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Uneven Agricultural Land Conversion and Clustered Patterns in Bandung Regency

A Subdistrict-Level Quantitative Analysis

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Abstract

This study examines the dynamics of transformational leadership in the development of Bilebante This study examines the structure of agricultural land conversion at the subdistrict level in Bandung Regency within the framework of Lahan Pertanian Pangan Berkelanjutan (LP2B). The study aims to analyze the distribution and intensity of land conversion, assess the relationship between land availability and conversion dynamics, and identify structural clustering patterns. A quantitative cross-sectional design was employed using secondary data from 29 subdistricts. Analytical methods include descriptive statistics, correlation analysis, linear regression (as a supporting test), and K-Means clustering based on conversion intensity and absolute conversion. The results reveal that agricultural land conversion is highly uneven and concentrated in a small number of subdistricts. Statistical analysis shows a weak and insignificant relationship between land availability and conversion ($r = -0.299$; $p = 0.115$), indicating that land size does not significantly determine conversion outcomes. Cluster analysis identifies three distinct groups—moderate/low pressure, high pressure, and extreme loss—demonstrating that land conversion follows non-random and structurally differentiated patterns. These findings suggest that land conversion is driven more by localized pressures and institutional dynamics than by land availability alone. This study contributes by advancing a non-spatial, statistically grounded approach to understanding land conversion and highlights the need for more targeted and adaptive policy interventions in agricultural land protection.

Keywords: agricultural land conversion; LP2B; conversion intensity; cluster analysis; land governance.

INTRODUCTION

The rapid conversion of agricultural land has emerged as one of the most pressing challenges for sustainable development, particularly in regions experiencing accelerated urban expansion. Beyond its immediate impact on land use, the loss of agricultural land directly threatens long-term food security, weakens ecological resilience, and undermines the stability of rural production systems. In this context, the protection of agricultural land is no longer a sectoral concern but a strategic imperative linked to national food sovereignty and sustainability (Nur Khotimah & Pusparini, 2023; Pitaloka, 2020; Raharja et al., 2021).

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Indonesia has formally recognized this challenge through the implementation of *Lahan Pertanian Pangan Berkelanjutan* (LP2B), a policy framework designed to designate and protect agricultural land from uncontrolled conversion. In principle, LP2B represents a regulatory commitment to ensure that productive farmland remains preserved for future generations. However, a critical issue persists: the designation of protected agricultural land does not necessarily translate into its effective protection in practice. Empirical realities suggest that land conversion continues to occur even in areas formally classified as sustainable agricultural land, raising questions about the effectiveness and enforcement of such policies (Gafuraningtyas et al., 2024; Hidayat, 2022).

A substantial body of literature has examined agricultural land conversion using spatial and geospatial techniques, particularly through Geographic Information Systems (GIS), to map land-use changes and identify spatial patterns (Christiawan & Lai Nguyen, 2024; Mtsetfwa et al., 2025). While these approaches have significantly advanced our understanding of where conversion occurs, they often provide limited insight into how conversion is distributed across administrative units and whether such changes exhibit systematic inequalities or structural clustering. In other words, existing studies tend to prioritize spatial visualization over statistical characterization, leaving a gap in understanding the internal structure of land conversion dynamics.

More importantly, the assumption that land conversion is primarily driven by land availability remains insufficiently tested. If larger agricultural areas are systematically more prone to conversion, a strong statistical relationship would be expected. However, if such a relationship is weak or inconsistent, it would imply that other structural factors—such as development pressure, governance capacity, or local economic dynamics—play a more decisive role. This unresolved question highlights a critical gap in the literature: the need to move beyond descriptive mapping toward analytical frameworks that can capture variation, inequality, and underlying patterns of land conversion.

This study addresses these limitations by examining agricultural land conversion through a non-spatial, quantitative framework at the subdistrict level in Bandung Regency. Rather than relying on spatial mapping, this research focuses on three analytical dimensions: (1) the measurement of *conversion intensity* to capture relative land-use pressure, (2) the assessment of statistical relationships between land availability and conversion, and (3) the identification of clustered patterns of land conversion using unsupervised learning techniques. This approach enables a more structured understanding of whether land conversion occurs randomly, proportionally, or in uneven and grouped patterns.

The novelty of this study lies in its explicit shift from spatial representation to statistical structuring. First, it introduces conversion intensity as a central analytical variable to reveal proportional pressure on agricultural land, rather than relying solely on absolute change. Second, it applies cluster analysis to uncover latent groupings of subdistricts, thereby demonstrating that land conversion may follow clustered and unequal patterns rather than uniform trends. Third, it critically evaluates the implicit assumption that land size determines conversion outcomes, providing empirical evidence on whether such a relationship holds.

