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Geospatial analysis of factors affecting index of rice harvest success in West Java using INLA-based Bayesian models

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Abstract

Rice production during the 2012-2022 period tends to decline. Many factors lead to a decline in production, one of which is the low on potential of rice success. This issue is an obstacle to achieve food security. West Java is the third largest rice producing province in Indonesia. For this reason, the aim of this research is to establish the potential value of harvest success in West Java Province and form a spatial Bayes regression model of the potential value of harvest success of rice plants in West Java whose inference using the *Integrated Nested Laplace Approximation* (INLA) approach. The spatial Bayes regression model created is a *linear mixed model* which includes spatial random effects using the BYM2 method. The explanatory variables of the model are the number of farmer economic institutions, the number of agricultural extension workers, the number of farmer groups, the human development index, and the number of disaster events from 27 districts/cities in West Java with the potential value of harvest success as the response variable. The results of the spatial model show that the variables of the number of farmer economic institutions and the number of farmer groups have a significant influence on the potential value of harvest success. From the results of spatial mapping, it can be seen that there are neighborhood relationships that influence the value of potential harvest success where the eastern region in West Java tends to have a higher probability of harvest success.

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INTRODUCTION

Indonesia is an agricultural country, namely a country that relies on the agricultural sector. The majority of Indonesian people rely on the agricultural sector both as a profession and to support development (Mulyadi et al., 2020). Based on data from the Central Statistics Agency, rice consumption is always increasing in Indonesia, so it is necessary to import rice every year to

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meet consumption levels. On the other hand, rice production over the last 10 years has tended to decline. This will be a problem if the rice supply is not sufficient for consumption levels. According to the Central Statistics Agency, West Java is the province with the largest population in Indonesia. The increase in population is directly proportional to the increase in rice consumption (Jiuhardi, 2023). To compensate for the increase in population, rice production must also be increased. Based on data from the Central Statistics Agency in 2020, West Java has rice fields covering an area of 1,578,836 hectares. With this land area, West Java is the third largest rice producing province in Indonesia. Rice production must be maximized so that there is no shortage of rice to meet consumption. One of the factors causing insufficient rice availability in Indonesia is production process problems, namely crop failure.

Harvest failure is an unsuccessful harvest that causes a decrease in production, resulting in losses due to various reasons experienced by farmers (Mendelsohn, 2007). Crop failure can be caused by various factors. However, crop failure can be prevented if every part of the agricultural sector carries out its duties, both the main actors, namely farmers, and other supporting aspects. Reducing the risk of crop failure will increase the potential for harvest success. Research conducted by (Zogar et al., 2022) proves that farmer institutions have a role in increasing agricultural productivity.

The Ministry of Agriculture as the main institution in the agricultural sector has attempted to increase the potential for harvest success by implementing several methods, including the existence of agricultural instructors and farmer economic institutions in each district/city. An agricultural instructor has the task of improving the welfare of farmers by maximizing harvest yields and preventing crop failures and increasing the potential for successful harvests. (Bagas & Sunaryanto, 2021) . Meanwhile, agricultural economic institutions were formed to assist farmers in carrying out farming activities from pre-planting to post-harvest. (Haryanto et al., 2022). In carrying out farming activities, farmers, agricultural extension workers and farmer economic institutions form an organization called a farmer group. Farming groups have an important role as a place to exchange information regarding technological updates, superior seeds, fertilizer and other components that support farming (Riani et al., 2021). Apart from that, there are other unavoidable factors that can cause crop failure, namely natural disasters. Extreme rainfall can affect rice production. (Faradiba, 2021). This extreme rainfall results in various kinds of disasters such as floods and landslides. In addition, the resulting temperature changes can result in hurricanes. Apart from that, crop failure can also be caused by economic factors due to high fertilizer distribution costs, high seed prices, and so on. The human development index as a socio-economic indicator can describe the economic conditions and human development in an area(Azfirmawarman et al., 2023). Factors that cause crop failure will result in a decrease in the potential for harvest success.

The author will use these factors as predictor variables in modeling the potential value of rice harvest success in West Java. In mathematical terms, the factors that influence the value of the potential success of a rice plant harvest are referred to as predictor variables, while the value of the potential success of a rice plant harvest as an influenced variable is called the response variable. To see the relationship between these variables, a mathematical model, namely Linear Mixed Model, will be used with parameter estimation using Integrated Nested Laplace Approximation (INLA) to determine the potential value of rice crop harvest success due to the influence of farmers' economic institutions, number of agricultural instructors, number of farmer groups, development index. people, and the number of disaster events. INLA parameter estimation is used because Bayesian estimation with other methods such as Monte Carlo Markov Chain (MCMC) can result in problems such as convergence and programming time. INLA can provide more accurate results in a shorter time. A successful harvest will increase production. Increasing production will create national food security. Therefore, it is important to know the potential for success of rice crop to achieve national food security.

