



RISK MODELING OF BLAST DISEASE (*PYRICULARIA ORYZAE*) IN RICE CROPS USING A REGRESSION APPROACH AND THE COBB-DOUGLAS MODEL

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ABSTRACT

Blast disease, caused by the fungus *Pyricularia oryzae*, is one of the major diseases affecting rice plants and can result in significant yield losses. Environmental factors, particularly climatic conditions, play a role in influencing the development of disease outbreaks. This study aims to develop a risk model for blast disease outbreaks in rice plants using a multiple linear regression approach and the Cobb-Douglas function model. The study was conducted in three rice-producing centers in North Sumatra Province—Deli Serdang, Langkat, and Serdang Bedagai Regencies—using data from five growing seasons between 2023 and 2026. The variables analyzed included temperature, humidity, rainfall, and the extent of rice blast disease outbreaks. The analysis was performed using the Ordinary Least Squares (OLS) method with the aid of statistical software. The results of the study indicate that climatic factors have varying effects across regions. Rainfall was the climatic factor that had the most dominant effect on blast disease outbreaks in Langkat Regency, with a significance value of 0.002 and a standardized coefficient of 0.641. Meanwhile, temperature and humidity did not show a significant effect in several observation areas. The resulting risk model can be used as a basis for developing a blast disease outbreak prediction system and to support more effective decision-making regarding disease control.

KEYWORDS: Blister disease, *Pyricularia oryzae*, linear regression, Cobb-Douglas, disease risk, climate.

INTRODUCTION

Rice (*Oryza sativa* L.) is a major food crop that plays a strategic role in supporting global food security. However, rice productivity still faces various obstacles, one of which is due to attacks by plant pests and diseases. One of the most significant diseases affecting rice is rice blast, caused by the fungus *Pyricularia oryzae*. This disease is one of the most damaging because it can attack all stages of plant growth—from the vegetative to the generative stages—and cause significant yield losses under favorable epidemic conditions (Molinari & Talbot, 2022).

The fungus *Pyricularia oryzae* is a highly adaptable pathogen with extensive genetic variation, enabling it to produce pathogen populations with varying levels of

virulence. The development of blast disease is influenced by complex interactions between the pathogen, the host plant, and environmental factors. Environmental factors play a role in determining the success of the infection process, from conidial germination and appressorium formation to penetration of plant tissues and the development of disease lesions (Baudin *et al.*, 2024).

Climatic factors are a key component in the development of blight epidemics. Changes in temperature, humidity, and rainfall can affect the pathogen's life cycle as well as the severity of the disease. High humidity and prolonged periods of leaf wetness are known to increase the likelihood of spore germination and the formation of new inoculum. In addition, rainfall plays a role in the spread of conidia through water splashes, thereby increasing the

risk of disease spread across larger cultivated areas (Wengler & Nicholas, 2025).

Global climate change is making the distribution patterns of plant diseases increasingly difficult to predict. Increased rainfall variability, temperature changes, and shifts in growing season patterns can alter disease risk levels in a given region. Therefore, modeling-based approaches are becoming increasingly important for understanding the relationship between environmental factors and the development of plant diseases. Climate-data-based prediction models can help identify high-risk periods, allowing for earlier and more efficient implementation of control strategies (Savary & Willocquet, 2021).

The development of plant disease prediction systems currently relies heavily on statistical approaches and mathematical modeling. Multiple linear regression analysis is one of the most widely used methods for determining the relationship between environmental variables and disease incidence rates. Through this approach, the dominant factors influencing disease development can be identified quantitatively. In addition, the Cobb-Douglas function model can be used to analyze the elasticity relationship between environmental factors as input variables and the risk of infection as an output variable.

Cobb-Douglas production function models have previously been widely used in economic production analysis, but this approach can also be applied in plant epidemiological studies to examine the relative contributions of each factor to changes in disease incidence. By understanding the magnitude of each factor's influence, mitigation strategies can be targeted at the environmental variables that contribute most significantly to increased disease risk.

Several recent studies have shown that modeling approaches can improve the accuracy of blast disease predictions. A study by Nettleton *et al.* (2021) demonstrated that integrating meteorological data with predictive models can enhance the ability to forecast blast disease risk compared to approaches based solely on field observations. Meanwhile, Kim *et al.* (2022) developed an environmental-condition-based early warning model for blight using relative humidity, precipitation, and temperature as the primary indicators of infection risk.

