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Positioning of Potential Rice Production Areas in Kalimantan Barat: A Multidimensional Scaling Approach

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ABSTRACT

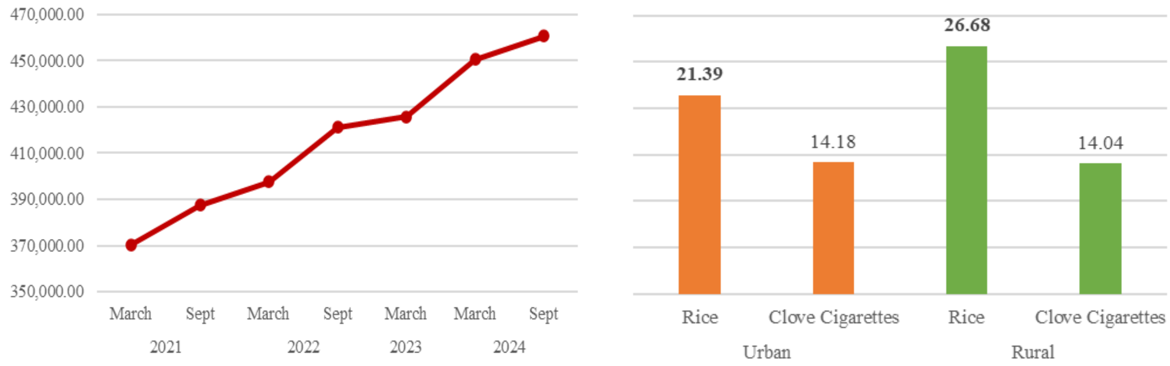
Food security in Kalimantan Barat remains relatively low, as the province ranks 24th out of 34 provinces in Indonesia. This condition is reflected in declining indicators of food availability and affordability, along with a continuously increasing food poverty line, in which rice—the main staple food—constitutes the largest contribution. When staple food demand cannot be adequately met, households are more likely to fall into poverty, adversely affecting education, health, and overall socio-economic stability. Therefore, this study aims to identify areas with potential rice production in Kalimantan Barat using a positioning approach visualized through a two-dimensional configuration map. The analytical method employed is Multidimensional Scaling (MDS).The results show that two regions located in Quadrant I possess high agricultural potential with optimal utilization. Five regions in Quadrant II exhibit relatively limited agricultural capacity (smaller harvested areas and modest total output) but comparatively higher productivity, reflecting more advanced resource utilization. Four regions in Quadrant III are characterized by limited agricultural potential across all indicators, while three regions in Quadrant IV demonstrate considerable rice production potential (large harvested areas and high total output) that has not yet been optimally utilized due to low productivity. Consequently, regencies and municipalities located in Quadrants III and IV should be prioritized by policymakers to ensure more targeted and effective agricultural development strategies.

Keywords: food security, multidimensional scaling, positioning, rice production.

INTRODUCTION

Each country is committed to achieving the second Sustainable Development Goal (SDG 2), namely Zero Hunger, through the implementation of national policies. This commitment is realized by ensuring adequate food availability for all citizens. The availability of sufficient, safe, and equitably distributed food reflects the level of food security within a region. Food security refers to a condition in which food needs are fulfilled in terms of quantity, quality, safety, equitable distribution, and cultural appropriateness, thereby enabling individuals to live healthy and productive lives on a sustainable basis (Dinas Ketahanan Pangan, 2023). Kalimantan Barat is one of the regions that continues to face challenges in achieving food security. Although the provincial Food Security Index increased from 70.81 in 2022 to 72.20 in 2023, Kalimantan Barat remains classified as a province with relatively low food security. In 2023, the province ranked 24th out of 34 provinces in Indonesia, with declining indicators offood availability and affordability compared to the previous year (Badan Pangan Nasional, 2023). This condition indicates limited access to basic food needs and contributes to food inequality, leading to the emergence of food-vulnerable populations (Bentham et al., 2020).

