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Original Article

Spatial analysis of factors influencing bacterial leaf blight in rice production

Análise espacial dos fatores que influenciam a praga bacteriana foliar na produção de arroz

T. M. Ahmad[a]*, M. S. Haider[a], T. O. Randhir[b], R. Randhir[c] and S. R. Ahmad[d]

[a]University of the Punjab, Faculty of Agricultural Sciences, Lahore, Pakistan
[b]University of Massachusetts, College of Natural Sciences, Department of Environmental Conservation, Amherst, MA, USA
[c]Springfield Technical Community College, Department of Biological Sciences, Springfield, MA, USA
[d]University of the Punjab, College of Earth and Environmental Sciences, Lahore, Pakistan

Abstract

Xanthomonas oryzae pv. oryzae (Xoo) causes bacterial leaf blight that is a major threat to rice production. Crop losses in extreme situations can reach up to75%, and millions of hectares of rice are affected each year. Management of the disease required information about the spatial distribution of BLB incidence, severity, and prevalence. In this study, major rice-growing areas of Pakistan were surveyed during 2018-2019 for disease occurrence, and thematic maps were developed using geographic information system (GIS). Results showed that Narowal district had highest percentage of disease incidence (54-69%), severity (42-44%), and prevalence (72-90%) meanwhile Jhung district had the lowest incidence (21-23%), severity (18-22%), and prevalence (45-54%). To understand the environmental factors contributing to this major rice disease, the research analyze, the spatial relationships between BLB prevalence and environmental variables. Those variables include relative humidity (RH), atmospheric pressure (A.P), minimum temperature, soil organic carbon, soil pH, and elevation, which were evaluated by using GIS-based Ordinary Least Square (OLS) spatial model. The fitted model had a coefficient of determination (R^2) of 65 percent explanatory power of disease development. All environmental variables showed a general trend of positive correlation between BLB prevalence and environmental variables. The results show the potential for disease management and prediction using environmental variable and assessment.

Keywords: *Xanthomonas oryzae*, bacterial leaf blight, disease incidence, correlation, environmental variables.

Resumo

Xanthomonas oryzae pv. oryzae (Xoo) causa o crestamento bacteriano das folhas, que é uma grande ameaça à produção de arroz. As perdas de safra em situações extremas podem chegar a 75% e a milhões de hectares de arroz são afetados a cada ano. O manejo da doença exigia informações sobre a distribuição espacial da incidência, gravidade e prevalência de BLB. Neste estudo, as principais áreas de cultivo de arroz do Paquistão foram pesquisadas durante 2018 e 2019 para ocorrência de doenças, e mapas temáticos foram desenvolvidos usando o sistema de informações geográficas (GIS). Os resultados mostraram que o distrito de Narowal teve a maior porcentagem de incidência da doença (54-69%), gravidade (42-44%) e prevalência (72-90%), enquanto o distrito de Jhung teve a menor incidência (21-23%), gravidade (18-22%) e prevalência (45-54%). Para compreender os fatores ambientais que contribuem para esta importante doença do arroz, a pesquisa analisa as relações espaciais entre a prevalência de BLB e as variáveis ambientais. Essas variáveis incluem umidade relativa (UR), pressão atmosférica (PA), temperatura mínima, carbono orgânico do solo, pH do solo e altitude, que sendo avaliadas a partir do modelo espacial Ordinary Least Square (OLS) baseado em GIS. O modelo ajustado teve um coeficiente de determinação (R^2) de 65 por cento de poder explicativo do desenvolvimento da doença. Todas as variáveis ambientais apresentaram tendência geral de correlação positiva entre prevalência de BLB e variáveis ambientais. Os resultados mostram o potencial de manejo e predição de doenças usando variáveis e avaliações ambientais.

Palavras-chave: *Xanthomonas oryzae*, crestamento bacteriano das folhas, incidência de doenças, correlação, variáveis ambientais.

*e-mail: taibaahmad@yahoo.com
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1. Introduction

Rice (*Oryza sativa*) provides 21% of human energy and 15% of human protein globally. It is an essential crop for global food security (Pérez-Montaño et al., 2014). Rice is Pakistan's second most important crop, with the ability to bring farmers economic prosperity through export. Pakistan is the world's 11th biggest rice producer and exporter. Rice contributes 3.2% to Pakistan's agricultural value added and 0.7% to its GDP (Shahzadi et al., 2018).

Bacterial leaf blight (BLB), caused by the bacterium *Xanthomonas oryzae pv. oryzae (Xoo)*, is one of the most damaging diseases of rice in Asia, causing yield losses of up to 30% in Pakistan (Rafi et al., 2013).

Disease assessment through measurement and quantification is having fundamental importance in studying and analyzing plant disease epidemics (Arshad et al., 2020). Bock et al. (2010) suggested that assessing disease on a plant is essential for quantitative epidemiological studies. Assessment of the disease is critical to decisions related to investments in disease management. It is also important to researchers and extension workers in developing precise methods for managing the disease (Awoderv et al., 2008). Due to development in information technology, now there are many opportunities to assess the disease. Geographic Information Systems (GIS) is being widely applied as an effective and powerful tool in assessing, visualizing the process effectively for disease (Anwer and Singh, 2019). GIS is a useful tool for field-specific and decision-making approaches. Disease spread and agricultural yields may be simulated on a broad scale using crop simulation models and GIS (Li et al., 2021). Kodong et al., (2020) also employed GIS technology to track the spread of numerous infectious diseases; This technology is useful for creating many types of maps that display various types of disease information. In apple producing regions of New Zealand, GIS was used to map European Canker (EC), which is transmitted *by Neonectria ditissima* (Di Iorio et al., 2019). Golmohammadi et al., (2020) worked for three years on rice farms in Iran's Guilan province to map rice weed prevalence using Geographic Information System (GIS) technologies (2014-2016). In plant pathology, geospatial analysis is used to feed data into risk assessment models and to quantify how disease thresholds are developing as a response of climate change (Bouwmeester et al., 2010).

