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COMPARATIVE ANALYSIS OF BCBIMAX AND PLAID BICLUSTERING ALGORITHM FOR PATTERN RECOGNITION IN INDONESIA FOOD SECURITY

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ABSTRACT

Biclustering is an unsupervised learning algorithm that simultaneously groups rows and columns in a data matrix. Unlike conventional clustering, which evaluates objects across all variables independently, biclustering identifies subsets of objects and variables that share similar patterns—revealing localized structures within complex datasets. This study applies the BCBimax and Plaid algorithms to examine food security patterns across 34 Indonesian provinces. The indicators cover three key dimensions: availability, accessibility, and utilization of food. The algorithms are evaluated using the Jaccard Index, Mean Squared Residue (MSR), and the number of provinces effectively clustered. Results show that BCBimax, using a binarization threshold based on the median value, generates eight biclusters covering 58.8% of provinces. Meanwhile, the Plaid algorithm, applying constant column model parameters, produces six biclusters with 55.88% coverage, including overlapping memberships. Overall, BCBimax demonstrates superior performance, as indicated by a lower average MSR value (0.035) compared to Plaid (0.209). The Jaccard Index similarity score of 14.61% suggests that the biclusters formed by each method are significantly distinct. Both approaches indicate that the majority of Indonesian regions exhibit low to moderate food security characteristics.

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1. INTRODUCTION

Biclustering is one of the unsupervised learning algorithms that can group objects simultaneously on rows and columns based on local patterns [1], [2], [3]. Unlike traditional clustering, which groups objects based on similarities across all variables-thereby identifying global pattern [4]. Biclustering focuses on local patterns. It identifies subsets of objects and subsets of variables that exhibit similar behaviors under specific conditions [5]. Over the past two decades, the application of biclustering techniques has expanded significantly across various fields. According to [6] the scope of biclustering applications has become more diverse. Biclustering has been successfully implemented in areas such as bioinformatics, market segmentation, disease type identification, and the analysis of energy and water consumption patterns [7], [8], [9], [10]. More recently, biclustering has gained attention in policy-related research, including the analysis of food security indicators, which typically involve high-dimensional data and considerable regional diversity.

To this day, food security remains one of the most strategic global and local issues, requiring continuous attention and action. According to The Economist Intelligence Unit (EIU), as reported in the Global Food Security Index (GFSI), Indonesia ranked 69th out of 113 countries in 2021, with a score of 59.2 [11]. This represents a decline from the previous year, where Indonesia ranked 65th with a score of 59.5 in 2020 [11]. Food security is a complex and multifaceted issue that remains a critical concern for Indonesia, a country with over 270 million people. Indonesia’s food security framework is anchored in three core dimensions. These are food availability, accessibility, and utilization [12].

According to the Global Food Security Index (GFSI), Indonesia's food security challenges are influenced by factors such as population growth [13], climate change [14], regional disparities [15], and the lingering effects of the COVID-19 pandemic. The pandemic has significantly disrupted food supply chains, making access and affordability more difficult. These impacts underscore the vulnerability of the food system [16]. Moreover, Indonesia is a large country with thousands of islands, and each with distinct socio-economic conditions. Therefore, accurate and insightful analysis of food security data is essential to inform targeted policies that address these regional disparities and strengthen national food security.

Over the past two decades, the scope of biclustering applications has expanded significantly. To date at least 47 algorithms have been developed [17]. Among them, the BCBimax (balanced and constrained binary inclusion maximal) and Plaid biclustering algorithm are two well-established methods that offer different approaches to pattern recognition. The BCBimax algorithm operates on binary data and is particularly effective in identifying large, dense submatrices with common attributes. In contrast, the Plaid model is a probabilistic model-based approach that can handle continuous data and capture overlapping biclusters.

To date, research applying the bicluster method to food security in Indonesia using real-world data is still limited, particularly those comparing binary-based and continuous-based approaches. This underscores the urgency and relevance of conducting a comparative evaluation of both algorithms. Such studies offer valuable insights across multiple dimensions—ranging from assessments of classical versus non-classical clustering techniques to the extent and nature of bicluster discovery, and the comparative performance of the algorithms themselves. By addressing these aspects, the analysis helps bridge methodological gaps and contributes to more informed strategies for tackling food security challenges.

This study focuses on comparing from the algorithm side, namely binary and non-binary, as well as comparison from the model and non-model side of biclustering with the BCBimax and Plaid algorithm. Specifically, this research examines how these algorithms identify region-specific patterns and provide actionable insights for improving food security policy. Furthermore, this research contributes to existing literature by demonstrating the practical application of biclustering in addressing complex policy issues related to Indonesia food security.