In addition, the food poverty line in Kalimantan Barat has shown a consistent upward trend. As illustrated in Figure 1a, the food poverty line increased from IDR 370,423.00 per capita per month in March 2021 to IDR 460,485.00 per capita per month in September 2024, exceeding the national food poverty line of IDR 443,433.00 per capita per month. The food poverty line represents the minimum expenditure required to meet basic food needs equivalent to 2,100 kilocalories per capita per day and is therefore a key indicator of poverty (BPS, 2025). Based on Figure 1b, rice is the largest contributor to the food poverty line in both urban and rural areas of Kalimantan Barat. InMarch 2024, rice accounted for 21.39% of the poverty line in urban areas and 26.68% in rural areas. This finding highlights the population's heavy dependence on rice as the primary staple food. An increasing food poverty line poses a serious threat to development, as it may trigger food insecurity that affects multiple socio-economic dimensions. According to Engel's Law, lower-income households allocate a larger proportion of their income to food consumption (Engel, 1857). Consequently, risingfood prices disproportionately burden low-income households, reducing their ability to meet non-food needs such as education, health, and housing (Deaton, 2019). This condition may lead to higher poverty levels, increased disease incidence, malnutrition, and declining overall welfare (Raihannabil & Wicaksono, 2024; Hakiki, 2020; Giovanni, 2018).



(a) (b)

Figure 1. Overview of Food Poverty in Kalimantan Barat: (a) Kalimantan Barat Food Poverty Line, 2021-2024 (IDR); (b) Commodities which Contributes the Largest to the Kalimantan Barat Poverty Line, March 2024 (percent)
Source: BPS, 2025.

Rice, as the staple food of the population of Kalimantan Barat, plays a crucial role in determining regional food security. Therefore, increasing rice production is one of the most effective strategies to enhance food security. Although Kalimantan Barat has considerable potential for rice production, various structural and productivity-related constraints limit its optimal utilization. Agricultural land in the province is predominantly rain-fed paddy fields, where rice productivity is significantly lower than in irrigated areas (Maliano et al., 2022). Furthermore, the continuous conversion of agricultural land into non-agricultural uses has reduced the availability of farmland. The rate of agricultural land conversion in Kalimantan Barat has increased over time and poses a serious threat to food self-sufficiency (Siti, 2019). If these challenges remain unaddressed, rice production may decline while public demand continues to increase. When staple food demand is not adequately met, households face a higher risk of falling into poverty, which in turn reduces access to education and healthcare services and weakens overall socio-economic stability (Masters et al., 2022; Sujai et al., 2013; Tono & Fauzia, 2022). Therefore, it is essential to identify areas with high rice production potential that have not yet achieved optimal output, as well as areas with limited agricultural potential.

This study has reviewed several previous studies on identifying areas with potential for rice production, such as research conducted by Tri Cahaya et al. (2024). The study grouped areas with potential for rice production at the sub-district level in Pagar Alam Municipality using the k-means method. It produced 3 clusters, namely areas with low, medium, and high rice production potential, with most sub-districts included in areas with low rice production potential. Then, Christiani (2024) analyzed areas with potential for rice production in NTT using k-means. The study produced 3 clusters where 7 regencies/municipalitywere classified as areas with high rice production potential, 10 regencies/municipalitywere classified as areas with medium rice production potential, and 5 regencies/municipalitywere classified as areas with low rice production potential. Suprapto (2022) also conducted a similar study to group provinces in Indonesia based on their rice production potential using the k-means method and obtained 3 clusters, namely the first cluster consisting of provinces with the highest rice production in Indonesia, the second cluster consisting of provinces with above average rice production, and the third cluster consisting of provinces with below average rice production. Then, Wijayanto & Fathoni (2021) conducted a study aimed at grouping rice productivity in Central Java using k-means cluster analysis and produced 3 clusters with 12 areas classified as having medium rice productivity, 18 areas classified as having low rice productivity, and 18 areas classified as having high rice productivity. In addition, Sanela et al. (2023) also grouped potential rice crop areas with loci in Sumatra at the provincial level. Through mapping using the k-means method, the study found that the number of clusters formed was 3, namely high, medium, and low rice potential levels. Another study by Khan et al. (2023) compared the k-medoids and k-means methods and found that k-means was the best method for grouping sub-districts with rice and secondary crop production potential. The optimum number of clusters produced is 6 clusters, including cluster 1 consisting of 1 sub-district, cluster 2 consisting of 3 sub-districts, cluster 3 consisting of 2 sub-districts, cluster 4 consisting of 3 sub-districts, cluster 5 consisting of 8 sub-districts, and cluster 6 consisting of 14 sub-districts.