A vulnerable host, a virulent pathogen, and favorable environmental factors combine to produce plant diseases (Garrett et al., 2006; Klopfenstein et al., 2009; Grulke, 2011). Environment has a big impact on infection development and has been researched extensively as disease outbreak predictions. Several epidemiological studies in the past have revealed that environmental factors like humidity and temperature play a important role in the spread of rice diseases (Madden et al., 2007).Ordinary least squares (OLS),a spatial regression method by ArcGIS commonly used to develop the relationships between disease and environmental factors (Sharma et al., 2011).

The term "digital farming" (also known as "precision agriculture"," "smart agriculture," "intelligent agriculture," "e-agriculture" or agriculture 4.0) covers a comprehensive information, from computer and mobile applications which also includes ArcGIS and GPS device for decision making. In the future, sustainable agriculture will necessitate e-agriculture or smart agriculture (Walter et al., 2017), which will rely on artificial intelligence (AI), the Internet of Things (IoT), cloud computing, and computer-based applications, with other technologies (Klerkx et al., 2019; Torky and Hassanein, 2020; Shang et al., 2021). The use of ArcGIS or spatial modeling for disease surveillance was discovered to be necessary for cost-effectiveness; additionally, it broadened the ways of assessing diseases in crop health at various levels. The leverage of advanced technologies and digital farming for BLB disease surveillance in different districts of Pakistan were brought into account to limit the impact of BLB disease spreading locally, and globally effectively.

The major objectives of this research are following (1) Explore spatial and temporal patterns of BLB incidence, severity and prevalence in order to find disease clusters and trends. The patterns could help researchers to identify geographical and non-geographical factors associated with disease occurrences. These patterns can also help policy makers to plan preventive measures for mitigating disease effects (2) Evaluate and analyze the spatial correlations that exist between disease prevalence and environmental factors that influence disease by using spatial modeling. With the use of GIS, we performed an OLS regression study. Hypotheses that will be tested that; there is significant relationship between disease prevalence and environmental variables.

2. Material and Method

2.1. Study area

More than 20 locations were surveyed and assessed for two consecutive years, 2018 and 2019, for disease incidence severity and prevalence. These locations include Sargodha, Hafizabad, Sheikhupura, Sialkot, Narowal, Narowal 2 (Pasrur) Gujranwala, Gujranwala 2 (Daska, sambrial) Gujrat, Gujarat(Malakwal, Bhera) Lahore, Kasur, Pakpattan, Okara, Okara 1 (Depalpur, Haveli Lakha) bahawalnagar, Jhung, Wazirabad, Muridke, Kala shah kaku, Faisalabad, Sahiwal and Nankana Sahib. These locations were geographically represented in Figure 1. A handheld GPS device was used to record location coordinates which are written in (Table 1) and were used to build comprehensive maps using GIS software. The GIS database was created using ArcGIS 10.3, a computerized mapping system. For each city, four random sites were selected; and data were collected for disease incidence, severity, and prevalence

2.1.1. Sample collection

Rice plant leaves with typical bacterial blight symptoms were obtained. The collected samples were placed in polythene bags and labeled appropriately before being transported to the laboratory for identification (Shaheen et al., 2019).

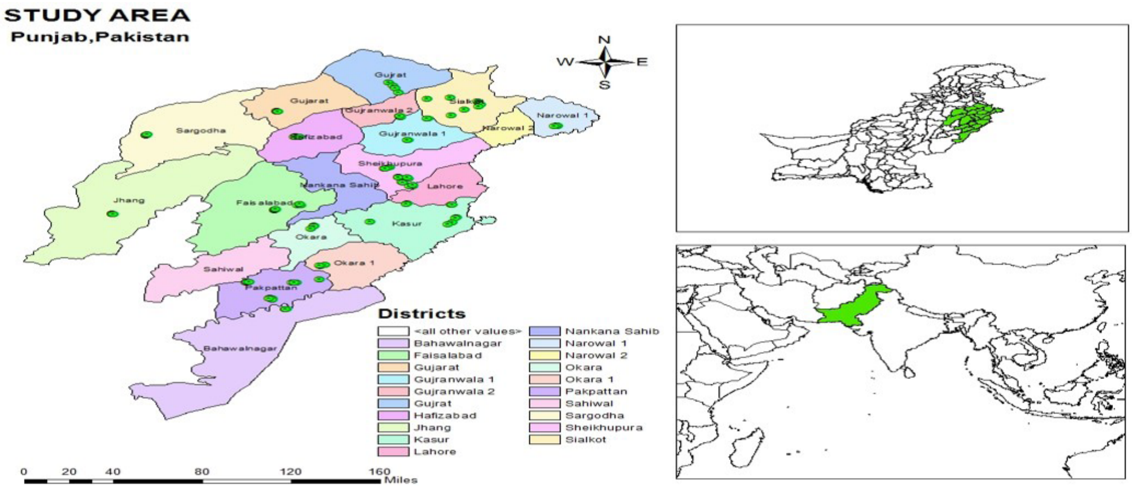

Figure 1. Geographical representation of location sites.

Table 1. Site surveyed from each city and their coordinates.