2. RESEARCH METHODS

2.1 Data Source

This study uses secondary data obtained from the Food Security Agency - Ministry of Agriculture, Ministry of Health, and Central Statistics Agency. The analysis was carried out at the provincial level, covering 34 provinces in Indonesia as observation units with variables based on 2020 data. The scope of the research variables includes three dimensions of food security, namely: aspects of food availability, food access, and food utilization, which are adapted from the Food Security and Vulnerability Analysis Atlas (FSVA). Detailed information about the variables is presented in the following Table 1:

Table 1. Research Variables

Aspect	Variable Name (Symbol)
Food Availability	The ratio of normative consumption per capita to net production of carbohydrates (X_1, Ratio)
Food Access	The percentage of population who live below the poverty line (X_2, %)
	The percentage of households with proportions expenses for food over 65% of the total expenditure (X_3, %)
	Proportion of households without access to electricity (X_4, %)
Food Utilization	Proportion of households without access to clean water (X_5, %)
	Inverse of Life expectancy $(X_6, \text{Year})^{-1}$
	Ratio of population to healthcare workers against to population density (X_7, Ratio)
	Inverse of average years of schooling for females above 15 years old $(X_8, \text{Year})^{-1}$
	Proportion of children with stunting criterion (X_9, %)

$^{-1}$Inverse value
Data Source: Food Security Agency - Ministry of Agriculture, Ministry of Health, and Central Statistics Agency

Variables X6 and X8 exhibit trends opposite to those of the other indicators. To facilitate interpretation, both variables were inverted so that all indicators carry the same meaning, where higher values consistently indicate lower levels of food security, and vice versa.

2.2 Research Stages

2.2.1 Data Preprocessing

In the initial stage of data preprocessing, we prepare the data matrix for analysis through scaling, ensuring uniformity in variable scales to maintain consistency in analytical outcomes. The preprocessed matrix with scaled data is defined as define $\boldsymbol{A}_{(NxM)}$ where N represents the number of rows (provinces) and M represents the number of columns (variables).

2.2.2 BCBimax and Plaid Biclustering Algorithm

Bicluster analysis is a development of cluster analysis that allows simultaneous grouping of objects based on row and column characteristics. BCBimax biclustering algorithm is one of the bicluster algorithms applied to binary data [18]. The BCBimax algorithm operates by systematically partitioning the binary data matrix into smaller segments. From these partitions, an iterative process is conducted to identify biclusters-submatrices where all elements have a value of 1. Fig. 1 illustrates this workflow, providing a step-by-step visualization of the algorithm's key processes.