Accordingly, the objectives of this study are to (1) analyze the distribution and intensity of agricultural land conversion, (2) examine the relationship between agricultural land availability and conversion dynamics, and (3) identify clusters of subdistricts exhibiting similar patterns of land conversion. By doing so, this research contributes to a more nuanced understanding of agricultural land protection and offers empirical insights into the challenges of implementing sustainable farmland policies such as LP2B.

RESEARCH METHODOLOGY

Research Design

This study employs a quantitative, cross-sectional research design to examine patterns of agricultural land conversion at the subdistrict (kecamatan) level in Bandung Regency. A cross-sectional approach is appropriate because the analysis focuses on variations across administrative units at a single point in time rather than temporal dynamics, enabling structural comparison between areas (Creswell & Creswell, 2018). The study is exploratory–analytical in nature, aiming not only to describe patterns of land conversion but also to identify underlying structural relationships and grouped dynamics using statistical modeling.

Importantly, this study deliberately adopts a non-spatial analytical approach, emphasizing statistical structure and distributional patterns rather than geographic visualization. This allows clearer identification of proportionality, randomness, and clustering in land conversion behavior across subdistricts.

Data and Sampling

The unit of analysis in this study is the subdistrict (kecamatan). The dataset consists of secondary data derived from official regional planning and land administration sources associated with the LP2B (Lahan Pertanian Pangan Berkelanjutan) framework, which designates protected agricultural land. The variables include (1) designated agricultural land (hectares) and (2) land conversion (hectares).

A purposive sampling approach was applied, whereby only subdistricts with complete and consistent data were included in the analysis (Etikan et al., 2016). After data cleaning, including the removal of missing values, a total of 29 subdistricts were retained for analysis.

Variable Construction

To ensure analytical robustness, both primary and derived variables were constructed. Designated Agricultural Land (DAL) represents the total agricultural land formally allocated for protection under the LP2B framework, while Land Conversion (LC) represents the net change in agricultural land area, where negative values indicate land loss.

To capture proportional land-use pressure across subdistricts of different sizes, Conversion Intensity (CI) is defined as the ratio of land conversion to designated land:

$$CI_i = \frac{LC_i}{DAL_i} \tag{1}$$

where CI_i is the conversion intensity in subdistrict i, LC_i is land conversion, and DAL_i is designated agricultural land.

In addition, Absolute Conversion (AC) is constructed to measure the magnitude of land-use pressure regardless of direction:

$$AC_i = |LC_i| \tag{2}$$

These derived variables allow comparison of both proportional pressure and absolute magnitude of land conversion across subdistricts.

Data Analysis Techniques

This study applies a combination of descriptive and inferential statistical methods to examine the structure of land conversion patterns. Descriptive statistics are first used to summarize the distribution of variables, including mean, standard deviation, minimum, and maximum values, providing an overview of general patterns (Field, 2013).

To identify extreme cases, subdistricts are ranked based on land conversion values, highlighting areas with the highest land loss as well as those exhibiting positive land growth. This ranking approach helps detect anomalies and outliers within the dataset. To examine the relationship between land availability and land conversion, the Pearson correlation coefficient is applied:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum\left((X_i - \bar{X})\right)^2 \sum(Y_i - \bar{Y})^2}} \tag{3}$$

where X represents designated agricultural land and Y represents land conversion. This analysis evaluates whether larger land areas are systematically associated with higher levels of conversion (Wooldridge, 2016).

A simple linear regression model is then used as a supporting analysis to further assess this relationship:

$$LC_i = \beta_0 + \beta_1 DAL_i + \varepsilon_i \tag{4}$$

where β_1 represents the effect of land size on conversion and εi\varepsilon_iεi is the error term. This model is not intended as the primary analytical focus but serves to confirm whether land availability significantly predicts conversion outcomes.

To identify structural groupings, K-Means clustering is applied using Conversion Intensity (CI) and Absolute Conversion (AC). The objective is to partition observations into kkk clusters by minimizing within-cluster variance:

$$min \sum_{j=1}^{k} \sum_{i \in C_j} ||x_i - \mu_j||^2 \quad (5)$$

where C_j represents cluster j and μ_j is the centroid of cluster j (Hastie et al., 2009). The number of clusters $(k = 3)$ is determined based on interpretability and the ability to distinguish between low, moderate, and high land conversion pressure groups.

