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Research Paper

Analysis of Geospatial Production Factors on Rice Productivity at IP 200 in Muara Lawai Village Muara Enim Regency of South Sumatra

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Abstract
This study aims to analyze the effects of production factors and spatial patterns on rice productivity under the CI 200 cropping system in Muara Lawai Village, Muara Enim Regency. The study is motivated by limited land availability, high cropping intensity, and variability in input management among farmers, resulting in heterogeneous productivity. A survey method involving 30 farmers was applied, followed by descriptive analysis, Cobb-Douglas regression, and GIS-based geospatial analysis. The results indicate that land area, rice variety, weed control, and fertilizer combination significantly affect rice productivity. The combination of NPK, urea, and liquid organic fertilizer (POC) is the most dominant factor ($\beta = 0.300$), followed by variety (0.220), weed control (0.180), and land area (0.280). The Adjusted R^2 value of 0.686 indicates strong explanatory power. Geospatial analysis reveals spatial heterogeneity influenced by irrigation conditions, accessibility, and input distribution. The study concludes that productivity improvement under CI 200 depends on integrated and site-specific management of production factors rather than land expansion.

Keywords
Cobb-Douglas; GIS; CI 200; productivity; rice.

1. INTRODUCTION

Rice (*Oryza sativa* L.) is the principal staple food in Indonesia and plays a fundamental role in maintaining national food security. As the population continues to increase, the demand for rice also rises, requiring continuous improvements in agricultural productivity (Zaini and Saitama, 2023). However, the expansion of agricultural land has become increasingly constrained due to land conversion, urbanization, and environmental degradation. Consequently, agricultural intensification has become the primary strategy for increasing rice production while maintaining sustainable land use (Tulungen, 2024).

One of the intensification programs widely implemented in Indonesia is the Cropping Index 200 (IP 200), which enables farmers to cultivate rice twice annually on the same agricultural land (Murtiningsih, 2021; Agustiani et al., 2022). Although this system increases annual production potential, productivity among farmers remains highly variable even within the same village. Such variability indicates that increasing the cropping index alone is insufficient to guarantee higher productivity because the effectiveness of production factors differs across locations.

The variability of rice productivity is closely associated with differences in production factors, including land size, rice varieties, fertilizer application, and weed management. These factors are influenced not only by farmers' management practices but also by spatial characteristics such as irrigation conditions, soil properties, topography, accessibility, and environmental conditions. Consequently, neighboring rice fields may exhibit different productivity levels despite implementing the same Cropping Index 200 system. This spatial heterogeneity highlights the need to incorporate geographic analysis into studies of rice productivity (Herdian et al., 2020).

Most previous studies have examined the influence of production factors using conventional statistical approaches, such as regression or Cobb-Douglas production functions, which identify significant determinants of productivity but provide limited information regarding their spatial distribution. As a result, these studies cannot adequately explain where production constraints occur or how productivity varies across agricultural landscapes. Such information is essential for implementing site-specific agricultural management and improving the effectiveness of policy interventions (Gautam, 2024).

Geographic Information Systems (GIS) provide an effective approach for integrating production factor analysis with spatial information. GIS enables the visualization and analysis of the spatial distribution of production factors and productivity, facilitating the identification of productivity clusters, spatial patterns, and location-specific constraints. Integrating GIS with production function analysis offers more comprehensive insights than conventional statistical analysis alone because it simultaneously explains both the magnitude of factor effects and their geographic distribution. This integrated approach supports precision agriculture and evidence-based agricultural planning (Mathenge et al., 2022).

Muara Lawai Village, Muara Enim Regency, South Sumatra, represents an appropriate case study because approximately 180 hectares of rice fields are managed under the Cropping Index 200 (IP 200) system. Despite relatively similar climatic conditions and cropping schedules, rice productivity differs considerably among farmers and across cultivation areas. These variations indicate the existence of spatial heterogeneity in production factors that has not yet been comprehensively investigated using an integrated geospatial approach. To date, studies combining production factor analysis based on the Cobb-Douglas production function with GIS at the village level remain limited, particularly in South Sumatra.