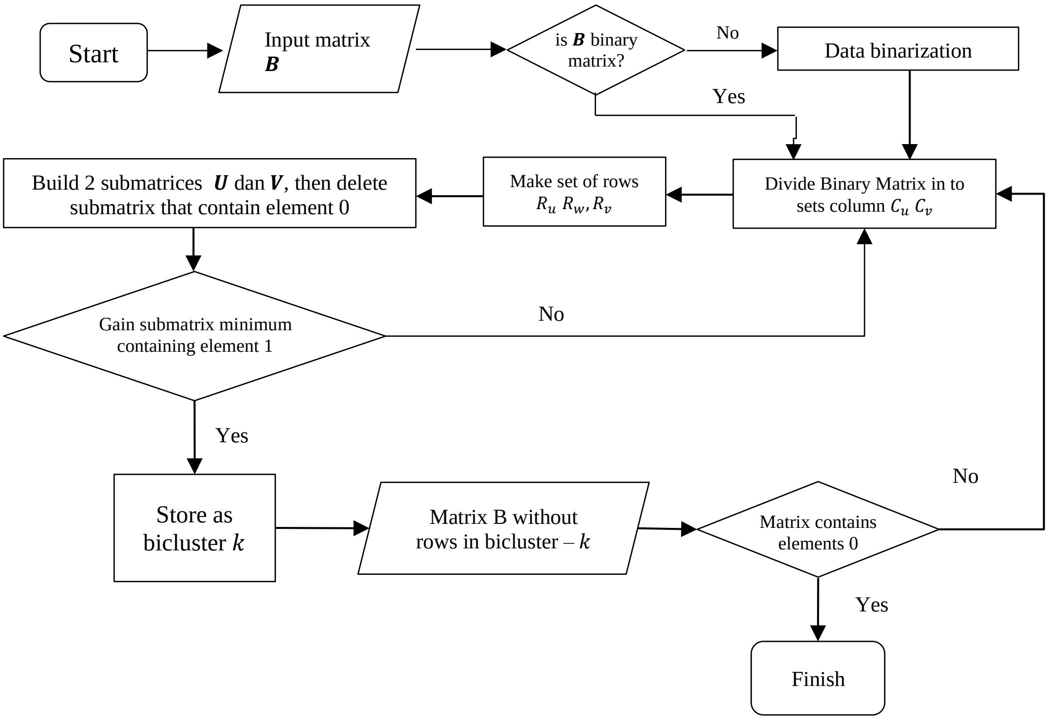

Figure 1. BCBimax Algorithm Flowchart

The workflow stages of the BCBimax algorithm are illustrated in Fig. 1 above, begins by receiving an input matrix $\boldsymbol{B}$. If the data is not already in binary format, a binarization step is applied to convert it. The algorithm then proceeds through two main stages [10], [19], [20]:

1. Arrange the rows and columns of the binary data matrix so that the elements with a value of 1 are positioned in the upper left corner of the matrix.
2. Partition the binary data matrix into three submatrices, one of which contains all elements with a value of 0 and will not be included in the bicluster discovery process. Biclusters will be formed in the two remaining submatrices, $\boldsymbol{U}$ and $\boldsymbol{V}$. To prevent overlapping rows, the search for subsequent biclusters will exclude rows that have already been identified.

Meanwhile the Plaid model algorithm works by dividing matrix $\boldsymbol{A}$ into k submatrices. Generally, there are four main stages in the Plaid model algorithm **[19]**, **[21]**, **[22]**:

1. Input the residual matrix ($\boldsymbol{Z}$) from the initial model
2. Initialize candidate biclusters
3. Estimate parameters including layer effects and row and column membership
4. Prune rows and columns

These four main stages are performed iteratively in the bicluster discovery process.

The first step in the analysis involves initializing the model from the initial data matrix, which may include the overall mean (μ), row effects (α_i), and column effects (β_j).

Next, the residuals from the model are calculated, resulting in what is referred to as the residual matrix ($\boldsymbol{Z}$). This residual matrix serves as the input for identifying candidate biclusters. Once candidate biclusters are identified, the next step is to estimate the model parameters, which include layer effects and row and column membership. This process is iterated S times with the aim of minimizing the sum of squared residuals of the model.

The next step is pruning the candidate biclusters. This stage aims to select rows and columns that contribute to a well-fitted model. The pruning process involves setting the row release value (τ_1) and column release value (τ_2). A candidate bicluster is confirmed as a bicluster after successfully passing the pruning stage. However, if all rows and columns are pruned, the algorithm terminates. Biclusters are discovered one at a time, and the algorithm repeats until the maximum number of layers is reached or no more biclusters are found. Fig. 2 illustrates the workflow of the Plaid Model Algorithm, which follows an iterative process to identify meaningful biclusters within a data matrix.