Location	Site	Coordinates		Location	Site	Coordinates	
Lahore	S.1	N 31°27'-10"	E 74°41'-09"	**M.B Din**	S.1	N 32°33'-01"	E 73°27'-34"
	S.2	N 31°26'-68"	E 74°41'-35"		S.2	N 32°32'-28"	E 73°27'-54"
	S.3	N 31°28'-26"	E 74°12'-46"		S.3	N 32°32'-35"	E 73°28'-15"
	S.4	N 31°27'-37"	E 74°12'-03"		S.4	N 32°32'-32"	E 73°28'-26"
Shekhupura	S.1	N 31°69'-45"	E 74°01'-13"	**Sargodha**	S.1	N 32°05'-21"	E 72°42'-56"
	S.2	N 31°68'-17"	E 73°99'-19"		S.2	N 32°05'-36"	E 72°42'-29"
	S.3	N 31°67'-95"	E 73°97'-43"		S.3	N 32°05'-55"	E 72°42'-58"
	S.4	N 31°67'-39"	E 73°97'-91"		S.4	N 32°06'-30"	E 72°43'-35"
sharaqpur	S.1	N 31°58'-64"	E 74°06'-64"	**Jhang**	S.1	N 31°17'-02"	E 72°20'-19"
	S.2	N 31°57'-49"	E 74°06'-94"		S.2	N 31°16'-57"	E 72°21'-04"
	S.3	N 31°52'-94"	E 74°08'-96"		S.3	N 31°16'-29"	E 72°20'-22"
	S.4	N 31°51'-92"	E 74°09'-18"		S.4	N 31°16'-28"	E 72°20'-54"
Muridke	S.1	N 31°48'-24"	E 74°16'-12"	**Hafizabad**	S.1	N 32°04'-11"	E 73°39'-54"
	S.2	N 31°48'-00"	E 74°16'-30"		S.2	N 32°03'-43"	E 73°38'-58"
	S.3	N 31°48'-07"	E 74°14'-03"		S.3	N 32°03'-29"	E 73°41'-58"
	S.4	N 31°49'-31"	E 74°16'-05"		S.4	N 32°03'-59"	E 73°42'-26"
Nankana Sahib	S.1	N 31°26'-16"	E 73°42'-33"	**Sahiwal**	S.1	N 30°39'-13"	E 73°07'-27"
	S.2	N 31°26'-41"	E 73°41'-23"		S.2	N 30°40'-10"	E 73°08'-33"
	S.3	N 31°26'-30"	E 73°43'-03"		S.3	N 30°40'-17"	E 73°08'-02"
	S.4	N 31°27'-47"	E 73°42'-13"		S.4	N 30°40'-02"	E 73°09'-54"
Kasur	S.1	N 31°12'-71"	E 74°44'-68"	**Narowal**	S.1	N 32°16'-18"	E 75°10'-15"
	S.2	N 31°11'-91"	E 74°44'-13"		S.2	N 32°15'-55"	E 75°10'-25"
	S.3	N 31°06'-86"	E 74°41'-39"		S.3	N 32°16'-24"	E 75°09'-54"
	S.4	N 31°05'-10"	E 74°38'-75"		S.4	N 32°15'-45"	E 75°08'-39"
Chunian	S.1	N 30°59'-22"	E 73°58'-59"	**Pasrur**	S.1	N 32°40'-79"	E 74°59'-68"
	S.2	N 30°57'-45"	E 73°56'-04"		S.2	N 32°39'-80"	E 74°60'-29"
	S.3	N 30°58'-09"	E 73°55'-42"		S.3	N 32°37'-81"	E 74°59'-10"
	S.4	N 30°42'-57"	E 73°55'-39"		S.4	N 32°34'-47"	E 74°49'-21"
Pattoki	S.1	N 31°07'-94"	E 73°87'-82"	**Daska**	S.1	N 32°31'-46"	E 74°43'-77"
	S.2	N 31°03'-10"	E 73°52'-00"		S.2	N 32°27'-89"	E 74°41'-15"
	S.3	N 31°02'-51"	E 73°51'-44"		S.3	N 32°24'-05"	E 74°26'-25"
	S.4	N 31°00'-02"	E 73°49'-30"		S.4	N 32°24'-03"	E 74°25'-48"
Faisalabad	S.1	N 31°20'-47"	E 73°26'-23"	**Sialkot**	S.1	N 32°46'-65"	E 74°25'-02"
	S.2	N 31°21'-31"	E 73°26'-02"		S.2	N 32°47'-84"	E 74°39'-95"
	S.3	N 31°21'-45"	E 73°26'-43"		S.3	N 32°43'-21"	E 74°58'-10"
	S.4	N 31°22'-01"	E 73°26'-46"		S.4	N 32°42'-39"	E 74°58'-69"

Table 1. Continued...

Location	Site	Coordinates		Location	Site	Coordinates	
Okara	S.1	N 30°39'-09"	E 73°38'-46"	**Wazirabad**	S.1	N 32°25'-53"	E 74°08'-14"
	S.2	N 30°39'-39"	E 73°37'-59"		S.2	N 32°27'-08"	E 74°08'-27"
	S.3	N 30°39'-45"	E 73°40'-34"		S.3	N 32°27'-29"	E 74°07'-35"
	S.4	N 30°39'-19"	E 73°39'-13"		S.4	N 32°27'-23"	E 74°07'-05"
Pakpttan	S.1	N 30°22'-17"	E 73°23'-15"	**Gujranwala**	S.1	N 31°56'-45"	E 74°13'-36"
	S.2	N 30°21'-43"	E 73°24'-26"		S.2	N 32°00'-08"	E 74°13'-30"
	S.3	N 30°20'-02"	E 73°24'-17"		S.3	N 32°00'-04"	E 74°12'-34"
	S.4	N 30°21'-37"	E 73°22'-26"		S.4	N 31°57'-45"	E 74°12'-24"
Bhawalnagar	S.1	N 30°09'-13"	E 73°34'-11"	**Gujrat**	S.1	N 32°64'-56"	E 74°00'-11"
	S.2	N 30°09'-35"	E 73°33'-29"		S.2	N 32°61'-46"	E 74°02'-76"
	S.3	N 30°09'-01"	E 73°33'-35"		S.3	N 32°58'-65"	E 74°04'-34"
	S.4	N 30°09'-04"	E 73°33'-16"		S.4	N 32°53'-49"	E 74°06'-49"

