC, K-S test statistic for *kharif* season

Models		2015	2016	2017	2018	2019
Weibull	α	1.08	0.93	0.84	2.10	2.19
	λ	3.28	2.37	4.44	12.43	11.01
	AIC	276.26	242.46	323.71	401.08	380.36
	BIC	280.55	246.75	328.00	405.37	384.65
	K-S test	0.15	0.17	0.25	0.15	0.16
	<i>p</i> -value	0.09	0.04	0.00	0.08	0.06
Gamma	α	1.00	0.85	0.70	2.15	2.48
	λ	0.31	0.34	0.14	0.19	0.24
	AIC	276.80	241.79	320.32	418.62	396.74
	BIC	281.09	246.08	324.60	422.90	401.03
	K-S test	0.16	0.16	0.25	0.22	0.23
	<i>p</i> -value	0.07	0.07	0.00	0.00	0.00
EE	α	0.97	0.83	0.69	2.02	2.35
	λ	0.30	0.36	0.16	0.13	0.15
	AIC	276.78	241.63	319.67	421.88	400.56
	BIC	281.07	245.91	323.95	426.17	404.85
	K-S test	0.16	0.16	0.26	0.23	0.24
	<i>p</i> -value	0.06	0.06	0.00	0.00	0.00
Normal	α	3.20	2.45	4.73	11.35	9.98
	λ	2.40	2.24	3.63	4.80	4.30
	AIC	293.53	284.52	345.43	381.80	366.68
	BIC	297.82	288.81	349.71	386.09	370.97
	K-S test	0.16	0.18	0.16	0.09	0.10
	<i>p</i> -value	0.05	0.02	0.06	0.64	0.48
Lognormal	α	0.58	0.20	0.70	2.18	2.08
	λ	1.39	1.46	1.78	1.07	0.94
	AIC	299.23	256.45	344.53	466.84	438.40
	BIC	303.52	260.74	348.81	471.13	442.69
	K-S test	0.25	0.22	0.28	0.27	0.29
	<i>p</i> -value	0.00	0.00	0.00	0.00	0.00