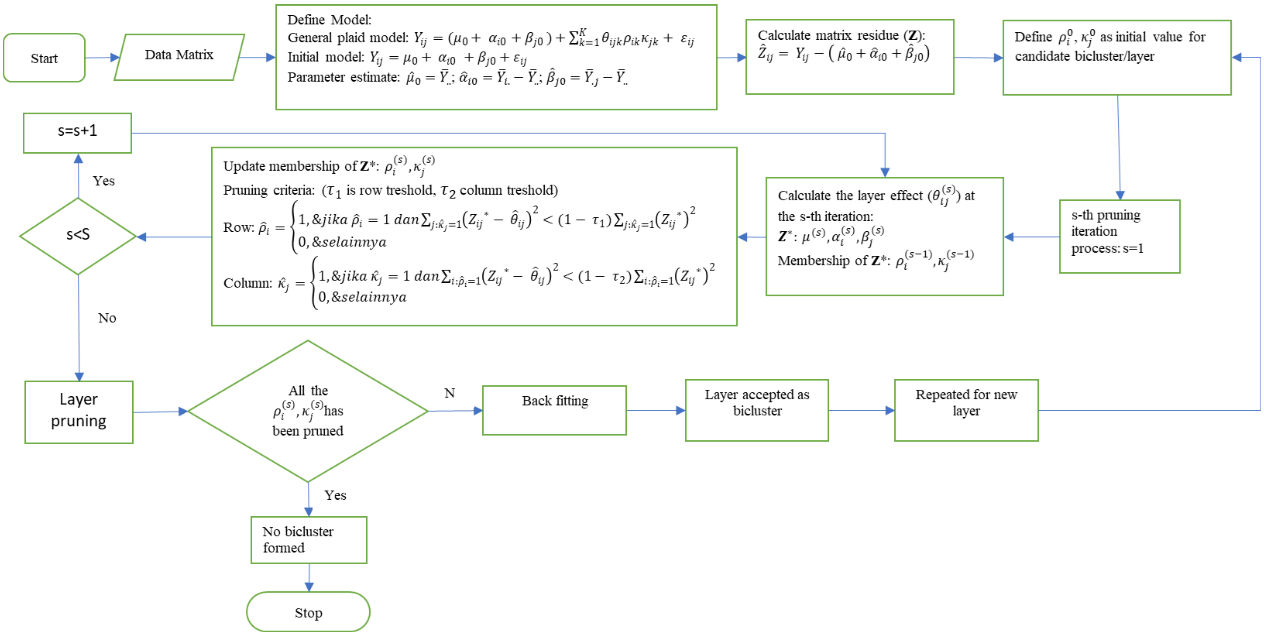

Figure 2. Plaid Model Algorithm Flowchart

The workflow consists of several key stages, including model initialization, matrix residue calculation, parameter estimation, pruning, and iterative refinement. The process begins by defining a model for the bicluster pattern, this could be a constant or additive model, depending on the expected structure of the biclusters. Next, the algorithm calculates the residual matrix ***(Z)*** by subtracting the defined model from the original data matrix. Once the residuals matrix is obtained, initial membership values are assigned to rows and columns for the first candidate bicluster (layer). These values essentially indicate which rows and columns are initially considered part of the bicluster. The algorithm then enters an iterative loop (s = 1 to S), where 's' represents the current layer being analyzed. In each looping the algorithm will calculate the layer effect also rows and columns memberships. Then, the algorithm performs layer pruning. This step assesses the significance of each layer and removes redundant or insignificant layers. The process continues until a stopping criterion is met, meaning that no further meaningful biclusters can be identified.

2.2.3 Performance Evaluation of Biclustering

The performance of the BCBimax and Plaid model biclustering algorithms is evaluated using the mean square residue (MSR) indicator [23]. A lower MSR value indicates a better-formed bicluster, as it reflects greater homogeneity within the bicluster. The algorithm with the lowest MSR value is considered the best for mapping food security patterns. The formula for MSR is formulated in Eq. (1):

$$MSR_{(I,J)} = \frac{1}{|I||J|} \sum_{i \in I, j \in J} (r_{ij})^2 \quad (1)$$

where r_{ij} is the residual value in the i-th row and j-th column, which can be calculated using the following formula:

$$r_{ij} = a_{ij} - a_{iJ} - a_{Ij} + a_{IJ}$$

where a_{iJ} is the average value of row i, a_{Ij} is average value of column j and a_{IJ} is average value of all elements in a bicluster.

If the biclustering analysis yields multiple biclusters (n), the average MSR (AvMSR) can be calculated as Eq. (2):

$$\text{AvMSR} = \frac{1}{n}\sum_{k}^{n} MSR_k\ (I,J) \tag{2}$$

In the external evaluation, the Jaccard index (JI) is used as a criterion to measure the similarity between the results produced by the two biclustering algorithms. The JI equation can be defined in Eq. (3).

$$JI(BC_1, BC_2) = \frac{1}{g}\sum_{i=1}^{g}\sum\nolimits_{j=1}^{t}\left(\frac{|R_{1g} \cap R_{2t}| + |C_{1g} \cap C_{2t}|}{|R_{1g} \cup R_{2t}| + |C_{1g} \cup C_{2t}|}\right) \tag{3}$$

Where g and t represent the number of biclusters produced by algorithm 1 and algorithm 2; R_{1g} is the set of rows of the g-th bicluster of algorithm 1; R_{2t} is the set of rows of the t-th bicluster of algorithm 2; C_{1g} is the set of columns of the g-th bicluster of algorithm 1; C_{2t} is the set of columns of the t-th bicluster of algorithm 2.

If there are overlapping biclusters, the calculation of the Jaccard Index (JI) needs to be normalized against the maximum Jaccard value as follows in Eq. (4):

$$JI(BC_1, BC_2)_{\text{adjusted}} = \frac{JI(BC_{1,}BC_2)}{\max\left(JI(BC_{1,}BC_1), JI(BC_{2,}BC_2)\right)} \tag{4}$$

Where $JI(BC_1,BC_1)$ represents the Jaccad index between biclusters resulting from algorithm 1; while $JI(BC_2,BC_2)$ represents the Jaccad index between biclusters resulting from algorithm 2.