DATA AND METHOD

The data used in this research are obtained from the Indonesian Central Statistics Agency in 2021. The spatial bayes method is used to determine the map of rice crop potential sucess in 27 regencies and cities in West Java. The characteristic data of the indicator used to determine the potential of rice crop sucess are depicted in Table 1.

1. Canonical Correlation Analysis

Canonical correlation analysis serves as a statistical method utilized to understand the correlation between two sets of multivariate variables (many variables). This technique identifies and measures the association among the optimal linear combinations of two sets of variables, with the main objective of finding the pair of variables that has the highest correlation (Osborne et al., 2024; Sherry & Henson, 2005; Wickramasinghe, 2019). Suppose that the set of dependent variables comprises q dependent variables. and the set of independent variables consists of p independent variables. Then the basic form of canonical correlation analysis is:

$$y_1 + y_2 + y_3 + \dots + y_q = x_1 + x_2 + \dots + x_p. \tag{1}$$

Before doing a correlation analysis, some assumptions must be made, such as: Multivariate normality of data, Multicollinearity test, and Homoscedasticity test (Purwadi et al., 2024; Wei et al., 2021).

2. Determination of Canonical Function and Canonical Estimator

Canonical correlation analysis investigates the association between the composite linear expressions of the dependent variables $Y' = (y_1, y_2, \dots, y_p)$. The combination of pairs of linear functions is called canonical functions, and the relationships between them are known as canonical correlations. The letter y represents dependent variables, while the letter x represents independent variables. Suppose that the number of dependent variables is denoted by q and the number of independent variables is denoted by p where $p \leq q$. Suppose Z is a matrix partitioned by $(p \times p)$ variance-covariance matrices Σ_{XX} , $(p \times p)$ variance-covariance matrices Σ_{YY} , and $(p \times q)$ and $(q \times p)$ matrix Σ_{XY} and Σ_{YX} . Therefore, its covariance matrix is

$$\Sigma_Z = \begin{bmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{bmatrix} \tag{2}$$

Σ_{XX} is the matrix of variance and covariance between X and X of size $(p\times p)$, Σ_{YY} is the matrix of variance and covariance between X and Y of size $(q \times q)$, Σ_{XY} is the matrix of variance and covariance between X and Y of size $(p \times q)$, and Σ_{YX} is the matrix of variance and covariance between Y and X of size $(q\times p)$. If there are p independent variables $x_1, x_2, \dots, x_p$ and q dependent $y_1, y_2, \dots, y_p$ then there are a minimum number of canonical variable pairs q and p. Suppose $a' = [a_1, a_2, \dots, a_k]$ and $b' = [b_1, b_2, \dots, b_k]$ the linear combination formed is

$$U = a_1x_1 + a_2x_1 + \cdots + a_qx_q = a_k' X, \tag{3}$$

$$V = b_1y_1 + b_2y_1 + \cdots + a_py_p = b_k'Y. \tag{4}$$

Then the canonical function k:

$$\begin{array}{ll} U_1 = a_1X & V_1 = a_1X \\ U_2 = a_2X & V_1 = a_2X \\ \vdots & \vdots \\ U_k = a_kX & V_k = a_kX \end{array} \tag{5}$$

where $X = \begin{bmatrix} x_1 \\ | \\ x_q \end{bmatrix}$ dan $Y = \begin{bmatrix} y_1 \\ | \\ y_p \end{bmatrix}$. (6)