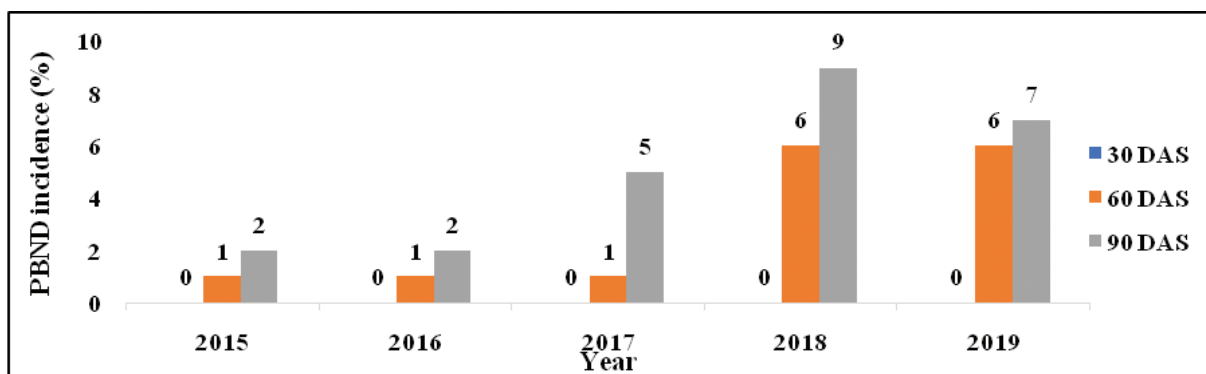


Fig. 1(a): Minimum PBND incidence during *kharif* season from 2015 to 2019

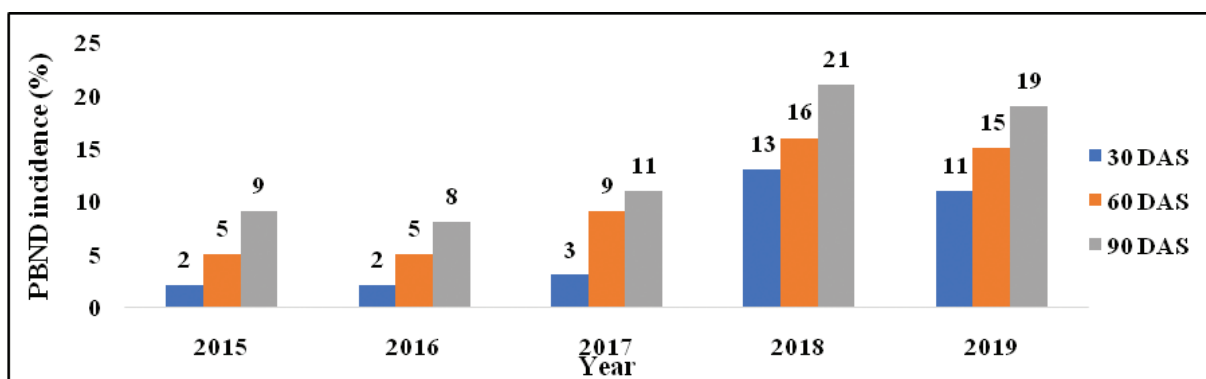


Fig. 1(b): Maximum PBND incidence during *kharif* season from 2015 to 2019

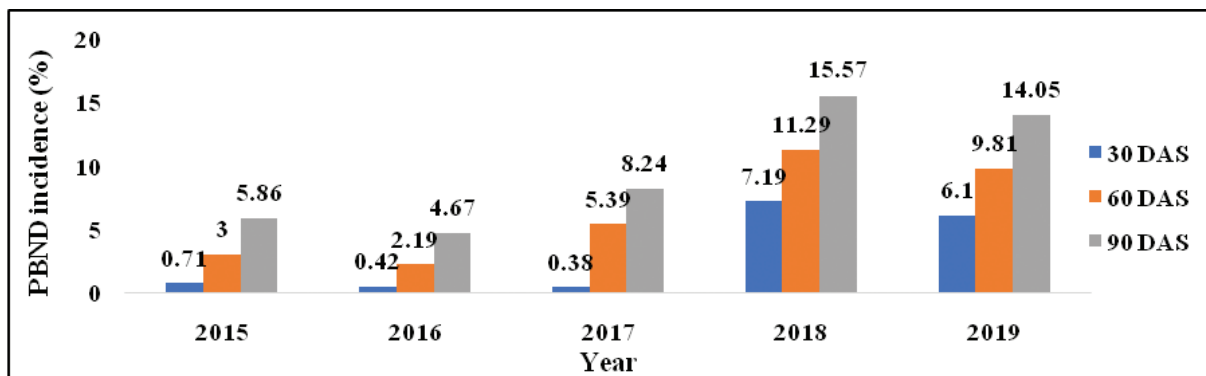


Fig. 1(c): Average PBND incidence during *kharif* season from 2015 to 2019

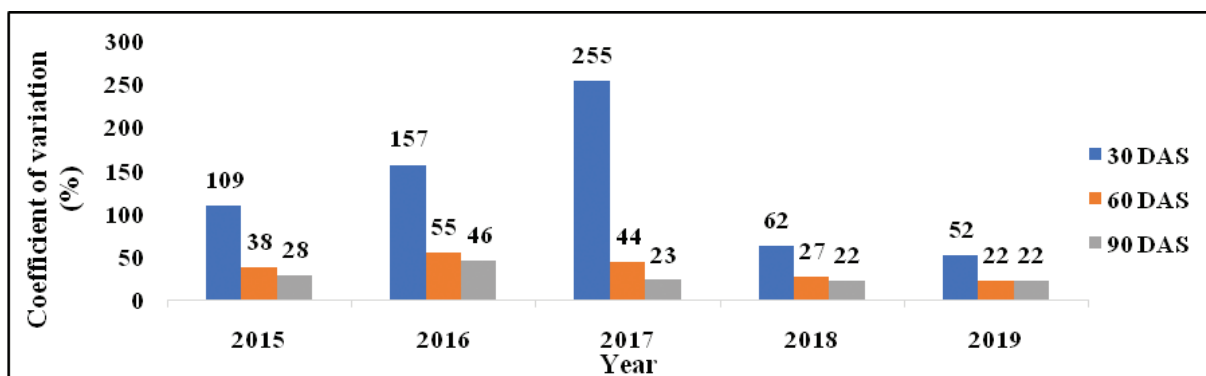


Fig. 1(d): CV (%) of PBND incidence during *kharif* season from 2015 to 2019

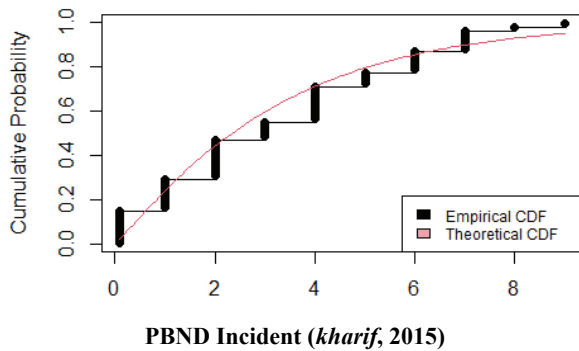


Fig. 2: CDF plot of Weibull distribution for *kharif* - 2015

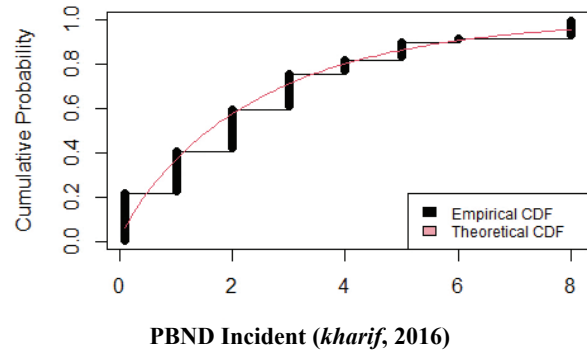


Fig. 3: CDF plot of EE distribution for *kharif* - 2016

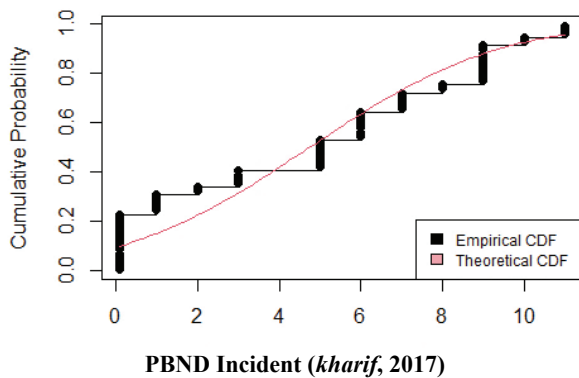


Fig. 4: CDF plot of normal distribution for *kharif*- 2017