3. RESULTS AND DISCUSSION

3.1 Data Exploration

The initial characteristics of regional food security based on the pillars of food security are illustrated through the scaled data matrix heatmap in Fig. 3. The heatmap provides an overview of the variation in food security levels across 34 provinces in Indonesia based on a set of nine variables (X1 to X9), where higher values indicate lower food security, and lower values indicate higher food security. The color gradient ranges from dark blue to dark red, with dark blue indicating lower scaled value (better food security) and the dark red representing higher scaled values (lower food security conditions).

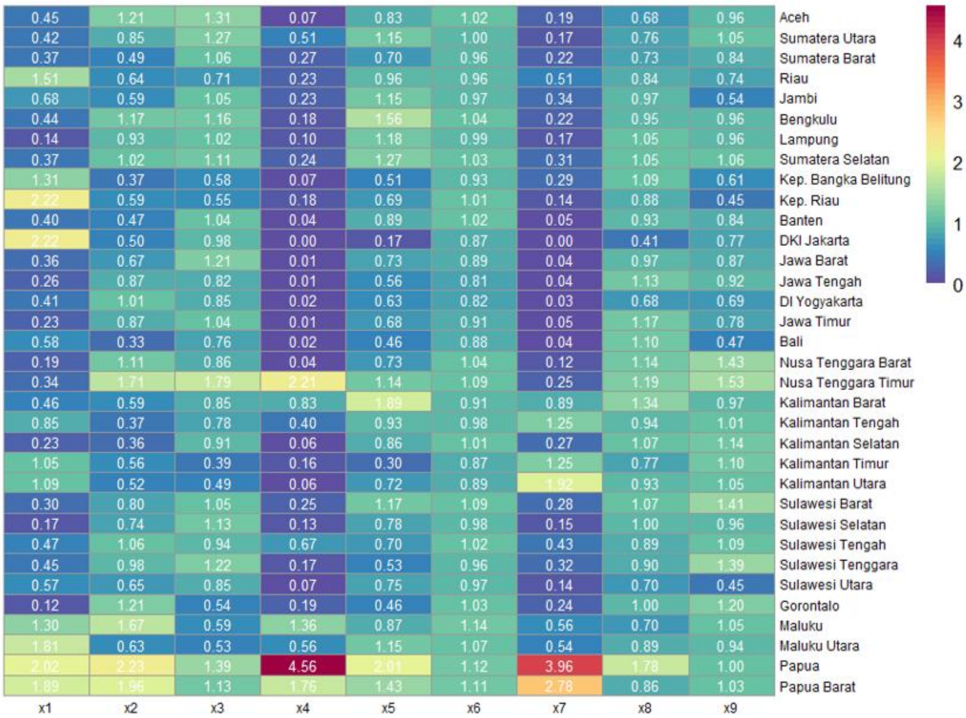

Figure 3. Heatmap of Scaled Matrix Data

Overall, the heatmap reveals that most regions tend to display colors ranging from light green to dark blue across the various aspects of food security, indicating a generally favorable situation for food security. However, Fig. 3 also highlights certain regions with significantly higher values, represented by dark red shades. One notable example is the food utilization aspect, specifically variable X7, which reflects the ratio of healthcare workers to the population relative to population density. This variable stands out in provinces such as Papua and Papua Barat, where the values are notably high (ranging from orange to dark red). These high values indicate a concern for lack of food security, particularly in relation to the availability of healthcare workers in these areas. This highlights the challenges these provinces face in ensuring adequate food security, as the availability of healthcare workers is a critical factor in improving overall well-being.

3.2 Results of Biclustering Using the BCBimax and Plaid Algorithms

The BCBimax algorithm results indicate that the optimal bicluster is obtained with at least 2 rows, 3 columns, and a median data binarization threshold. The algorithm groups 20 provinces or 58.82% of the provinces into 8 distinct biclusters, with their membership and regional characteristics presented in Table 2 and Fig. 4. In this case study, BCBimax has the potential to leave some provinces unclustered. The optimal biclusters identified by BCBimax have non-overlapping memberships, meaning that each province is included in only one bicluster. Meanwhile, the variable memberships are overlapping. Overall, the results from Table 2 show that the identified patterns of food security in Indonesian regions that are clustered tend to have low to moderate status regarding the indicator variables of food security aspects. The categorization of each food security indicator is approximated by a normal distribution, with a mean μ and a standard deviation σ. The low category is around 2.5%, moderate 95%, and high 2.5%.