Based on the problems and related research that have been reviewed, most studies have grouped potential rice production areas using clustering techniques, such as k-means and k-medoids. However, no research has examined this in Kalimantan Barat by applying other positioning methods. Thus, through this research gap, this study aims to identify potential rice production areas in Kalimantan Barat at the regency/municipality level through positioning. This study uses the Multidimensional Scaling (MDS) method for positioning regencies/municipalities in Kalimantan Barat based on the characteristics of potential rice production areas. This approach enables the visualization of regional similarities and differences through a two-dimensional configuration map, facilitating the identification of areas with underutilized potential and those with structural agricultural constraints. The results are expected to provide a clearer spatial depiction of rice production potential in Kalimantan Barat and serve as a basis for more targeted and effective agricultural policy formulation.

METHODOLOGY

Data and Data Sources

This study uses secondary data from BPS–Statistics Kalimantan Barat Province, derived from the Area Sampling Frame (KSA) Survey and the Crop-Cutting Survey. Table 1 presents the variables, definitions, units, and data types used in the analysis.

Table 1. Description of Research Variables

Variable	Description	Unit	Type
(1)	(2)	(3)	(4)
Harvest Area	Rice Harvest Area by Regency/Municipality in Kalimantan Barat	Hectare	Continuous
Productivity	Rice Productivity by Regency/ Municipality in Kalimantan Barat	Quintal/ Hectare	Continuous
Production	Rice Production by Regency/ Municipality in Kalimantan Barat	Ton	Continuous

Source: BPS-Statistics Kalimantan Barat Province (2024).

Multidimensional Scaling

Multidimensional Scaling (MDS) is a multivariate analysis technique used to map several objects based on the similarity or proximity of distances between objects in a low-dimensional space, usually dimension 2. The main goal of MDS is to find a representation of objects in several dimensions so that the distances between objects in the mapping results approach the original observed similarity or distance (Johnson & Wichern, 2014). The procedure for performing multidimensional scaling is shown in Figure 2.

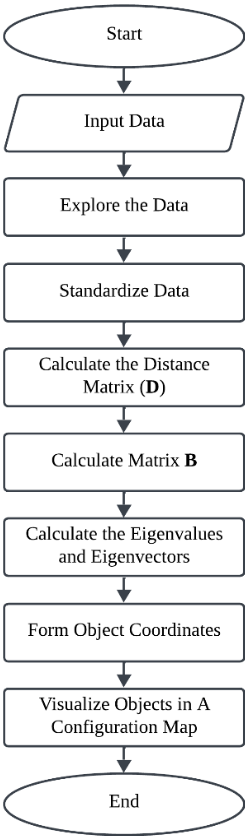


Figure 2. Research Flow Diagram
Source: Author, 2025.

Based on Figure 2, the procedure for performing MDS can be described as follows.

1. Input Data
   Before conducting the analysis, the initial stage is to input data from 14 regencies/municipalities in Kalimantan Barat for each variable used, namely harvested area, productivity, and rice production, into the R Studio software for processing.
2. Explore the Data
   Conduct the data exploration stage by presenting each variable's mean, minimum, and maximum values.
3. Standardize Data
   Standardization of variables in MDS aims to eliminate differences in scale between variables so that the analysis results are more accurate because there is no dominance of certain variables (Hair et al., 2019). Because there are unit differences between variables, the data will first be standardized using the z-score. The standardized value of object i on variable k is defined as follows.

$$z_{ik} = \frac{x_{ik} - \bar{x}_k}{s_k} \tag{1}$$

where:

z_{ik} = standardized value (z-score) of object i on variable k,
x_{ik} = original value of object i on variable k,
$\bar{x}_k$ = mean of variable k,
s_k = standard deviation of variable k.

4. Calculating the Distance Matrix (**D**)
In MDS, the distance matrix is generally calculated using the Euclidean distance, which measures the proximity between points in low-dimensional space (Johnson & Wichern, 2014). The formula for calculating the Euclidean distance is as follows.
$$d_{ij} = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{ip} - x_{jp})^2} \quad (2)$$
where:
d_{ij} = distance between object i and object j,
x_{ik} = coordinate of object i,
x_{jk} = coordinate of object j,
p = number of variables.