2.1.2. Identification of bacterial pathogen from rice

The causal organism *Xanthomonas oryzae* was found in infected leaf from affected crops. Water-soaked lesions formed on the leaf margin, develop in length downward along with the veins, and eventually changed into light yellow or straw colored stripes with distinctive curly borders. When the lesioned leaf was held up to a light source, the water-soaked patches in the adjoining areas around the lesions became visible. When the crop was damp or moist, the surface of lesions displayed yellowish, opaque, and turbid drops of bacterial ooze. The bacterial cells in these droplets dried up and form little yellowish round beads on the lesions. In rice fields that were badly afflicted by BLB, yellowish or amber colored beads like bacterial exudates were frequently detected. When the contaminated leaves were cut into small pieces and placed in a glass of water for 30 minutes, the water became turbid and yellowish (Rajarajeswari and Muralidharan, 2006).

2.1.3. Isolation of Xanthomonas oryzae from rice plant

The causal agent of bacterial leaf blight, *Xanthomonas oryzae* was isolated from affected rice plants. A sterile blade was used to cut away a 1 cm long diseased leaf piece of rice. Clorox was used to disinfect the leaf's surface for around 3 minutes before being washed with distilled water. The diseased pieces were dried before being transferred to a nutrient agar (NA) medium and cultured for 72 hours at room temperature 25-27°C (Jabeen et al., 2012). To obtain pure culture, the developing colonies were sub-cultured on NA plates.

2.1.4. Potassium hydroxide (KOH) test

The KOH analysis was performed to determine the biochemical properties of the Xoo pathogen. Bacterial culture was placed on a glass slide and agitated with a 3% KOH solution for 60 seconds. Bacterial DNA emerged as a thread from the bacterial cell, suggesting the presence of gram-negative bacteria (Shaheen et al., 2019).

2.2. Disease assessment

2.2.1. Prevalence

The area was visually inspected for bacterial leaf blight presence or absence. In order to determine disease prevalence, four farms from each city were chosen and examined. The %age of fields revealing the disease from the total number of fields examined was used to calculate disease prevalence (Mounde et al., 2009). The Equation 1 was used to calculate prevalence percentage.

$$Prevalence\% = \frac{Farms\ showing\ symptoms}{Total\ farms\ examined} X\,100 \tag{1}$$

2.2.2. Incidence

Taking four places in the field, the incidence of BLB was estimated. Starting ten meters within the field, these points were selected at random five paces apart. Four plants were examined for BLB symptoms at each spot. The Equation 2 below was used to calculate disease incidence (Teng and James, 2002).

$$Disease\ Incidence\ \% = \frac{Number\ of\ infected\ plants}{Total\ number\ of\ plants\ examined} X\,100 \tag{2}$$

2.2.3. Severity

Five plants were chosen at random from each field. Then from each plant five leaves were selected, data on length of lesions and total area of leaf was collected, and the percent disease severity was calculated. The scale was applied to measure the severity of BLB in Table 2 (Chaudhary, 1996; Khan et al., 2012).

2.3. Geographic Information System

Using ArcGIS software, the incidence, severity, and prevalence can be calculated using area weighted means. The following method was used for this purpose: A GPS device was used to record location coordinates, which were then downloaded into GIS software to create detailed maps. Arc map 10.3 was used to create thematic maps for disease severity incidence and prevalence. A CSV file was prepared with data for X and Y coordinates in relation to sampling sites. The boundary of the selected study region was prepared as a shapefile (vector data). In the projected window, the CSV file was opened, and in the X-field, the X-coordinate was selected, and in the Y-field, the Y-coordinate was selected. Each town's disease prevalence, incidence, and severity were calculated using the Z field. The interpolation method employed was applied by Inverse

Table 2. Disease severity scale for evaluation of BLB.

Disease Rating	0	1	3	5	7	9
Lesion size (% of leaflength)	Zero	>1-10%	>11-30%	>31-50%	>51-75%	>76-100%

Distance Weighted (IDW) method (Hussain et al., 2014). After this, area-weighted means were calculated in ArcGIS.

The area-weighted mean of disease was calculated using the following Equation 3:

$$A = \frac{\sum_{i=1}^{n} aiwi}{\sum_{i=1}^{n} wi} \quad (3)$$

$\sum_{i=1}^{n} wi$ Where A is the area-weighted mean of disease, ai is the area of the i^{th}town, wi is the weight of the i^{th} town (Looga et al., 2018).

2.4. OLS model for spatial relationship

The OLS technique is the most common method for estimating a linear regression model. This is due to the ease of use and optimal nature of the model coefficients for cross-sectional data sets. This strategy has been used to study samples that are distributed in space, with the presumption that the relationships are spatially constant (Ivajnsic et al., 2014).

A regression model is expressed in Equation 4:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \ldots \beta_n X_n + \varepsilon \quad (4)$$

Where Y is the dependent variable (BLB prevalence), the betas $\beta 0$ to βn represent the consequent number of the coefficients of predictors while $X_1 \, to \, X_n$ depicts the corresponding number of predictors and ε is error of residuals. Ordinary least square ANOVA contain different statistical tests which includes Joint F-statistics, Koenker statistics, Wald statistics and Jarque and Bera statistics which define the explanatory variables are significant to independent value or not (Nkeki and Osirike, 2013; Ahmad et al., 2021).