Table 2. Membership of Indicator Variables and Provinces in the BCBimax Algorithm

Bicluster	Province	Indicator Variables for Food Security Aspects								
		X1	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**	**X9**
1	Papua	L	L	L	L	L	L	L	L	M
1	Papua Barat	L	L	L	L	L	L	L	H	M
2	Bengkulu		L	L		L	L		M	M
2	Lampung		M	M		L	M		L	M
2	Nusa Tenggara Timur		L	L		L	L		L	L
2	Sumatera Selatan		M	L		L	L		L	L
3	Nusa Tenggara Barat		L	M			L		L	L
3	Sulawesi Tengah		L	M			L		M	L
3	Sulawesi Tenggara		M	L			M		M	L
4	Kalimantan Barat			M		L	H		L	M
4	Kalimantan Selatan			M		M	L		L	L
4	Sulawesi Barat			L		L	L		L	L
5	Jawa Barat			L			H		M	M
5	Sulawesi Selatan			L			M		M	M
6	Kalimantan Tengah					M	M		M	M
6	Maluku Utara					L	L		M	M
7	Banten			M		M	L		M	
7	Jambi			L		L	M		M	
8	Kalimantan Timur	L					H	L		
8	Kalimantan Utara	L					H	L		
Low (L)		$x_i \geq \mu + Z\alpha/_2\sigma$								
Moderate (M)		$\mu - Z\alpha/_2\sigma < x_i < \mu + Z\alpha/_2\sigma$								
High (H)		$\leq \mu - Z\alpha/_2\sigma$								

To better understand the food security situation across regions, the data from Table 2 has been categorized and visualized to highlight the differences in food security levels. The classification of regions is based on the number of indicator variables falling into low-category groups. This categorization is illustrated in Fig. 4, offering a clearer understanding of how regions are classified according to their food security indicators. Overall, the clustered regions are divided into three categories based on the number of indicator variables with low categories. The first category includes 11 provinces with fewer than four low-category indicator variables, represented in orange. These provinces are Jambi, Banten, Jawa Barat, Kalimantan Tengah, Kalimantan Timur, Kalimantan Utara, Maluku, Sulawesi Selatan, Sulawesi Tengah, Sulawesi

Tenggara, and NTB. The second category, indicated in bright red, includes provinces with four to six low-category indicator variables: NTT, Sumatra Selatan, Bengkulu, Lampung, Sulawesi Barat, Kalimantan Selatan, and Kalimantan Barat. The third category, shown in dark red, consists of provinces with more than six low-category indicator variables: Papua and Papua Barat.

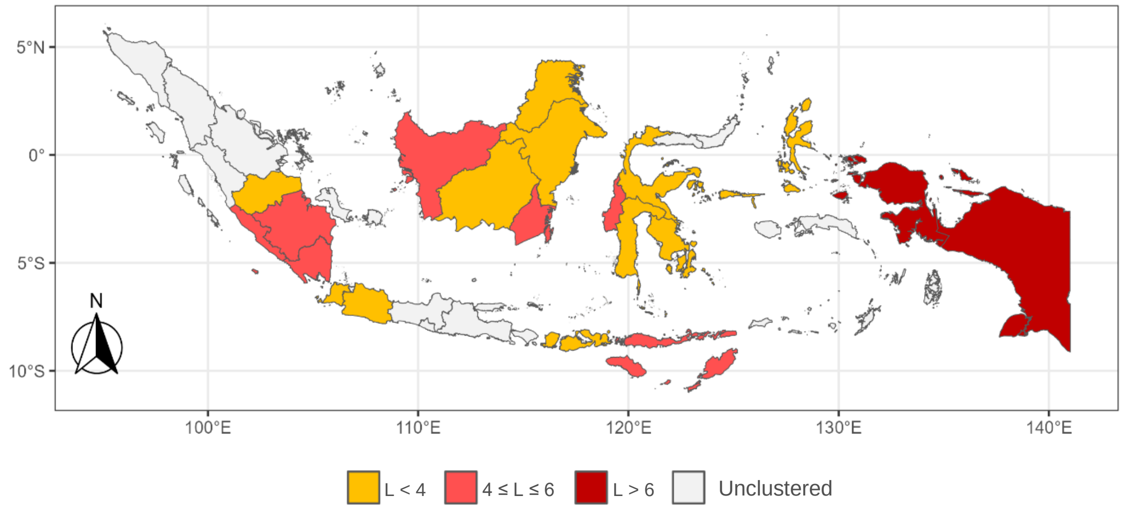

Figure 4. Visualization of Food Security Pattern Mapping Using the BCBimax Algorithm

The food security pattern mapping for Indonesian regions using the Plaid model algorithm indicates that the optimal bicluster is achieved with parameters $\tau_1 = 0.1$ and $\tau_2 = 0.4$, utilizing a column constant model. As shown in Table 3, that the identified patterns of food security in Indonesian regions also clustered tend to have low to moderate status regarding the indicator variables of food security aspects. Bicluster (BC) 1 – 5 are groups of provinces that indicates tend to have low food security, indicated by the specific indicators within each group. Meanwhile, bicluster 6, the provinces within this bicluster tend to have strong food security, indicated by spending less than 65% of their total expenditure on food, higher life expectancy at birth, and lower rates of stunting. Despite these positive indicators, there is some overlap in the provinces that belong to bicluster 2. The algorithm successfully groups 19 provinces (55.88%) into 6 biclusters. Unlike BCBimax, the Plaid model algorithm allows for overlapping row memberships, meaning a province can belong to multiple biclusters.