North Sumatra Province is one of Indonesia's key rice-producing regions, with several major production centers such as Deli Serdang, Langkat, and Serdang Bedagai Regencies. The region has a tropical climate characterized by variations in rainfall and humidity that can influence the development of blast disease. Therefore, a risk modeling study based on environmental conditions is needed to understand the factors that most

significantly contribute to increased outbreaks of blast disease.

Based on previous research, an analysis of climatic factors affecting blast disease outbreaks reveals variations in their impact across regions. In Langkat Regency, rainfall was found to be a factor with a significant influence on the extent of blast disease outbreaks, with a significance value of 0.002 and a beta coefficient of 0.641. Meanwhile, in Deli Serdang and Serdang Bedagai Regencies, climatic variables have not shown a significant effect on the incidence of blast disease. These findings indicate that the disease's response to environmental factors is location-specific, necessitating a risk model that accounts for regional characteristics (Manurung, 2026).

Based on these issues, this study aims to develop a risk model for blast disease (*Pyricularia oryzae*) in rice plants using multiple linear regression and the Cobb-Douglas model. The resulting model is expected to provide quantitative information on the environmental factors that most influence disease development and to serve as a basis for the development of an early warning system and more effective blast disease control strategies.

MATERIALS AND METHODS

a) Research Location and Time

The study was conducted in rice-producing areas in North Sumatra Province, covering three regencies, namely:

1. Deli Serdang Regency,
2. Langkat Regency,
3. Serdang Bedagai Regency.

These three regions were selected because they are the main rice-producing areas in North Sumatra and have a variety of environmental conditions that allow for differences in the progression of blast disease.

The research data covers a period of five growing seasons: the main growing season (Main Season) from October 2023 to March 2026 and the secondary growing season (Off Season) from April 2024 to September 2025.

b) Research Materials

The research data consists of secondary data, which includes:

1. Data on blight outbreaks

Data on the extent of blast disease (*Pyricularia oryzae*) outbreaks were obtained from field observations through the Plant Pest Early Warning System (OPT).

The data used include

- a. Extent of the blight outbreak,
- b. Observation period,
- c. Location of the outbreak,
- d. Incidence rate of the outbreak.

This data is used as the dependent variable in disease risk

modeling.

2. Climate factor data

Climate data are derived from meteorological data that include several variables, as shown in Table 1 below.

Table 1: Variable data obtained from the BMKG.

Variables	Symbol	Unit
Air temperature	X_1	°C
Air humidity	X_2	%
Rainfall	X_3	mm

Climate data were used as predictor variables believed to influence the development of blast disease. The selection of climate variables was based on the biological relationship between environmental conditions and the infection process of *Pyricularia oryzae*, particularly in facilitating conidia germination, appressorium formation, and inoculum dispersal.

c) Research Methodology

This study employed a survey method using a quantitative approach. The analysis was conducted using statistical modeling to determine the relationship between climatic factors and the incidence of blast disease.

The research stages included

1. Collection of early warning data on blast disease.
2. Collection of data on the extent of blast disease outbreaks.
3. Collection of climate data.
4. Statistical processing and analysis.
5. Development of a risk model for blast disease outbreaks.

The research process consisted of preparing early-warning data covering five growing seasons, data on the severity of disease outbreaks, and data on climatic factors such as temperature, humidity, and rainfall.

d) Data Analysis

1. Multiple Linear Regression Analysis

Multiple linear regression analysis was used to determine the effect of climatic factors on the extent of blast disease infestation.

The regression model used

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + e$$

Description

Y	= blight incidence (% or incidence area)
a	= constant
b_1, b_2, b_3	= regression coefficients
X_1	= temperature
X_2	= humidity
X_3	= rainfall
e	= error

The analysis was conducted to determine

- 1) The effect of each climatic factor,
- 2) The significance level of the variables,
- 3) The dominant factors influencing disease incidence.

2. Cobb-Douglas Function Modeling

The Cobb-Douglas function approach was used to determine the elasticity relationship between climatic factors and the risk of downy mildew infection.