Therefore, this study aims to analyze the influence of production factors on rice productivity using the Cobb-Douglas production function and to examine their spatial distribution through Geographic Information Systems (GIS). The integration of econometric and geospatial analyses constitutes the novelty of this research by providing both statistical evidence and spatial visualization of production factor variability. The findings are expected to support location-specific agricultural management, improve production efficiency, and contribute to sustainable rice development under the Cropping Index 200 system.

2. EXPERIMENTAL SECTION

2.1 Study Area and Time

This study was conducted in Muara Lawai Village, Muara Enim Regency, South Sumatra, Indonesia. The area is characterized by lowland rice farming systems implementing the Cropping Index 200 (CI 200), where rice is cultivated twice a year. The total rice field area in the village is approximately 180 hectares. The research was carried out from January to March 2025.

2.2 Types and Sources of Data

This study utilized both primary and secondary data.

Primary data were collected through direct interviews with farmers using structured questionnaires, field observations, and land measurements using GPS. The collected data included land size, rice production, rice varieties, weed control methods, and fertilizer usage. Secondary data were obtained from relevant institutions such as the Department of Agriculture of Muara Enim Regency, the Central Bureau of Statistics (BPS), as well as literature and previous studies. Satellite imagery from Google Earth Pro was also used to support geospatial mapping of production factors and rice productivity (Pandita et al., 2024).

2.3 Sampling Method

The sampling method used in this study was purposive sampling. A total of 30 rice farmers were selected as respondents based on the following criteria:

1. Farmers implementing the CI 200 system,
2. Farmers actively managing rice farming,
3. Farmers willing to provide complete and accurate information.

2.4 Data Analysis Methods

Data analysis consisted of statistical and geospatial analyses. Statistical analysis was conducted using the Cobb-Douglas production function, which is widely applied to estimate the relationship between agricultural inputs and production (Gautam, 2024).

Geospatial analysis was performed using **Google Earth Pro**. The spatial analysis workflow included: (1) collecting field coordinates using a Global Positioning System (GPS); (2) identifying and digitizing rice field locations on Google Earth Pro; (3) linking the spatial locations with attribute data on production factors and rice productivity; (4) creating thematic maps showing the spatial distribution of production factors and rice productivity; and (5) interpreting spatial patterns to identify variations in rice productivity under the Cropping Index 200 (IP 200) system.

Rice productivity was classified into three productivity zones (low, medium, and high) using the **Equal Interval** classification method to facilitate the visualization and comparison of productivity across the study area.

2.4.1 Descriptive Analysis

Descriptive analysis was used to describe farmer characteristics and production factors, including land size, rice varieties, weed control methods, and fertilizer usage. The results were presented in the form of tables, percentages, and descriptive narratives.

2.4.2 Geospatial Mapping

Geospatial mapping was performed using Google Earth Pro to visualize the spatial distribution of rice productivity and production factors in Muara Lawai Village. Spatial data were obtained from field GPS measurements and Google Earth Pro imagery. The workflow consisted of: (1) recording the geographic coordinates of each sampled rice field using GPS; (2) digitizing the rice field locations based on Google Earth Pro imagery; (3) linking spatial coordinates with attribute data, including land size, rice variety, fertilizer application, weed control method, and rice productivity; and (4) producing thematic maps illustrating the spatial distribution of these variables following thematic mapping procedures using satellite imagery (Pandita et al., 2024).

Rice productivity was categorized into low, medium, and high productivity classes based on predetermined productivity ranges to facilitate visual comparison among rice fields. The resulting maps were used for descriptive spatial interpretation to identify the geographic distribution of production factors and productivity within the study area. No spatial statistical analyses, such as spatial autocorrelation or hotspot analysis, were performed.

2.4.3 Cobb-Douglas Production Function Analysis

Quantitative analysis was conducted using the Cobb-Douglas production function, which was transformed into a natural logarithmic (ln) form to allow linear regression analysis.