Table 3. Membership of Characteristic and Provincial Variables on the Plaid Model Algorithm

BC	Province	Indicator Variables for Food Security Aspects								
		X1	X2	X3	X4	X5	X6	X7	X8	X9
1	Papua	L	L		L			L		
1	Papua Barat	L	L		L			L		
2	DKI Jakarta	L								
2	Kep. Bangka Belitung	L								
2	Kep. Riau	L								
2	Maluku	L								
2	Maluku Utara	L								
2	Riau	L								
3	Papua		L		L					
3	Maluku		L		L					
3	Nusa Tenggara Timur		L		L					
4	Kalimantan Barat	H						L		
4	Kalimantan Tengah	M						L		
4	Kalimantan Timur	L						L		
4	Kalimantan Utara	L						L		
4	Papua	L						L		
5	Bengkulu				M	L				
5	Kalimantan Barat				L	L				
5	Nusa Tenggara Timur				L	L				
5	Papua				L	L				
5	Sulawesi Barat				M	L				
5	Sumatera Selatan				M	L				

BC	Province	Indicator Variables for Food Security Aspects								
		X1	X2	X3	X4	X5	X6	X7	X8	X9
6	DI Yogyakarta			M		H	H	H		H
6	Bali			H		H	H	H		H
6	DKI Jakarta			M		H	H	H		H
6	Kalimantan Timur			H		H	H	L		L
6	Kep. Bangka Belitung			H		H	H	M		H
6	Kep. Riau			H		H	M	H		H
6	Sulawesi Utara			M		H	M	H		H

Low (L)	$x_i \geq \mu + Z\alpha_{/2}\sigma$
Moderate (M)	$\bar{\mu} - Z\alpha_{/2}\sigma < x_i > \mu + Z\alpha_{/2}\sigma$
High (H)	$x_i \leq \mu - Z\alpha_{/2}\sigma$

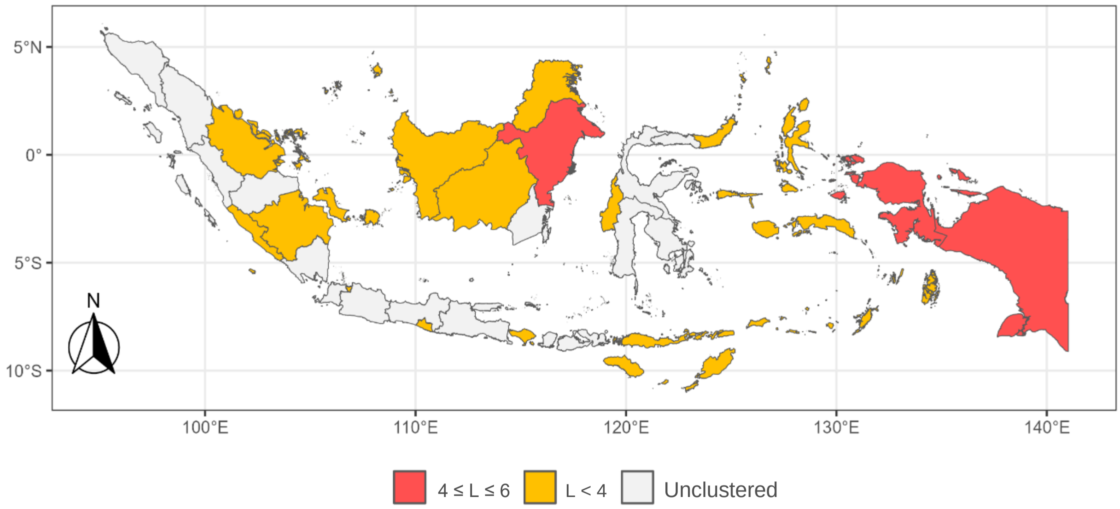

Figure 5. Visualization of Food Security Pattern Mapping Using the Plaid Model Algorithm

As shown in Fig. 5, regions with four to six low-category indicator variables are depicted in bright red, including Papua, Papua Barat, and Kalimantan Timur. The remaining clustered regions, which have fewer than four low-category indicators, are shown in orange. These regions include Riau, Kep. Bangka Belitung, Kep. Riau, Sumatera Selatan, Bengkulu, Jakarta, Yogyakarta, Bali, Kalimantan Barat, Kalimantan Tengah, Kalimantan Utara, Sulawesi Barat, Sulawesi Utara, NTT, Maluku, and Maluku Utara.