General form of the model

$$Y = AX_1^{b_1}X_2^{b_2}X_3^{b_3}$$

Next, a logarithmic transformation is performed to convert it into a linear form:

$$\ln Y = \ln A + b_1 \ln X_1 + b_2 \ln X_2 + b_3 \ln X_3$$

Description

Y = rate of blast disease incidence

A = model constant

X_1 = temperature

X_2 = humidity

X_3 = rainfall

b = elasticity coefficient

The coefficient values indicate the relative contribution of each climatic factor to changes in the risk of downy mildew infection.

e) Model Statistical Tests

Model validation was performed using several statistical tests, namely:

1. Normality Test: Used to determine the distribution of the model's residual data.
2. Multicollinearity Test: Used to determine the relationships among the independent variables.
3. Heteroscedasticity Test: Used to determine the equality of residual variances.
4. Coefficient of Determination (R^2) Test: Used to determine the model's ability to explain the variation in blast disease incidence.
5. Significance Test

The tests were conducted using:

- a. The F-test to determine the simultaneous effect of the variables,
 - b. The t-test to determine the effect of each variable.
- Statistical analysis was performed using SPSS software, as used in the main study.

f) Criteria for Interpreting Risk Models

The model was interpreted based on:

1. Regression coefficient values.
2. Significance levels of the variables.
3. Standardized beta coefficient values.
4. Coefficient of determination (R^2) values.

Variables with the highest coefficient values and the greatest statistical influence are considered the dominant factors determining the risk of blast disease.

RESULTS

1. The Effect of Climatic Factors on the Risk of Blast Disease (*Pyricularia oryzae*) Outbreaks

Risk modeling for blast disease outbreaks was conducted using multiple linear regression analysis with the Ordinary Least Squares (OLS) method. The variables used in the model consisted of temperature, humidity, and rainfall as predictor variables, while the severity of blast disease outbreaks was used as the response variable. The results of the analysis showed that the relationship between climatic factors and the development of blast disease exhibited different patterns in each observation area.

Differences in disease response to climatic factors indicate that downy mildew epidemics are complex processes influenced by interactions among the

pathogen, the host plant, and the environment. According to Upadhyay and Bhatta (2020), the development of blast disease is not determined by a single environmental factor but is the result of interactions between temperature, humidity, the presence of inoculum, and the condition of the host plant. Consequently, the impact of climatic factors on the disease can vary from one location to another, even within relatively similar agroclimatic regions.

2. Risk Model for Blast Disease Outbreaks in Deli Serdang Regency

The results of the regression analysis in Deli Serdang Regency yielded the following equation:

$$Y = 248,883 - 3,130X_1 - 1,874X_2 + 0,015X_3$$

Table 2: Results of Modeling the Risk of Blast Disease Outbreaks Based on Climate Factors in Deli Serdang Regency.

Climatic Factors	Coefficient B	Beta	Sig.	Interpretation
Temperature	-3,130	-0,150	0,590	Tends to reduce attacks, but not significantly
Humidity	-1,874	-0,489	0,086	The largest relative factor, but not a significant one
Rainfall	0,015	0,106	0,641	Tends to increase attacks, but not significantly

Table 2 above shows that temperature and humidity have a negative relationship with the incidence of blast disease, while rainfall has a positive relationship. The temperature variable has a regression coefficient of -3.130 with a significance value of 0.590, humidity has a coefficient of -1.874 with a significance value of 0.086, and rainfall has a coefficient of 0.015 with a significance value of 0.641.

The negative relationship between temperature and disease incidence indicates that rising temperatures tend to reduce the development of blast disease. This phenomenon is believed to be related to the optimal temperature range for the development of *Pyricularia oryzae*. According to Akçalı and Kurt (2021), the highest severity of blast disease occurs at temperatures around 28°C, while temperatures that are too low or too high can inhibit pathogen development. Similarly, Du *et al.* (2021) reported that blast disease infection increases under temperature conditions suitable for the development of *Magnaporthe oryzae* but decreases when environmental conditions fall outside the optimal range.

The results of the study indicate that although temperature has a negative effect on disease incidence, this effect is not yet statistically significant. This suggests that temperature does not act independently in determining the progression of blast disease, but is influenced by other environmental factors such as humidity, rainfall, and plant condition.

Humidity also showed a negative correlation with the incidence of disease. These results differ from the general theory of plant disease epidemiology, which states that high humidity typically promotes the

development of downy mildew. According to Kirtphaiboon *et al.* (2021), high humidity can increase the risk of downy mildew when combined with optimal temperatures and a sufficiently long period of leaf wetness. Therefore, high humidity does not always lead to an increase in disease if other contributing factors are not under optimal conditions.