The model is specified as follows:

$$\ln Y = \alpha + \beta 1 \ \ln X1 + \beta 2 \ D2 + \beta 3 \ D2 + \beta 4 \ D3 + €$$

where

- (Y) = = Rice productivity (ton/ha)
- ($X1$) = Land size (ha)
- ($D1$) = Dummy variable for rice variety (1 = Inpari 32, 0 = others)
- ($D2$) = Dummy variable for weed control (1 = combined method, 0 = otherwise)
- ($D3$) = Dummy variable for fertilizer (1 = combination of NPK + Urea + POC, 0 = otherwise)
- α = Constant
- β = Regression coefficients
- €= Error term

2.5 Statistical Testing

The regression analysis was performed using SPSS software. The following statistical tests were conducted:

- t-test to examine the partial effect of each independent variable,
- F-test to assess the simultaneous effect of all variables,
- Coefficient of determination (R^2 and Adjusted R^2) to evaluate the explanatory power of the model.

3. RESULTS AND DISCUSSION

3.1 Characteristics of Production Factors

a. Land Size Distribution

The distribution of land size indicates that rice farming in Muara Lawai Village is dominated by smallholder farmers. Approximately 50.00% of farmers cultivate land between 0.15-0.24 ha, followed by 23.33% with land less than 0.15 ha. Only 10.00% of farmers manage land between 0.35-0.45 ha, and none own land larger than 0.45 ha.

This structure confirms that rice farming operates at a **small-scale level**, which limits economies of scale, mechanization, and efficiency of input use. Therefore, improving productivity relies more on optimizing input management rather than expanding land which is consistent with the findings of Noviwiyanah and Yudhistira (2024), who reported that farm size influences agricultural production and production efficiency.

b. Rice Varieties

The majority of farmers (80.00%) use the high-yielding variety Inpari 32, while 16.67% use AGR 303 and only 3.33% use Cakrabuana.

The dominance of Inpari 32 indicates that most farmers have adopted improved rice varieties with good adaptation and high yield potential. This finding is consistent with Dewi and Nurita (2022), who reported that improved rice varieties contribute to higher productivity because of their adaptability under different cultivation environments.

c. Weed Control Methods

Weed control is predominantly conducted using a combination of manual and chemical methods (96.67%), while only 3.33% of farmers do not apply proper weed control.

The combined method effectively suppresses weed competition for nutrients, water, and sunlight, thereby improving crop growth and productivity. Similar findings were reported by Abbas et al. (2021), Bhat et al. (2023), and Zarwazi et al. (2017) , who concluded that integrated weed management significantly improves rice yield.

d. Fertilizer Use

Fertilizer application patterns vary among farmers:

- NPK + Urea + POC: 40.00%
- NPK + POC: 33.33%
- NPK + Urea: 10.00%
- NPK only: 16.67%

These findings indicate that although many farmers have adopted balanced fertilization, some still apply incomplete fertilizer combinations. Balanced fertilization enhances nutrient availability and improves crop performance, as reported by Halim et al. (2022).

3.2 Rice Productivity Analysis

3.2.1 Land Size Characteristics

The results show that the majority of respondents cultivated relatively small rice fields, ranging from 0.10 to 0.45 ha, with an average farm size of 0.24 ha. This indicates that rice farming in Muara Lawai Village is dominated by small-scale agricultural holdings. The relatively small land size reflects the limited scale of farming practiced by respondents. However, this study did not specifically investigate whether the observed farm size distribution resulted from land fragmentation, inheritance patterns, or land tenure and ownership dynamics. Therefore, further research is required to examine the underlying factors affecting landholding size. Similar observations regarding the importance of farm size in determining agricultural productivity have been reported by Noviwiyanah and Yudhistira (2024).

3.2.2 Effects of Production Factors on Rice Productivity

The Cobb-Douglas production function was employed to evaluate the influence of production factors on rice productivity under the Cropping Index 200 (CI 200) system. The regression results indicate that land size, rice variety, weed control method, and fertilizer application significantly affected rice productivity, which is consistent with the Cobb-Douglas approach commonly used in agricultural production analysis (Gautam, 2024).

Land size exhibited a positive and significant coefficient, indicating that larger cultivated areas were associated with higher rice productivity, assuming other production factors remained constant. Similar findings were reported by Herdian et al. (2020).

The dummy variable for rice variety was positive and statistically significant. Farmers who cultivated the Inpari 32 variety (dummy = 1) achieved higher rice productivity than farmers who cultivated other rice varieties (reference category, dummy = 0), indicating the superior production performance of Inpari 32 under the CI 200 system.