Overall, the food security patterns identified by the biclusters formed through both algorithms reveal that each region possesses distinct characteristics in terms of food security. This variation highlights the complexity and diversity of food security across different regions, as no single pattern or solution applies uniformly. Each region's unique combination of factors, such as availability of resources, access to food, and utilization of food, contributes to its specific food security profile. These differences emphasize the need for adjustable approaches in addressing food security challenges, recognizing that what may work for one region might not be suitable for another. This means every region has their own specific characteristics of food security. The analysis emphasizes that regional food security is influenced by a range of variables, each requiring careful consideration to develop effective, context-specific strategies for improving food security.

3.3 Biclustering Algorithm Evaluation

The performance evaluation focuses on analyzing the characteristics of the optimal biclusters generated by each algorithm, as summarized in Table 4. A key metric used to assess the similarity between the biclustering results is the Jaccard Index, which in this case yields a value of 14.61%. This suggests a low degree of similarity between the biclusters produced by the two algorithms, indicating that their results are quite different. In other words, the sets of provinces and variables grouped together in each bicluster differ substantially depending on the algorithm used. As a result, the membership assignments of provinces and the defining indicators within each bicluster vary significantly between the two methods. The BCBimax algorithm creates 8 biclusters with non-overlapping memberships, while the Plaid model results in 6 biclusters with overlapping memberships.

In the context of food security analysis, overlapping biclusters offer the advantage of capturing the multifaceted nature of provincial characteristics, as one region may simultaneously exhibit distinct patterns in food availability, accessibility, and utilization. This reflects the real-world complexity where provinces are rarely homogeneous and often influenced by overlapping factors. However, such flexibility can introduce challenges in interpretation, especially when a province belongs to multiple biclusters with conflicting signals, making policy recommendations less straightforward. Additionally, overlapping structures may lead to information redundancy and complicate performance evaluation due to blurred boundaries between clusters, increasing the risk of overfitting and reducing generalizability. Therefore, while overlapping biclusters can enrich insight, they require careful handling to ensure clarity and policy relevance.

Table 4. Performance Evaluation

Algorithm	Jaccard Index	Bicluster		Average MSR	Row Membership
		Number	Overlapping		
BCBimax	14.61%	8	No	0.035	20
Plaid Model		6	Yes	0.209	19

The homogeneity value intra bicluster for each algorithm is calculated using Eq. (2). A lower average MSR value indicates greater homogeneity within the biclusters. Additionally, a higher row membership coverage tends to result in more informative biclusters. Table 4 shows that the average MSR for the BCBimax algorithm is lower (0.035) compared to the Plaid model (0.209). Similarly, the BCBimax algorithm has a higher row membership (20) than the Plaid model (19). Based on these considerations, it can be concluded that the BCBimax algorithm performs better than the Plaid model.

4. CONCLUSION

The bicluster analysis of food security data using the BCBimax algorithm produced eight non-overlapping biclusters, while the Plaid model resulted in six overlapping biclusters, meaning some regions belong to multiple groups. Overall, regions grouped by both algorithms tend to exhibit low to moderate food security patterns based on key food security indicators. The performance evaluations of the BCBimax and Plaid algorithms for optimal biclusters are relatively similar. However, based on the MSR values, biclustering with the BCBimax algorithm tends to be better than the Plaid algorithm.

Although both methods consistently classify most regions as having low to moderate food security characteristics, BCBimax yields better interpretability due to its exclusivity and lower MSR values, making it more suitable for targeted policy interventions. In contrast, the overlapping structure of Plaid biclusters captures the multifaceted nature of food insecurity, offering deeper insights into provinces facing complex, interrelated challenges. These results suggest a combined modeling (hybrid) approach can help tailor more nuanced food security strategies using BCBimax to define core intervention zones, and Plaid to uncover cross-cutting vulnerabilities that require integrated policy support.

Author Contributions

I Made Sumertajaya: Conceptualization, Supervision, and Writing the Original Draft. Nur Hikmah: Data Curation, Software Development, Formal Analysis, Visualization, Writing – Review and Editing. Farit Mochamad Afendi: Methodology Development, Literature Review, Writing – Review and Editing. All authors have read and approved the final manuscript.

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Declarations

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