Rainfall shows a positive correlation with the incidence of blast disease, although this correlation is not yet statistically significant. Increased rainfall can raise micro-humidity in the plant canopy and prolong the period during which leaves remain wet, thereby facilitating pathogen infection. This is consistent with the findings of Rifai *et al.* (2020), who stated that rainfall plays a role in the development of plant pests by altering microclimatic conditions around plants.

The coefficient of determination (R^2) for Deli Serdang Regency, at 0.128, indicates that temperature, humidity, and rainfall together account for only 12.8% of the variation in blast disease incidence, while 87.2% is influenced by other factors outside the model.

The low coefficient of determination indicates that climate is not the sole factor determining the development of blast disease. Other factors, such as crop variety, plant age, planting patterns, cultivation techniques, fertilization, fungicide use, and inoculum sources, also play important roles. According to Kirtphaiboon *et al.* (2021), blight epidemics in tropical regions are influenced by a combination of interacting environmental factors and cropping conditions.

3. Risk Model for Blast Disease Outbreaks in Langkat Regency

Langkat Regency shows a stronger relationship with climatic factors than other regions. The regression

equation obtained is:

$$Y = -55,351 + 1,721X_1 + 0,112X_2 + 0,057X_3$$

Table 3: Results of Modeling the Risk of Blast Disease Based on Climate Factors in Langkat Regency.

Climatic Factors	Coefficient B	Beta	Sig.	Interpretation
Temperature	1,721	0,144	0,409	A positive but not significant effect
Humidity	0,112	0,160	0,368	Tends to increase the risk, but not significantly
Rainfall	0,057	0,641	0,002	Dominant factors with a significant effect

The results of the analysis of the above model (Table 3) show that all climate variables have a positive relationship with downy mildew infection. Temperature has a coefficient of 1.721 with a significance value of 0.409; humidity has a coefficient of 0.112 with a significance value of 0.368; and rainfall has a coefficient of 0.057 with a significance value of 0.002.

Rainfall is the most dominant climatic factor in the Langkat Regency model, with a standardized beta coefficient of 0.641. This indicates that an increase in rainfall contributes most significantly to an increased risk of blast disease compared to other climatic variables.

Biologically, the positive correlation between rainfall and blight can be explained by its role in creating environmental conditions conducive to pathogen development. Rainfall increases air humidity, prolongs the duration of leaf wetness, and aids in the dispersal of conidia through rain splashes. These conditions increase the likelihood that spores will germinate and penetrate plant tissues.

These findings are consistent with the study by Kirtphaiboon *et al.* (2021), which explains that rainfall and humidity are important factors in downy mildew epidemics because they are related to the spread of the inoculum and the success of pathogen infection.

Furthermore, Chiu *et al.* (2022) explain that the development of blast disease is influenced more by relative humidity and the duration of leaf wetness than by rainfall amounts directly.

The R^2 value for Langkat Regency, at 0.328, indicates that the variables of temperature, humidity, and rainfall account for 32.8% of the variation in blast disease incidence. This value suggests that climatic factors contribute more significantly to the dynamics of blast disease in Langkat Regency than in Deli Serdang Regency. However, 67.2% of the variation in disease incidence is still influenced by other factors, such as crop variety, plant age, plant density, cultivation practices, fungicide use, and the presence of pathogen inoculum. This is consistent with the view of Savary and Willocquet (2021) that the risk of plant disease results from the interaction between environmental factors, disease-causing organisms, and the crop production system.

4. Risk Model for Blast Disease Outbreaks in Serdang Bedagai Regency

The regression model for Serdang Bedagai Regency yields the following equation:

$$Y = -38,473 - 3,811X_1 + 1,827X_2 - 0,016X_3$$

Table 4: Results of Modeling the Risk of Blast Disease Outbreaks Based on Climatic Factors in Serdang Bedagai Regency.

Climatic Factors	Coefficient B	Beta	Sig.	Interpretation
Temperature	-3,811	-0,247	0,389	Not significant, negative correlation
Humidity	1,827	0,370	0,081	Largest contributor, positive trend
Rainfall	-0,016	-0,134	0,616	Not significant, negative correlation

The research results in Table 4 above show that temperature and rainfall have a negative correlation with the severity of disease outbreaks, while humidity has a positive correlation. Temperature has a coefficient of -3.811 with a significance value of 0.389; humidity has a coefficient of 1.827 with a significance value of 0.081; and rainfall has a coefficient of -0.016 with a significance value of 0.616.