Similarly, the dummy variable representing weed control methods showed a positive and significant effect. Farmers who applied the combined manual and chemical weed control method (dummy = 1) obtained higher rice productivity than those using other weed management practices. This finding agrees with previous studies conducted by Abbas et al. (2021), Bhat et al. (2023), and Zarwazi et al. (2017).

The dummy variable for fertilizer application had the highest positive coefficient, indicating that the combination of **NPK + Urea + POC** contributed most significantly to rice productivity. This result supports previous studies by Halim et al. (2022) and Rachmadtullah et al. (2024), which emphasized the importance of balanced fertilization and organic amendments in improving soil fertility and crop productivity.

Overall, these findings demonstrate that appropriate management of production factors plays an essential role in improving rice productivity under the CI 200 system. In addition, increasing farmers' knowledge and adoption of appropriate production technologies is expected to further improve production efficiency, as suggested by Rasanjali et al. (2021).

3.3 Geospatial Analysis of Land and Productivity

3.3.1 Geospatial Distribution of Respondents' Land Size

Figure 1 presents the spatial distribution of respondents' land size based on thematic mapping using Google Earth Pro.

Land size was classified into five categories: **<0.15 ha, 0.15-0.24 ha, 0.25-0.34 ha, 0.35-0.44 ha, and >0.44 ha.** The map shows that most respondents cultivated small to medium sized land parcels (0.15-0.34 ha), while relatively larger parcels were less common. The distribution of land size varies across the study area, indicating differences in farm

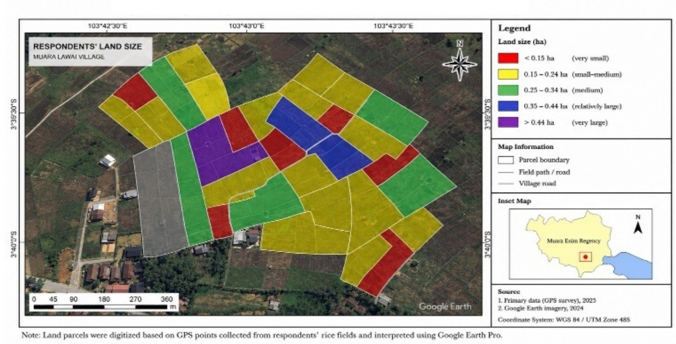

Figure 1. Map of Respondents' Land Size Distribution in Muara Lawai Village

size among respondents. This thematic map provides a descriptive visualization of land-size distribution and complements the statistical analysis of production factors under the Cropping Index 200 (CI 200) system.

3.3.2 Geospatial Distribution of Rice Varieties

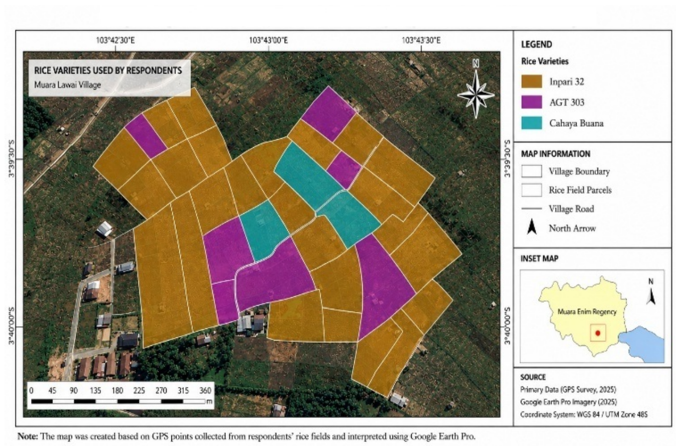

Figure 2. Spacial Distribution of Rice Varieties Used by Respondents in Muara Lawai Village

Figure 2 presents the spatial distribution of rice varieties cultivated by respondents in Muara Lawai Village based on thematic mapping using Google Earth Pro.

Three rice varieties were identified, namely Inpari 32, AGT 303, and Cahaya Buana. The map shows that Inpari 32 is the dominant variety and is cultivated in most of the rice fields within the study area. In contrast, AGT 303 and Cahaya Buana are planted in relatively fewer fields and are distributed in several locations.

The observed distribution indicates that farmers predominantly prefer Inpari 32, which may reflect its adaptability and suitability for cultivation under the Cropping Index 200 (CI 200) system. The thematic map provides a descriptive visualization of varietal distribution and complements the regression analysis by illustrating the spatial distribution of rice varieties across the study area.