According to the matrix $\Sigma_{YY}^{-1}\, \Sigma_{YX}\, \Sigma_{XX}^{-1}\, \Sigma_{XY}$ using the eigenvectors $f_1, f_2, \ldots, f_k$ and $\Sigma_{XX}^{-1}\, \Sigma_{XY} \Sigma_{YY}^{-1}\, \Sigma_{YX}$ using the eigenvectors $e_1, e_2, \ldots, e_k$, we will obtain the coefficient vectors a and b by finding $\lambda_1^2 > \lambda_2^2 > \ldots > \lambda_k^2$. The canonical coefficient vectors a and b are obtained as follows:

$$a_k = \left(\frac{1}{\sqrt{(e_k' \Sigma_{XX} e_k)}}\right) e_k \tag{7}$$

$$b_k = \left(\frac{1}{\sqrt{(f_k' \Sigma_{YY} f_k)}}\right) f_k \tag{8}$$

with k = 1,2,3, ..., r being the minimum number of p and q. Canonical correlation U and V:

$$\rho_{(U,V)} = \frac{\mathrm{Kov}(U,V)}{\sqrt{\mathrm{Var(U)Var(V)}}} = \frac{a'\,\Sigma_{\mathrm{XY}}}{\sqrt{a'\Sigma_{\mathrm{XX}}\,a}\sqrt{b'\Sigma_{\mathrm{YY}}\,b}} \tag{9}$$

eigenvalue:

$$\Sigma_{XX}^{-1}\, \Sigma_{XY}\, \Sigma_{YY}^{-1}\, \Sigma_{YX} - \lambda I = 0 \tag{10}$$

$\Sigma_{YY}^{-1}\, \Sigma_{YX} \Sigma_{XX}^{-1}\, \Sigma_{XY} - \lambda I = 0$. The selection of canonical functions is also considered with large to small eigenvalues. To determine the number of canonical variables to be interpreted, several criteria can be used. Several criteria should be considered and linked to each other to select the right canonical variables, including the magnitude of canonical correlation and redundancy measures for the percentage of diversity that can be explained by canonical variables and the significance level of each function.

3. Canonical Weight

Canonical weights are normalized canonical coefficients and can be interpreted as a measure of the contribution of the original variable to the canonical variable. If the sign of a variable's weight is opposite to the sign of its canonical variable, it indicates an inverse correlation with the other variable. However, canonical weights have some drawbacks the fact that it only shows the amount of contribution of the original variable to the canonical variable, making them inaccurate in describing the correlation between variables (Weinberger, 2016).

4. Canonical Loading

The original variable's correlation strength and direction with the canonical variable are indicated. A high canonical load value (>0.5) for an original variable suggests its importance in the group of variables, with the load's sign showing the correlation direction. The larger the load value, the more crucial the original variable's role in the group. The formula obtains the independent canonical loading

$$\Sigma_{XU} = \Sigma_{XX}\, ak, \tag{11}$$

the simple correlation between X and a is the canonical coefficient vector of the variate U. While the formula obtains the independent canonical loading.

$$\Sigma_{YV} = \Sigma_{YY}\, bk, \tag{12}$$

the simple correlation between Y and b is the vector of canonical coefficients of variate V. Canonical weights are more effective in interpreting the correlation between variables than canonical weights, as canonical weights have some disadvantages.

5. Canonical Cross Loading

Shows the correlation between the original variables from one set and the canonical variables from the other set, identifying interactions between sets of variables. The formula obtains the independent canonical cross-loading

$$\Sigma_{XV} = \Sigma_{XU}\, \rho k, \tag{13}$$

Σ_{XV} is the canonical charge of the independent variable and ρk is the correlation value of the k-th canonical function. The formula is used to obtain the dependent canonical cross-charge.

$$\Sigma_{YU} = \Sigma_{YV}\, \rho k, \tag{14}$$

Σ_{YU} is the canonical charge of the dependent variable and ρk is the correlation value of the k-th canonical function.

RESULTS AND DISCUSSIONS

1. Assumption Check

Before processing the data, data testing is needed to ensure the fulfillment of several assumptions, namely data normality, multicollinearity, and homoscedasticity. The QQ-Plot results in Figure 1 show that, descriptively, the data spreads double normal because the data plot or the black dots are still around the straight line. Next, multicollinearity testing is conducted by examining the correlation between variables or by checking the values of the variance inflation factor (VIF) (Frima Aji Umargani, 2022).

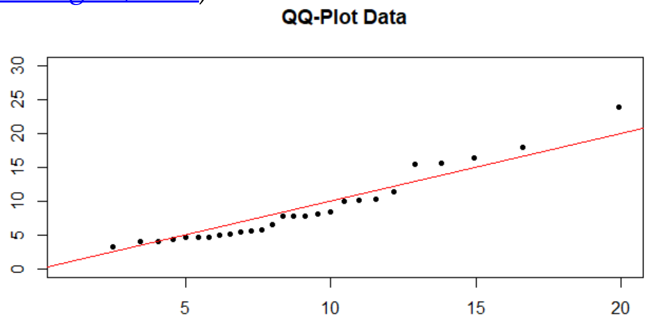

Figure 1. QQ-Plot of data distribution.