Environmental factors that were used as explanatory variables were:

X_1 = RH

X_2 = Surface pressure (A.P)

X_3 = Minimum temperature (T.min)

X_4 = Soil pH (S.pH)

X_5 = Soil Organic Carbon (SOC) and

X_6 = elevation

- Environmental data of RH, Minimum temperature, Relative Humidity, Surface pressure data was taken from NASA Power Data Access Viewer
- Soil pH, and Soil Organic Carbon data taken from soil grids
- Elevation by Diva GIS

Data was interpolated by kriging method; it is a process that includes data from known nearer points to estimate the optimum values of data at other points. Kriging interpolation is a technique that uses semivariogram structural features to estimate unbiased spatial changes at unsampled sites. The fact that a variance value may be calculated for each projected point or area distinguishes the Kriging method from other interpolation methods. In Kriging, the basic Equation 5 is as follows:

$$Z(X_o) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (5)$$

Where Z(x) represents the estimator at the point x, λ_i represents the weight of each sample point, and *n* means the number of the sample point (Kuo et al., 2021). The R.H., Surface pressure (A.p) and Min. temperature, soil pH soil organic carbon and elevation were then calculated using the zonal statistic. The zonal statistics tool (ArcGIS 10.3's Spatial Analyst tool) calculates statistics for a raster's value within a zone of another dataset. As a result, the zonal statistic tool explains the value inside the city and reports the mean, maximum, lowest, and range values (Bakhash and Kanwar, 2004; Tiwari and Sharma, 2009).

2.4.1. Model evaluation criteria

The spatial relation between BLB prevalence and environmental factors was investigated using OLS spatial statistical methods (Oh et al., 2021).

2.4.2. Overall model performance

a: Adjusted R-squared:

For a disease prevalence that is the dependent variable, the adjusted R-squared value is a statistical metric that shows the proportion of the variance in a regression model that can be explained by the independent variables, which in this case are environmental factors (Liu et al., 2019)

b: AICc:

The Akaike information criterion (AIC) is a model evaluation performance metric (Pan et al., 2019). The corrected Akaike's information criterion (AICc) is a second order correction for small datasets. The AICc values of superior models are lower.

2.4.3. Model bias

a: VIF:

It featured a multicollinearity check (redundancy among predictors). If the VIF values are larger than 7.5, it suggests that the predictors are multicollinear (Meng et al., 2015).

b: Jarque and Bera statistics:

This test is used to determine if there is any model bias. It's a means of determining how far the residuals deviate from a normal distribution. It's a goodness-of-fit test that analyses whether sample data has the same skewness and kurtosis as a normal distribution which is describe in Equation 6. (Jarque and Bera, 1987; Hastie et al., 2009).

$$JB = \frac{n-k}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{6}$$

Where n is the number of observations and k is the sample kurtosis, S is the sample skewness, when examining residuals to an equation.

2.4.4. Model stationary

a: The Koenker (BP) Statistic:

This test is used to determine whether or not the model is stationary. It represents that whether the explanatory components in the model have a consistent correlation with the dependent variable in both geographic and data space (Mitchel and Griffin, 2005; Yang et al., 2020).

2.4.5. Model significance

a: F- statistics:

It is used to assess model significance. Both tests the Joint F-Statistic and Wald Statistic are statistical significance indicators for the overall model (Büchse et al., 2007). The value of F can be measured by Equation 7:

$$F = \frac{MS_t}{MS_e} \tag{7}$$

Where, MS_t *and* MS_e are mean square treatment and error respectively.

b: Wald statistics:

The Wald test (also known as the Wald Chi-Squared Test) determines the significance of independent variables in a model (Martin et al., 2013):

$$W_t = \frac{\left|\hat{\theta} - \theta_0\right|^2}{1/I_n(\widehat{\theta})} \tag{8}$$

Where, $\hat{\theta}$ is maximum likelihood estimator and $I_n\hat{\theta}$ is expected fisher information.

2.4.6. Spatial autocorrelation

a: Moran's I index:

The autocorrelation statistic was used to see if the residuals had any spatial autocorrelation or clustering, which would break the OLS assumption. The spatial independence of the residuals was gradually tested using the global spatial autocorrelation method (Wang et al., 2017; He et al., 2019). The pattern of mean disease prevalence among districts was determined using this test (Fortin and Dale, 2009) of spatial autocorrelation in ArcGIS to see if it was randomly distributed, evenly distributed, or clustered.

3. Results

3.1. Percentage bacterial leaf blight disease prevalence

The areas that showed the prevalence of bacterial leaf blight were mapped out below;

Hafizabad, Gujranwala and Narowal districts showed the highest prevalence in 2018 that was 80, 77 and 72% respectively, while the lowest prevalence was (54%) in Jhung. In 2019 maximum prevalence was recorded in Narowal and Sialkot (90 and 86%, respectively) and the minimum was recorded in Jhung and Sargodha (45 and 44%, respectively) (Figure 2). In this case, Narowal and Jhung showed high and low intensity of BLB respectively in both years.

3.1.1. Percentage bacterial leaf blight disease incidence

The map showed the percentage incidence of BLB in districts of Punjab.