3.3.3 Spatial Distribution of Weed Control Methods

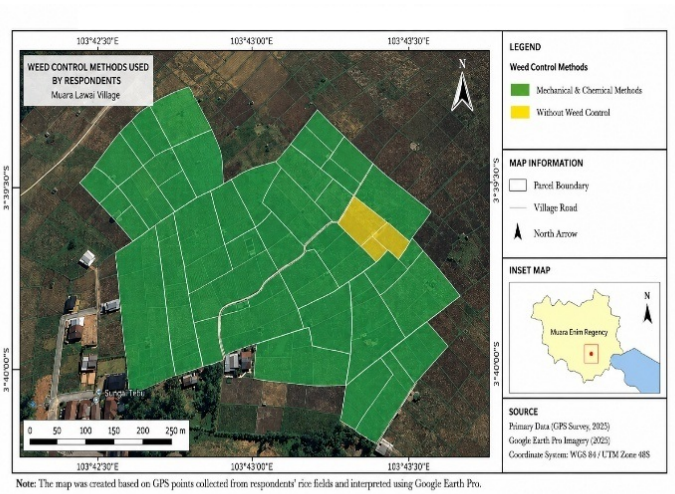

Figure 3. Spacial Distribution of Weed Control Methods Used by Respondents in Muara Lawai Village

Figure 3 presents the spatial distribution of weed control methods used by respondents in Muara Lawai Village based on thematic mapping using Google Earth Pro.

Two weed control practices were identified: mechanical and chemical weed control and no weed control. The map shows that the majority of respondents applied a combination of mechanical and chemical weed control, while only a few rice fields were managed without weed control. The thematic map indicates that the adoption of weed control practices was relatively consistent across the study area. This descriptive spatial visualization complements the regression analysis by illustrating the distribution of weed management practices under the Cropping Index 200 (CI 200) system.

3.3.4 Spatial Distribution of Fertilizer Application

Figure 4 presents the spatial distribution of fertilizer application practices used by respondents in Muara Lawai Village based on thematic mapping using Google Earth Pro.

Four fertilizer application patterns were identified, namely NPK only, NPK + POC, NPK + Urea, and NPK + Urea + POC. The map shows that the NPK + Urea + POC combination was the most widely adopted fertilizer practice, while NPK + Urea was the second most common application. In contrast, the use of NPK + POC and NPK only was observed in a smaller number of rice fields. These findings indicate that fertilizer management practices varied among respondents across the study area. The thematic map provides a descriptive visualization of fertilizer application patterns and complements the regression analysis by illustrating the spatial distribution of fertilizer use under the Cropping Index 200 (CI 200) system.

Figure 4. Spacial Distribution of Fertilizer Application Used by Respondents in Muara Lawai Village

3.3.5 Spatial Distribution of Rice Productivity

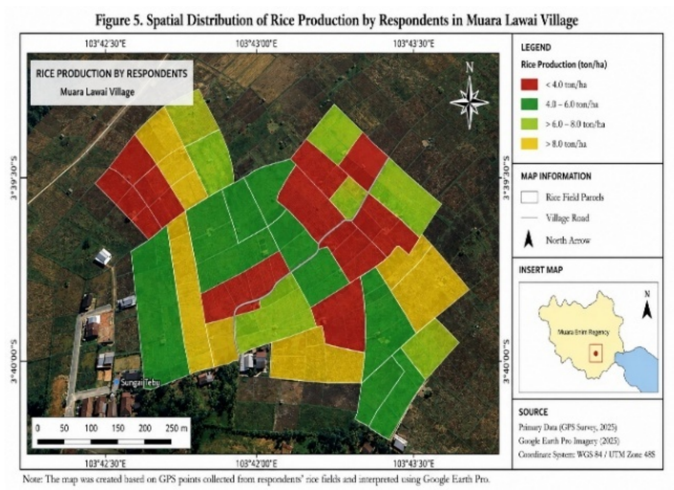

Figure 5. Spacial Distribution of Rice Production Used by Respondents in Muara Lawai Village

Figure 5 presents the spatial distribution of rice productivity in Muara Lawai Village based on thematic mapping using Google Earth Pro.