5. Calculating Matrix **B**
MDS does not work directly using the distance matrix but changes it into a **B** matrix form with a double-centering approach obtained from the average of the squared distances for each object, either in rows, columns, or overall. The **B** matrix is used in the matrix decomposition method to determine an object's position in a lower-dimensional space (Johnson & Wichern, 2014). The **B** matrix has elements containing b_{ij}, which can be calculated as follows.
$$b_{ij} = -\frac{1}{2}\left(d_{ij}^2 - d_{i.}^2 - d_{.j}^2 + d_{..}^2\right) \quad (3)$$
where:
d_{ij}^2 = squared distance between object i and object j,
$d_{i.}^2 = \frac{1}{n}\sum_j d_{ij}^2$ = row-wise average squared distance for object i,
$d_{.j}^2 = \frac{1}{n}\sum_i d_{ij}^2$ = column-wise average squared distance for object j,
$d_{..}^2 = \frac{1}{n^2}\sum_{ij} d_{ij}^2$ = overall average squared distance.

6. Calculate the Eigenvalues and Eigenvectors
Eigenvalues determine the proportion of variance of the distance matrix (**D**) that can be explained by each dimension in a low-dimensional space (Johnson & Wichern, 2014). Eigenvalues ($\boldsymbol{\lambda}$) are obtained from solving equation (4).
$$\det(\mathbf{B} - \boldsymbol{\lambda}\mathbf{I}) = 0 \quad (4)$$
Meanwhile, eigenvectors (**E**) are obtained by substituting $\boldsymbol{\lambda}$ into equation (5).
$$(\mathbf{B} - \boldsymbol{\lambda}\mathbf{I})\mathbf{E} = 0 \quad (5)$$
Eigenvectors are used to form the final coordinates representing a low-dimensional space (Johnson & Wichern, 2014).

7. Form Object Coordinates
The final coordinates of an object in q dimensions are obtained by multiplying the eigenvectors and the square root of the eigenvalues (Johnson & Wichern, 2014). The coordinates of the object can be expressed as follows.
$$\mathbf{X} = \mathbf{E}_q\boldsymbol{\Lambda}_q^{1/2} \quad (6)$$
where:
$\mathbf{E}_q$ = the matrix containing the first q eigenvectors,
$\boldsymbol{\Lambda}_q$ = the diagonal matrix containing the q largest eigenvalues.

8. Visualize Objects in A Configuration Map
   Configuration maps visualize each object in a low-dimensional space based on previously formed object coordinates. This study uses a 2-dimensional space because it makes visualization easier, allows for a more intuitive understanding, and helps gain more precise insights. On the other hand, using a 3-dimensional or higher space can complicate interpretation and analysis.

Evaluation of Positioning Results

a. Proportion of Inertia

The proportion of inertia indicates how much of the total variation in the data can be explained by each dimension. The higher the proportion of inertia, the better the low-dimensional space represents the position of objects (Johnson & Wichern, 2014). The proportion of inertia is usually expressed as a cumulative percentage indicating the total variation a given number of dimensions can explain. The formula for calculating the proportion of inertia is as follows.

$$Prop.\ of\ Inertia = \frac{\lambda_k}{\sum_{i=1}^{q} \lambda_i} \tag{7}$$

where:
λ_k = eigenvalue for the k-th dimension,
$\sum_{i=1}^{q} \lambda_i$ = total sum of eigenvalues across all dimensions.

b. Stress Value

The stress value indicates the measure of agreement between the original distance and the estimated distance in low-dimensional space. The smaller the stress value, the better the low-dimensional space represents the data (Johnson & Wichern, 2014). The formula for calculating the stress value is as follows.

$$Stress\ Value = \sqrt{\frac{\sum_{i<j}\left(d_{ij} - \hat{d}_{ij}\right)^2}{\sum_{i<j} d_{ij}^2}} \tag{8}$$

where:
d_{ij} = the original distance between objects,
$\hat{d}_{ij}$ = the estimated distance between objects.

The categorization of stress value for evaluating positioning results is as follows.

Table 2. Stress Value Category

Stress Value	Category
(1)	**(2)**
> 20%	Poor Fit
10% < stress value ≤ 20%	Fair Fit
5% < stress value ≤ 10%	Good Fit
2.5% < stress value ≤ 5%	Excellent Fit
< 2.5%	Perfect Fit

Source: Johnson & Wichern (2014).

RESULTS AND DISCUSSION

Multidimensional Scaling

Before positioning the potential rice production areas in Kalimantan Barat, data exploration needs to be done to get a general picture of the characteristics of the rice farming sector in the region. The exploration results through minimum, maximum, and average values are as follows.