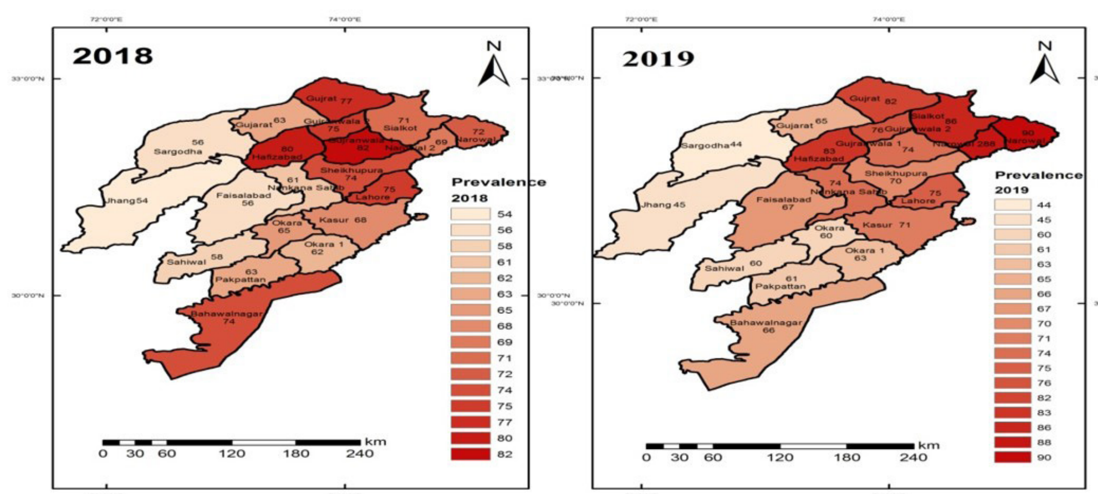

Figure 2. Percentage of Prevalence of BLB in the study area.

Results showed (Figure 3) that Gujrat and Narowal districts were areas of the highly diseased incident that range (58 and 54%) while the lowest diseased incident areas were Jhung and Okara showed (21 and 18%) respectively in 2018. Similarly in 2019 maximum disease incidence appeared in district Sialkot and Narowal (69 and 66%) respectively while the minimum was in Jhung (23%). In both years Narowal appeared to be highly incident while Jhung appeared lowest BLB incident city.

3.1.2. Percentage bacterial leaf blight disease severity

The map below showed the percentage severity of bacterial leaf blight in areas of Punjab.

In 2018, Narowal and Hafizabad districts showed maximum severity of (42 and 40%) respectively. Figure 4 displays minimum severity (18%) was in Jhung district. In 2019 Narowal and Gujrat were highly severed areas for BLB (44 and 43%) respectively and the lowest was Jhung that represented 22%severity. Thus, in both years, Narowal was highly severed, and Jhung was the lowest severed area for BLB.

3.2. Spatial modeling

3.2.1. OLS model

The ordinary least square (OLS) model was applied to determine whether the independent variables were multicollinear (Table 3) display the findings of the OLS model, which discovered that all predictors gave VIF values less than 7.5, representing that no one of the variables was redundant. With AICc=157.66, the OLS global model explained around 65% (adjusted R^2 =0.654) variation in BLB prevalence. The Wald statistic test produced a significant result about Chi-squared value of 129.9585, but the ANOVA produced a significant F-value of 6.998. In general, this signifies that the model was statistically significant. The Jarque-Bera (JB) statistic provided a chi-squared value of 0.347, which specified that the model's forecast was not biased (that showed the residuals were normally distributed). The chi-squared score of 7.486 in the Koenker statistic was statistically non-significant. To explore the distributive pattern of the residuals, the ordinary least square produced residuals that were mapped out. The

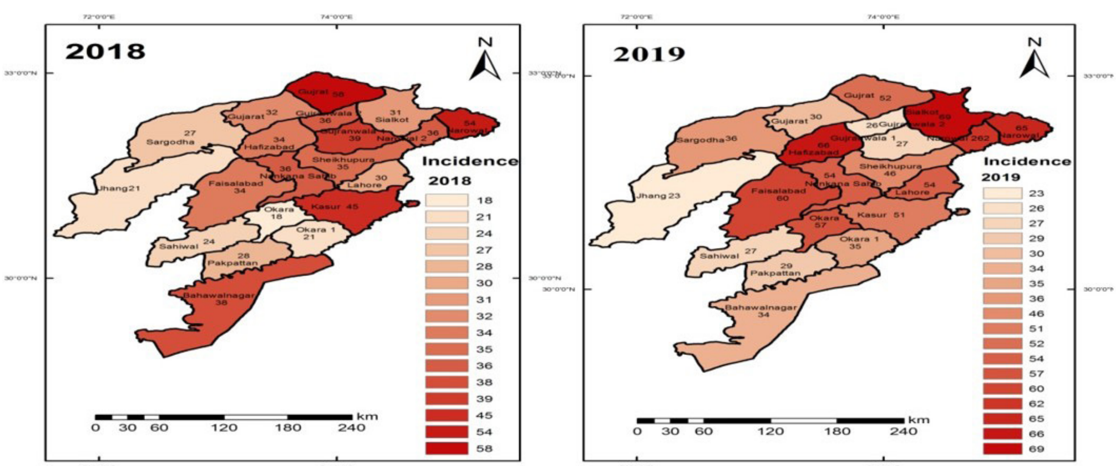

Figure 3. Percentage of incidence of BLB in the study area.