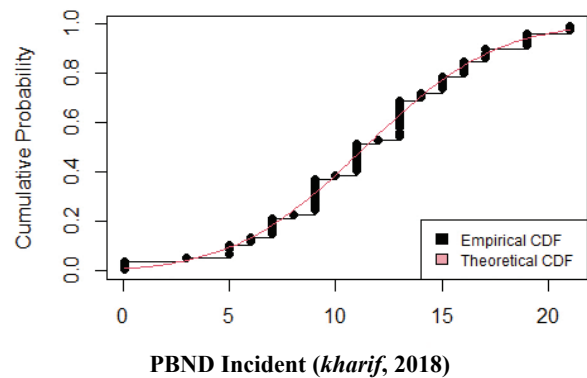


Fig. 5: CDF plot of normal distribution for *kharif* - 2018

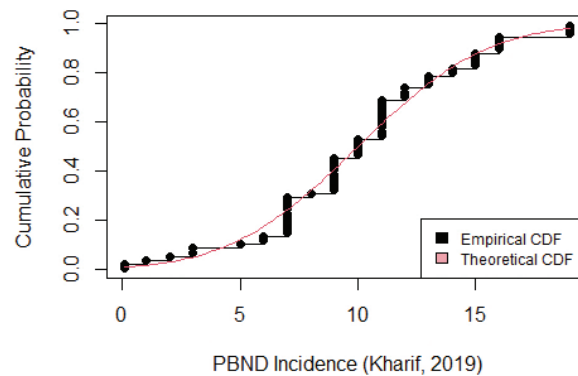


Fig. 6: CDF plot of normal distribution for *kharif*- 2019

distribution, demonstrating a better agreement between theoretical and empirical CDFs which indicates PBND incidence follows the normal pattern.

CONCLUSION

The pattern of disease incidence was found mostly for veterinary diseases only. An attempt has been made to analyse the plant diseases also. The results show that in most of the cases Weibull and Normal distribution has been found to be most suitable models for fitting the data. This can be extended to other plant diseases also.

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