Humidity was the variable with the greatest contribution in the Serdang Bedagai model, with a beta value of 0.370. This indicates that an increase in humidity tends to increase the risk of blast disease, although this

increase is not yet statistically significant.

The positive correlation between humidity and blast disease is consistent with the pathogen's biological mechanisms. High humidity can prolong the period of leaf wetness, thereby increasing the likelihood of conidia germination and pathogen penetration. According to Akçalı and Kurt (2021), an increase in the duration of leaf wetness is a key factor determining the success rate of blast disease infection.

Rainfall shows a negative correlation with disease incidence. This indicates that high rainfall does not

necessarily increase disease incidence, as heavy rain can wash spores off leaf surfaces, thereby reducing the likelihood of infection. This phenomenon is also explained by Tabonglek *et al.* (2022), who note that the relationship between rainfall and blight is not always linear, as it is influenced by rainfall intensity and distribution.

The R^2 value for Serdang Bedagai Regency, at 0.220, indicates that climatic factors account for 22% of the variation in blast disease outbreaks, while 78% is influenced by other factors.

3. Comparison of Blast Disease Risk Models Across Regions

The modeling results show that the dominant factors contributing to blast disease vary across the study areas. This is shown in Table 2 below.

Table 5: Dominant Factors Contributing to Blast Disease Vary Across Research Regions.

Region	Dominant Factors	Influence Value
Deli Serdang	Temperature	$\beta = -0,150$
Langkat	Humidity	$\beta = 0,641$
Serdang Bedagai	Rainfall	$\beta = 0,370$

These differences (Table 5) indicate that the risk of blast disease is location-specific. Climatic factors that are the primary triggers in one region may not necessarily have the same impact in another region.

According to Savary and Willocquet (2021), plant disease risk modeling must take local characteristics into account because disease development results from the interaction between climatic conditions, cropping systems, and pathogen populations.

Thus, the regression and Cobb-Douglas models developed in this study can be used as a basis for developing an early warning system for blight, particularly by incorporating the dominant factors for each region.

CONCLUSION

Based on the results of risk modeling for rice blast (*Pyricularia oryzae*) using multiple linear regression and the Cobb-Douglas model in Deli Serdang, Langkat, and Serdang Bedagai Regencies, it can be concluded that climatic factors have varying effects across regions on the development of rice blast.

1. The regression model indicates that the relationship between climatic factors (temperature, humidity, and rainfall) and downy mildew outbreaks is location-specific. Environmental factors do not have the same effect in every observation area because disease development is influenced by the interaction between climatic conditions, host plants, and cultural practices.

2. Langkat Regency is the region with the strongest climatic response to the development of blast disease. The regression model yielded a coefficient of determination (R^2) of 0.328, indicating that temperature, humidity, and rainfall collectively account for 32.8% of the variation in blast disease incidence. The most dominant factor is rainfall, with a significance value of 0.002 and a standardized beta coefficient of 0.641; thus, increased rainfall is the primary climatic factor that elevates the risk of blast disease outbreaks in this region.
3. Deli Serdang Regency showed a lower contribution of climatic factors to the variation in downy mildew outbreaks. The regression model had an R^2 value of 0.128, indicating that temperature, humidity, and rainfall could explain only 12.8% of the variation in disease outbreaks. Temperature was negatively correlated with disease outbreaks, while rainfall was positively correlated; however, none of the variables showed a statistically significant effect.
4. Serdang Bedagai Regency indicates that humidity is the most influential environmental factor in the model, although it is not yet statistically significant. The model has an R^2 value of 0.220, with humidity having the largest beta coefficient (0.370). This suggests that humidity conditions tend to increase the risk of downy mildew outbreaks more than other climatic variables.
5. Regression analysis and the Cobb-Douglas model can be used as a basis for modeling the risk of blast disease; however, predictive ability is still influenced by other factors beyond climatic variables. Factors such as rice variety, plant age, cultivation techniques, plant density, fungicide use, the presence of inoculum, and microclimatic conditions need to be considered in the development of advanced models to improve the accuracy of the blast disease risk prediction system.
6. The resulting risk model can support the development of an early warning system for blast disease, particularly by taking into account the dominant climatic factors in each region. Implementing a location-based model can help identify high-risk periods, enabling disease control strategies to be implemented in a more timely and effective manner.

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