Table 3. Minimum and Maximum Values and Average Harvest Area, Production, and Productivity of Rice in Kalimantan Barat, 2024

Variable	Minimum	Maximum	Average
(1)	(2)	(3)	(4)
Harvest Area	117	58,031	16,005
Productivity	26	38	31.8
Production	410	177,411	50,020.7

Source: BPS-Statistics of Kalimantan Barat, processed (2025).

Based on Table 3, the rice harvest area in Kalimantan Barat is in the range of 117 to 58,031 hectares, with an average harvest area of 16,005 hectares. Then, rice productivity in Kalimantan Barat ranges from 26 to 38 quintals/hectare, with an average productivity of 31.8 quintals/hectare. Meanwhile, rice production in Kalimantan Barat is between 410 and 177,411 tons, with an average production of 50,020.7 tons. The range between regencies/municipalities in Kalimantan Barat with the lowest and highest rice harvest areas and production is quite large, indicating disparities between regions in the rice farming sector.

Since each variable has different units, standardization will be done using a z-score. The standardization result data is as follows.

Table 4. Data Standardization Results

Regency/ Municipality	Harvest Area	Productivity	Production
(1)	(2)	(3)	(4)
Sambas	2.79	-0.21	2.72
Bengkayang	-0.39	0.60	-0.32
⋮	⋮	⋮	⋮
Pontianak Municipality	-1.05	0.88	-1.06
Singkawang Municipality	-0.83	1.15	-0.80

Source: BPS-Statistics Kalimantan Barat Province, processed (2025).

Calculating the distance matrix using Euclidean distance produces a 14×14 matrix. The distance matrix formed is as follows.

$$\mathbf{D} = \begin{bmatrix} 0.00 & 4.47 & \cdots & 5.50 & 5.23 \\ 4.47 & 0.00 & \cdots & 1.03 & 0.85 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 5.50 & 1.03 & \cdots & 0.00 & 0.44 \\ 5.23 & 0.85 & \cdots & 0.44 & 0.00 \end{bmatrix}$$

Then, the average of the squared distances for each object in rows, columns, and overall forms b_{ij} becomes an element of matrix $\mathbf{B}$. The matrix $\mathbf{B}$ formed is as follows.

$$\mathbf{B} = \begin{bmatrix} 15.21 & -2.09 & \cdots & -6.00 & -4.74 \\ -2.09 & 0.62 & \cdots & 1.28 & 1.28 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -6.00 & 1.28 & \cdots & 3.00 & 2.73 \\ -4.74 & 1.28 & \cdots & 2.73 & 2.65 \end{bmatrix}$$

After forming the matrix **B**, the next step is to calculate the eigenvalues and eigenvectors of the matrix **B**. The eigenvalues used are only positive ones. The formation of object coordinates uses $\mathbf{\Lambda}^{1/2}$, which is as follows.

$$\mathbf{\Lambda}^{1/2} = \begin{bmatrix} 5.09 & 0.00 & \cdots & 5.50 & 5.23 \\ 0.00 & 3.61 & \cdots & 1.03 & 0.85 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0.00 & 0.00 & \cdots & 2.54e^{-8} & 0.00 \\ 0.00 & 0.00 & \cdots & 0.00 & 2.25e^{-8} \end{bmatrix}$$

Meanwhile, the positive eigenvectors ($\mathbf{E}$) formed from the matrix **B** are as follows.

$$\mathbf{E} = \begin{bmatrix} 0.77 & -0.00 & \cdots & 0.00 & 0.00 \\ -0.10 & 0.16 & \cdots & -0.31 & 0.34 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -0.30 & 0.22 & \cdots & 0.35 & -0.42 \\ -0.24 & 0.30 & \cdots & 0.10 & 0.19 \end{bmatrix}$$

Then, object coordinates are formed using $\mathbf{\Lambda}^{1/2}$ and $\mathbf{E}$, which were calculated previously. The object coordinates formed are as follows.

Table 5. The Object Coordinates

Regency/ Municipality	**Dimension 1**	**Dimension 2**
(1)	**(2)**	**(3)**
Sambas	3.90	-0.003
Bengkayang	-0.54	0.58
⋮	⋮	⋮
Pontianak Municipality	-1.54	0.79
Singkawang Municipality	-1.21	1.08

Source: Author (2025).

The coordinates of the objects that have been formed will be plotted into a two-dimensional space that describes the position of each object. The results of object positioning are visualized in the MDS configuration map as follows.