Table 2. Variance Inflation Factor (VIF)

Dimension	Variable	VIF
	Y1	3.8578
Public Health Diseases	Y2	1.7649
	Y3	1.3173
	X1	2.0069
	X2	1.4221
Ecology	X3	2.9934
	X4	2.2167
	X5	2.2074

Based on Table 2, all Varian Inflation Factor (VIF) value is lower than 10, and it is concluded that there is no multicollinearity or that the assumption of non-multicollinearity is met. In the next stage, with the help of RStudio software tests, the assumption of homoscedasticity of the data is tested by the results of the standardized Breusch-Pagan test. The p-value is 0.2266, which means there is not enough evidence to reject the assumption of homoscedasticity at the 0.05 level of significance. Therefore, we cannot conclude the presence of heteroscedasticity in the data.

2. Canonical Correlation Analysis Results

With the assumptions of the canonical correlation test fulfilled, the analysis can proceed. Data processing in the canonical correlation analysis uses the RStudio version 4.3.1 program. The minimum number of variables used determines the number of canonical functions formed. In this research, the independent variable group consists of 6 variables, while the dependent variable group only consists of 3 variables, so the canonical function forms as many as 3 canonical functions. Determination of canonical functions that can be used must consider statistical significance tests, diversity contributions, and correlations within the canonical functions.

Table 3. Canonical Function Analysis and Its Significance

CanR	CanRSQ	Eigen	Percent	Pr (> F)
0.86	0.75	30.52	78.5	0.00
0.60	0.36	0.58	15.0	0.16
0.44	0.19	0.24	6.4	0.32

The results of the program according generated a total of three functions which explain that function number 1 accommodated 78.5% of the canonical correlation, while the rest were very small and possibly meaningless. Using the minimum limitation criterion of diversity contribution above 70%, it is sufficient to take the first canonical function only. The table above shows that the canonical correlation number for the first function is 0.86 and has a redundancy coefficient of 0.75, while for functions number 2 and number 3, there is a very weak correlation with a limit of 0.5 for the strength of the correlation of two variables. The significance of function number 1 is far below 0.05, while functions number 2 and 3 are far above 0.05, so they are considered unable to be processed further into further analysis

3. Canonical Weight

The table below displays the relative contribution of the independent variable and the dependent variable to the variate variable as indicated by the value of the coefficient or canonical weight.

Table 4. Coefficient of relative contribution of independent variable group

Variable	Function 1
X1	0.001
X2	-0.036
X3	0.008
X4	-0.778
X5	-0.002
X6	-0.003

Table 5. Coefficient of the relative contribution of the dependent variable group

Variable	Function 1
Y1	-0.006
Y2	-0.040
Y3	-0.010

Based on Table 5 and 4, By ignoring the second and third functions based on the size of the coefficients, it can be concluded that the order of relative contribution from the largest to the smallest of the dependent variables is pneumonia (Y3), DHF (Y1), and malaria (Y2). In this case, the cluster of public health diseases, the pneumonia variable is the most concerning in increasing other health diseases. The order of relative contribution from largest to smallest in the dependent variable is Temperature (X4), Humidity (X2), Rainfall (X3), Proper Sanitation (X6), Total Garbage Disposal (X5), Population (X1). In this case in the ecological variable cluster, the temperature variable is most concerned about the increase in public health diseases. Then the equation Based on the canonical correlation coefficient analysis that has been carried out, a linear combination of the two variable groups is obtained as follows

$$U_1 = -0.001\, X_1 - 0.036\, X_2 + 0.008\, X_3 - 0.778 X_4 - 0.002\, X_5 - 0.003 X_6 \quad (15)$$

$$V_1 = -0.063\, Y_1 - 0.040\, Y_2 - 0.010 Y_3 \tag{16}$$

4. Loading

The canonical load reflects the relationship between the initial variable and the canonical variables or variates. According to the program that has been run, the results of the canonical load on the dependent and independent variables are as follows Shown in the table 6, the canonical charge

Table 6. Canonical charge in the canonical variable function

Dimension	Variable	Weight
Public Health Diseases	Y1	-0.911
	Y2	-0.712
	Y3	-0.977
Ecology	X1	-0.667
	X2	0.297
	X3	0.605
	X4	-0.605
	X5	-0.953
	X6	-0.003

of public health disease variables that have the closest correlation with the first canonical function are DHF (Y1), malaria (Y2), and pneumonia (Y3) with negative correlation values of -0.911, -0.712, and -0.977 respectively. Meanwhile, the canonical load of ecological independent variables that have the closest correlation with the first canonical function is the amount of waste transported to landfill (X5), population (X1), temperature (X4), and rainfall (X3) with correlation values of -0.953, -0.667, -0.605, and 0.605.