Rice productivity was classified into three categories: <4 ton ha^{-1}ha^{-1}, 4-6 ton ha^{-1}, and >6 ton ha^{-1}. The map shows that rice productivity varied across the study area, with most rice fields producing between 4 and 6 ton ha^{-1}, while several fields achieved productivity above 6 ton ha^{-1} and others produced less than 4 ton ha^{-1}. This variation indicates differences in rice production performance among respondents. The thematic map provides a descriptive visualization of the spatial distribution of rice productivity and complements the regression analysis by illustrating productivity patterns under the Cropping Index 200 (CI 200) system.

3.4 Cobb-Douglas Regression Analysis

The estimated regression model is:

$$\ln Y = 1.102 + 0.280 \ \ln \ X_1 + 0.220D_1 + 0.180D_2 + 0.300D_3$$

Model indicators:

- R^2 **= 0.720**
- **Adjusted** R^2 **= 0.686**
- **F-statistic = 18.37 (p<0.001)**

This indicates that **68.6% of productivity variation is explained by the model,** which is relatively strong for farm-level data.

a. Land Size Effect

The coefficient (**0.280**) is positive and significant (p = 0.013), meaning that a 1% increase in land size increases productivity by 0.28%. This reflects a **scale effect**, where larger landholdings allow better input allocation and management efficiency.

b. Variety Effect

The coefficient (**0.220**) indicates that using Inpari 32 increases productivity by approximately **22%**. This confirms that improved varieties significantly contribute to yield enhancement under intensive cropping systems.

c. Weed Control Effect

The coefficient (**0.180**) shows that combined weed control increases productivity by about **18%**. Effective weed control reduces competition for nutrients, water, and light, thus improving crop performance.

d. Fertilizer Combination Effect

The highest coefficient (**0.300**) indicates that using **NPK + Urea + POC** increases productivity by approximately **30%**. This highlights that balanced fertilization is the most dominant factor affecting productivity.

Scientifically:

- NPK supplies macro nutrients
- Urea enhances vegetative growth
- POC improves soil structure and nutrient efficiency

3.5 Discussion

The results demonstrate that rice productivity in Muara Lawai is primarily driven by input management quality rather than land expansion.

Key findings include:

- Fertilizer combination is the most influential factor
- Variety and weed control play supporting roles
- Land size has a structural but less dominant effect

The interaction among these factors is complementary and synergistic, indicating that productivity improvement requires integrated management. Furthermore, the CI 200 system increases pressure on soil fertility, making organic input (POC) essential for maintaining long-term sustainability.

4. CONCLUSION

Based on the results of this study on the Geospatial Analysis of Production Factors and Rice Productivity under the Cropping Index 200 (CI 200) System in Muara Lawai Village, Muara Enim Regency, the following conclusions can be drawn:

1. The majority of respondents cultivated relatively small rice fields (0.10-0.43 ha), with most farms measuring less than 0.24 ha. Inpari 32 was the dominant rice variety due to its high productivity and adaptability. Most farmers applied a combination of mechanical and chemical weed control, while the NPK + Urea + Liquid Organic Fertilizer (POC) combination was the most commonly used fertilizer practice, although its adoption varied among respondents.
2. The Cobb-Douglas regression analysis showed that all production factors significantly affected rice productivity. Land size, the use of the Inpari 32 variety, integrated weed control, and the application of NPK + Urea + POC had positive and significant effects on rice productivity, with fertilizer application showing the greatest contribution. The model explained 68.6% of the variation in rice productivity (Adjusted R^2 = 0.686), indicating a strong relationship between the production factors and rice productivity.
3. Thematic mapping using Google Earth Pro showed that land size, rice varieties, fertilizer application, weed control practices, and rice productivity were spatially distributed across the study area. The maps provide a descriptive visualization of the variation in production factors and rice productivity among respondents and complement the statistical analysis by illustrating their geographic distribution.
4. Improving rice productivity under the CI 200 system should focus on the adoption of high-yielding rice varieties, balanced fertilizer application, integrated weed management, and the use of geospatial information to support location-based agricultural planning and decision-making. These strategies are expected to enhance production efficiency and contribute to sustainable rice farming in Muara Lawai Village.

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