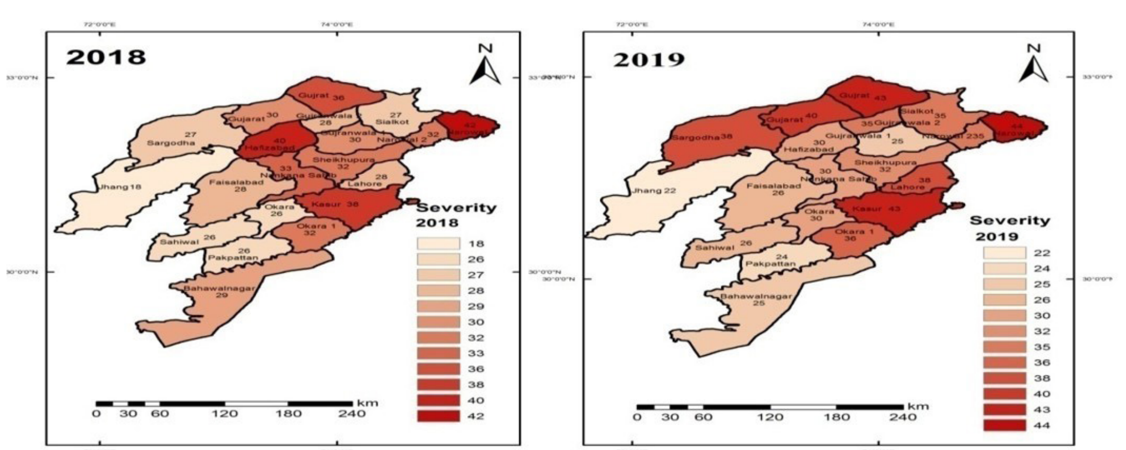

Figure 4. Percentage of the severity of BLB in the study area.

Table 3. OLS model.

Variable	Coefficient	Std.Error	t-Statistic	Probability	VIF
Intercept	-472.291943	194.883265	-2.423461	0.030702*	-----
R.H	0.515880	0.332350	1.552218	0.144614	3.879592
A.P	4.040366	1.992486	2.027802	0.063588	2.872833
T.MIN	0.544963	1.064092	0.512139	0.617146	1.463097
S.OC	0.174088	0.182656	0.953088	0.357927	3.786490
S. pH	5.058112	7.848321	0.644483	0.530469	1.224880
Elev	0.234366	0.094519	2.479577	0.027629*	3.209497
OLS Diagnostics					
Joint F-Statistic:	6.998002	Prob(>F), (6,13) degrees of freedom:		0.001713*	
Joint Wald Statistic:	129.985470	Prob(>chi-squared), (6) degrees of freedom:		0.000000*	
Koenker (BP) Statistic:	7.486837	Prob(>chi-squared), (6) degrees of freedom:		0.278158	
Jarque-Bera Statistic:	2.113642	Prob(>chi-squared), (2) degrees of freedom:		0.347559	

*Significant parameter at 0.05; R^2 = 0.763585; Adjusted R^2 = 0.654470; AICc = 157.666112.

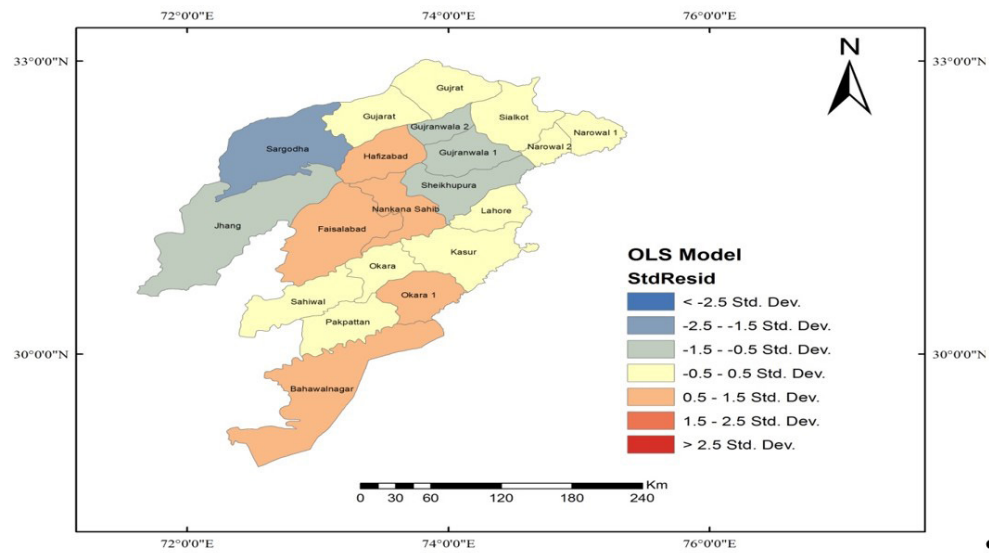

Figure 5. Standard Deviation in the OLS model.

residuals of the model reflect random sound, indicated that there was no clustering of over and below predictions in the model, according to a visual analysis of the results. The under-predicted residuals (positive) were depicted in red in Figure 5, while the over-predicted residuals (negative) were depicted in blue (negative residuals).

3.2.2. Correlation of variables with disease prevalence

The data represented a significant effect of R.H, surface pressure, minimum temperature, soil organic carbon, soil pH, and elevation on the disease prevalence in the field (Table 3). All factors showed positive relation while surface pressure and soil pH depicted strong positive relation with disease prevalence. Moreover, using Global Moran's I, the conclusion was statistically verified. Significant clustering or a random pattern in the residuals was automatically found. With a Moran's *I* index value of -0.036 and a z-score value of 0.114, according to Moran's I report (Figure 6), and the pattern did not appear to be statistically different from random. That is, there was no statistically significant geographical autocorrelation in the residuals. All empirical evidence suggests that the OLS residuals fit correctly in this scenario.

4. Discussion

Bacterial leaf blight is a serious disease that has spread over Pakistan's rice-growing regions and causing significant losses in both quantity and quality. BLB was observed with variable intensities in all visited districts during the surveys of rice-growing areas of Punjab (Junaid et al., 2009).