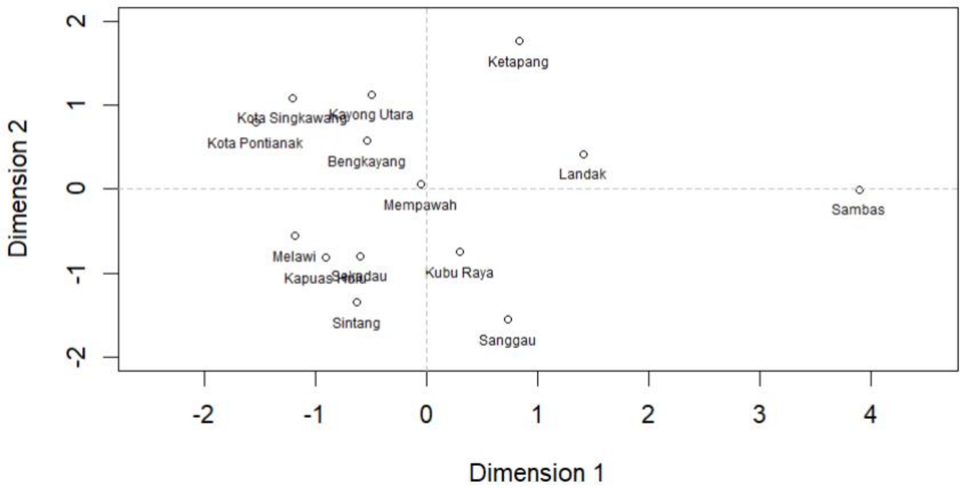


Figure 3. MDS Configuration Map
Source: Author, 2025.

Evaluation of Positioning Results

After visualizing the object in the two-dimensional MDS configuration map, the next step is to evaluate the positioning results through the inertia proportion and stress value.

a. Proportion of Inertia

The inertia proportion determines whether the two-dimensional MDS configuration map is sufficient to maximize the distance matrix's variance. The inertia proportion of each dimension and its cumulative are as follows.

Table 6. Proportion of Inertia

Dimension	Proportion	Cumulative Proportion
(1)	**(2)**	**(3)**
1	0.5728	0.5728
2	0.4064	0.9792

Source: Author (2025).

Based on Table 6, the cumulative inertia proportion produced is 0.9792, which means that the proportion of distance matrix variance that can be explained by the MDS configuration map in dimension 2 is 97.92%. This figure is > 75%, so dimension two can represent the object's position well.

b. Stress Value

The resulting stress value of 0.0787% indicates that the difference between the original distance in the distance matrix and the distance calculated after reducing the dimensions to 2 dimensions is minimal. The perfect fit criteria include a minimal stress value of less than 2.5%. Thus, the MDS model has represented data in 2 dimensions very well because the distance between points in 2-dimensional space is almost the same as between points in the original space.

Interpretation of Positioning Results

The positioning results will be grouped according to quadrants so that the members of each quadrant are as follows.

Table 7. Positioning Results Group Members

Quadrant	Member
(1)	**(2)**
I	Ketapang Regency and Landak Regency
II	Kayong Utara Regency, Pontianak Municipality, Singkawang Municipality, Bengkayang Regency, and Mempawah Regency
III	Melawi Regency, Sekadau Regency, Kapuas Hulu Regency, and Sintang Regency
IV	Sambas Regency, Kubu Raya Regency, and Sanggau Regency

Source: Author (2025).

The average number of members of each quadrant for all characteristics is used to interpret positioning results, which can be shown as follows.

Table 8. Average Quadrant of Positioning Results

Quadrant	Harvest Area	Productivity	Production
(1)	**(2)**	**(3)**	**(4)**
I	26,955.50	35.50	94,190.00
II	7,949.40	34.60	26,951.20
III	6,953.50	28.75	19,747.75
IV	34,199.33	28.67	99,387.67

Source: Author (2025).