5. Canonical Cross Loading

According to the program that has been run, the canonical cross-loading contained in the first canonical function on the independent and dependent variables is as follows:

Table 7. Canonical cross-loading in variable functions

Dimension	Variable	Weight
Public Health Diseases	Y1	-0.790
	Y2	-0.618
	Y3	-0.848
Ecology	X1	-0.579
	X2	0.258
	X3	0.525
	X4	-0.525
	X5	-0.827
	X6	-0.002

As shown in the table 7 above the canonical cross-loading between the independent variables to the canonical function shows that the most closely related to the first canonical function is the amount of waste transported to the landfill (X5) with a negative correlation value of -0.827 the total population (X1) with a negative correlation value of -0.579, temperature (X4) with a negative correlation value of -0.525, and rainfall (X3) with a positive correlation value of 0.525. Meanwhile, the canonical cross-loading between the dependent variables and the canonical function shows that the most closely related to the first canonical function is the proportion of DHF (Y1) with a correlation value of -0.790, malaria (Y2) with a correlation value of -0.618, dan pneumonia (Y3) with a correlation value of -0.848.

DISCUSSION

From the output of the canonical correlation analysis, three canonical functions were found, but only the first function was significant with a correlation coefficient of 0.82. This result indicates a very close correlation between public health diseases and ecological factors such as climate, population, access to proper sanitation, and the amount of waste transported to landfills. This close correlation indicates that changes in these ecological factors significantly affect the incidence of diseases in the community.

In this research, the most dominant public health diseases were Dengue Hemorrhagic Fever (DHF), malaria, and pneumonia. The most dominant constituent ecological factors include the amount of waste transported to landfills, with a negative correlation value of -0.827, population with a negative correlation value of -0.579, temperature with a negative correlation value of -0.525, and have a significant effect on disease incidence. The combination of these variables shows how environmental conditions and demographics affect the level of public health.

When there is less waste going to landfills, less population, and lower temperatures, the incidence of dengue hemorrhagic fever (DHF), malaria, and pneumonia tends to decrease. A cleaner environment and reduced population pressure can decrease the spread of these diseases. Other findings showed that an increase in rainfall with a positive correlation value of 0.525 intensity correlated with a decrease in the incidence of dengue hemorrhagic fever (DHF), malaria, and pneumonia This may be due to the effects of excessive rainfall, which can reduce populations of disease vectors such as mosquitoes through washing and inundating their habitats, or changes in human habits during rainy periods. Although pneumonia is generally not directly linked to rainfall, high rainfall conditions can increase air humidity which may improve air quality and help reduce the risk of transmission of respiratory diseases.

CONCLUSION

Three canonical functions were found from the canonical correlation study of ecological factors on public health disease using data from 2019 to 2023. Only the first function, which had a high correlation coefficient of 0.86 and a determination coefficient of 0.75, was statistically significant, explaining 78.5% of the total variation. These findings demonstrate that ecological factors, including climate, population density, and waste management, play a crucial role in the spread of public health diseases. The study highlights that dengue hemorrhagic fever (DHF), malaria, and pneumonia are the dominant public health diseases, while key ecological factors influencing their spread include waste accumulation in landfills, population density, temperature, and rainfall. Statistically, every 1-ton reduction in waste sent to landfills can decrease the incidence of DHF, malaria, and pneumonia with a negative correlation of -0.827. Every 1 million decrease in population can reduce disease incidence with a negative correlation of -0.579. Every 1°C decrease in temperature can lower disease incidence with a negative correlation of -0.525. Meanwhile, every 1 mm/day increase in rainfall can reduce disease incidence with a positive correlation of 0.525.

Overall, this study confirms the importance of managing ecological factors to improve public health. Efforts to control population size, improve access to proper sanitation, and implement effective waste management can have a positive impact on reducing the incidence of communicable and non-communicable diseases in West Java. For future research, it is recommended to expand the scope of ecological variables, such as air quality, and other socio-economic factors that may affect public health.

AUTHOR CONTRIBUTIONS

Each author of this article played an important role in the process of method conceptualization, simulation, and article writing.

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