To map the geographic distribution of the BLB and determine its current state, as well as give baseline data and hot spots to priorities research challenges, it was necessary to assess the incidence, prevalence, and severity of plant diseases (Eshte et al., 2015). The assessed areas in this study revealed a high level of rice infestation in Pakistan. BLB incidence varies from 20-60% in Punjab, which indicates the seriousness of the situation.

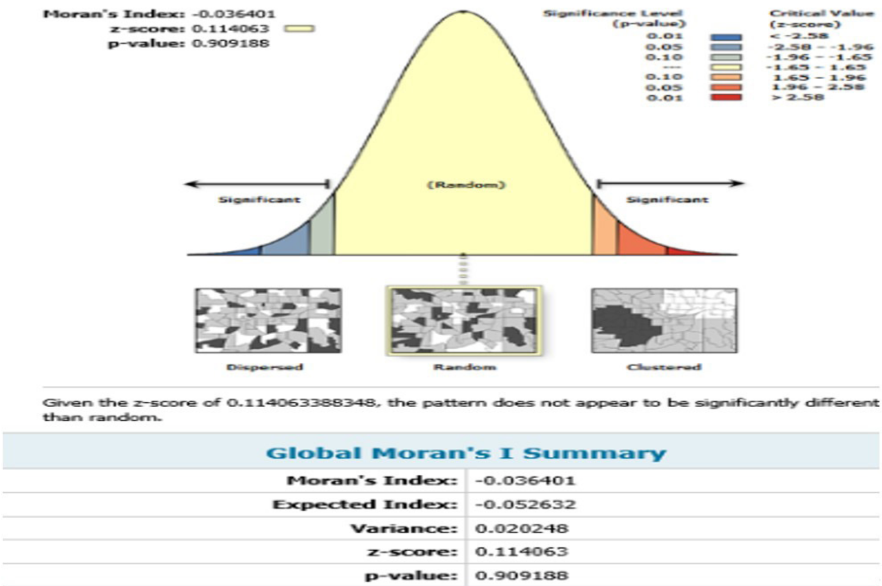

Figure 6. Spatial autocorrelation reports.

By surveying for two years consecutively from 2018-2019, it was found that the highest incidence, severity and prevalence of BLB hot spots areas were Narowal, Gujrat, and Sialkot, whereas Jhang has the lowest rate of disease incidence. Akhtar et al. (2003) and Rafi et al. (2013) also revealed that Kasur had the highest disease severity, followed by Narowal and Gujrat districts. According to Shaheen et al. (2019), Sialkot district had the highest incidence followed by Narowal and Nankana Sahib had the lowest incidence of BLB.

The first fundamental geographic question (the where question) about BLB incidence, severity, and prevalence in the study area has been answered. The following logical geographic questions are "why" such a clustering pattern? And "what" are the most likely variables contributing to this linear relation? The OLS is intended to provide answers to such scientific questions as, does the relationship between the BLB prevalence and the environmental factors vary across area? which independent variable has the greatest influence in a particular region? (Nkeki and Osirike, 2013).

All factors RH, minimum temperature, surface pressure, soil pH, soil organic carbon, and elevation that were evaluated through OLS model showed positive relationships and increased disease prevalence with an increase of R.H increase in lowering of temperature, surface pressure, soil pH, soil carbon, and elevation of the land. The humidity was also cited as the most potential factor for disease progression, particularly during the period of wetness (Peng et al., 2016). Bacterial Leaf Blight is most prevalent in the areas having more rainfall. Webb et al. (2010) found that rice plant resistance becomes more effective at higher temperatures and lesions on leaves develop more quickly (shorter lesions) at lower temperatures. Low temperature and high humidity favored the development of the disease in agreement with our findings that low temperature and relative humidity have a positive effect and help prevail in BLB disease (Naqvi et al., 2016). As atmospheric pressure (AP) contain CO_2 and O_2 that has a great influence on bacterial growth and disease prevalence, and the increased level of (AP) causes the emergence of plant disease epidemics (Eastburn et al., 2010).

As *Xanthomonas oryzae* live in soil, so soil pH and carbon also affect its growth. Both have a positive correlation with the prevalence of disease, which was also confirmed by Suresh and his colleagues in 2013 and (Rousk et al., 2008). Bacteria were more responsive to changes in elevation than other microorganisms. The relationship between prevalence and elevation was positive. Because higher altitudes had higher levels of soil organic matter (SOM) and nutrients, that cause a significant increase in bacterial microbial activity (Liu et al., 2019; Siles et al., 2016).

5. Conclusion

This research includes survey and assessment of BLB disease of rice in Pakistan and development of distribution thematic maps by using GIS. Spatial OLS regression model was also applied to determine the environmental factors affecting the disease prevalence.

The study's findings revealed that the surveyed areas had a high level of rice infection in these rice growing areas. The geographical pattern of bacterial leaf blight risk in Pakistan provides information about hot spot areas of disease. Narowal district showed maximum BLB incidence, prevalence, and severity, while Jhung district indicated the lowest level of BLB prevalence incidence and severity. OLS regression model identified that RH, minimum temperature, surface pressure, soil pH, soil organic carbon, and elevation as the most powerful environmental factors for developing disease.

The risk maps enable us to focus our attention, chemicals, and other resources on small areas with high disease risk, allowing us to make better use of our BLB management resources. Spatial modeling has already proven to be a valuable and important tool for providing information about BLB monitoring. It does not only provide information about present situation of risk of disease but also forecast the future aspects of diseases of not only of rice but also for other crops. These techniques can be applied on tactile level and also on strategic or operational level for managing disease. It would be valuable to make additional efforts to clarify the involvement of many elements in the BLB and other rice disease epidemics.

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