Based on Table 8, the regencies/municipality included in quadrant I, namely Ketapang Regency and Landak Regency, have characteristics of high harvested area, rice production, and very high rice productivity. This condition indicates that the area has excellent agricultural potential. With high harvested area and rice production, as well as very high productivity, Ketapang Regency and Landak Regency can be categorized as areas with comparative advantages in the agricultural sector, which indicate the existence of supporting factors such as soil fertility, adequate agricultural infrastructure, and the use of efficient agricultural technology and practices. In addition, this area has the potential to become a food supply center for other Kalimantan Barat areas with lower agricultural production to help reduce dependence on rice imports from outside the province. Thus, increasing local production plays an important role in realizing food independence (Ramadhanty et al., 2024). Then, quadrant II, consisting of Kayong Utara Regency, Pontianak Municipality, Singkawang Municipality, Bengkayang Regency, and Mempawah Regency, has the characteristics of a high harvested area and rice production but low productivity. Although productivity is high, rice production will also be low if the harvested area is low. Urban areas, such as Pontianak and Singkawang Municipality, reflect the progress of agricultural technology and optimal utilization of human resources in the agricultural sector despite facing land limitations due to the conversion of agricultural land into residential, industrial, and urban infrastructure. Rapid urbanization drives the conversion of agricultural land to meet economic and development needs, directly impacting the decline in harvested area and rice production in aggregate, although productivity per hectare remains high. This phenomenon is common in urban areas of Indonesia due to rising land prices and the expansion of the property sector, which causes farmers to lose access to productive agricultural land (Reykasari et al., 2021). The consequences of this land conversion include increased dependence on food supplies from other areas, changes in the economic structure of rural communities shifting to non-agricultural sectors, and the potential for environmental degradation due to reduced green areas and water absorption capacity (Zhang et al., 2023).

Meanwhile, quadrant III, consisting of Melawi Regency, Sekadau Regency, Kapuas Hulu Regency, and Sintang, has a low harvest area, rice production, and productivity. This condition indicates the limitations of agricultural potential in the area, so agricultural results are not optimal. This area is the area most at risk of experiencing food vulnerability, which can directly impact the quality of public health. The health risks that can occur due to lack of access to staple foods are the nutritional status of the community, especially vulnerable groups such as infants, children, pregnant women, and the elderly, which are getting worse (Hartline-Grafton & Hassink, 2021). The nutritional status in Kalimantan Barat needs special attention, considering that this area is one of the areas with a prevalence of malnutrition problems on the island of Kalimantan (Raihannabil, 2024). Then, Sambas Regency, Kubu Raya Regency, and Sanggau Regency, which are included in quadrant IV, have high harvest areas and rice production but very low productivity. This area is classified as an area that has considerable rice production potential, but its management is less than optimal. The resulting rice production looks high because the harvest area is large, so the agricultural land has been utilized optimally compared to other areas. Its utilization is not good because its productivity is the lowest. Low rice plant productivity can be caused by less fertile soil conditions, limited irrigation, minimal use of modern agricultural technology, and low access for farmers to production facilities such as fertilizers and superior seeds (Kulyakwave et al., 2022; Bashir & Yuliana, 2019; Effendy et al., 2022). However, if this sizeable agricultural potential is utilized correctly, this area can become a food barn for Kalimantan Barat Province. Thus, the regencies/municipalities included in quadrants III and IV are prioritized areas for the government to receive more attention in developing the agricultural sector.

CONCLUSIONS AND RECOMMENDATIONS

This study classifies regencies/municipalities in Kalimantan Barat into four quadrants based on their rice production potential. The analysis identifies regencies/municipalities in quadrants III and IV as priority areas requiring greater attention. Regencies/Municipalities classified in quadrant III—namely Melawi Regency, Sekadau Regency, Kapuas Hulu Regency, and Sintang Regency —are characterized by limited agricultural potential. Meanwhile, regencies/municipality in quadrant IV, including Sambas Regency, Kubu Raya Regency, and Sanggau Regency, exhibit considerable rice production potential that has not yet been fully utilized, resulting in relatively low yields. Quadrant I represents regions with high agricultural potential and optimal resource utilization, while quadrant II includes areas with relatively limited potential but efficient agricultural management that supports high productivity. Overall, these findings highlight that spatial disparities in rice production across Kalimantan Barat are shaped not only by differences in production capacity but also by variations in the effectiveness of resource utilization across regions.

This study recommends that the Kalimantan Barat Provincial Government develop policies that improve agricultural infrastructure and access to modern technology and empower farmers through intensive training and mentoring, especially in priority areas. In addition, for areas not classified as priorities, the government must continue to encourage sustainable production by increasing the efficiency of agricultural systems, strengthening supply chains, and ensuring the sustainability of environmentally friendly agricultural practices. Thus, food security and community welfare in Kalimantan Barat can be achieved and guaranteed.

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