Prior to clustering, variables are standardized using z-score normalization to ensure comparability across different scales:

$$Z = \frac{X - \mu}{\sigma} \quad (6)$$

where Z is the standardized value, μ is the mean, and σ is the standard deviation.

Analytical Framework and Validity Considerations

This study evaluates whether agricultural land conversion is proportional to land availability, randomly distributed, or unevenly structured across subdistricts. The analytical approach integrates statistical inference and pattern recognition to ensure that conclusions are grounded in empirical evidence rather than descriptive observation alone.

Because the data are cross-sectional, the analysis does not establish causal relationships but instead identifies structural associations and distributional patterns. Despite this limitation, the findings provide meaningful insights for policy evaluation, particularly in relation to the effectiveness of the LP2B framework in protecting agricultural land from conversion pressures.

RESULTS AND DISCUSSION

Overview of Agricultural Land Conversion

The analysis reveals substantial variation in agricultural land conversion across subdistricts in Bandung Regency. As presented in Table 1, a total of 16,915.76 hectares of designated agricultural land was identified, with a net conversion of –3,809 hectares, indicating a significant overall loss of agricultural land. More importantly, this loss is not evenly distributed. A small number of subdistricts account for a disproportionately large share of total land conversion. For example, Cileunyi alone contributes 10.79% of total conversion, followed by Kutawaringin (10.24%) and Cikancung (10.13%), while other areas show minimal or even positive changes, such as Bojongsoang (+56 hectares) and Banjaran (+12 hectares).

This pattern suggests that land conversion is not uniformly distributed but instead concentrated in specific locations. Such concentration indicates that land-use change is likely shaped by uneven development processes rather than proportional land availability, reinforcing the view that land conversion reflects localized pressures rather than a generalized regional trend.

Figure 1 visually reinforces this finding by showing a highly skewed distribution, where a small number of subdistricts dominate total land loss while the majority experience relatively moderate changes. This skewness indicates the presence of structural imbalance rather than random variation.

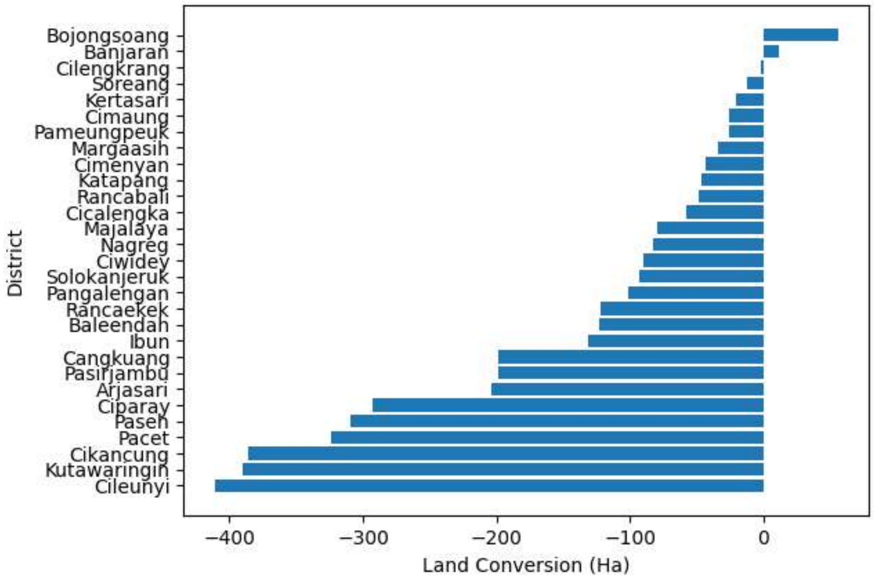

Figure 1. Distribution of land conversion across subdistricts

Descriptive Statistical Patterns

Descriptive statistics further confirm the uneven distribution of land conversion (Table 2).

Table 2. Descriptive Statistics of Key Variables

Variable	Mean	Std Dev	Min	Max
Designated Agricultural Land (Ha)	583.29	480.18	29.99	2178.58
Land Conversion (Ha)	-130.38	131.81	-411	56
Conversion Intensity	-0.496	0.977	-5.108	0.154
Absolute Conversion	135.07	126.82	2	411

The mean land conversion of –130.38 hectares indicates a general trend of agricultural land decline. However, the relatively high standard deviation (131.81) suggests that this decline is not uniform across subdistricts. More critically, conversion intensity exhibits extreme variation, ranging from –5.108 to 0.154. This wide range indicates that some subdistricts experience disproportionately high land-use pressure relative to their size.

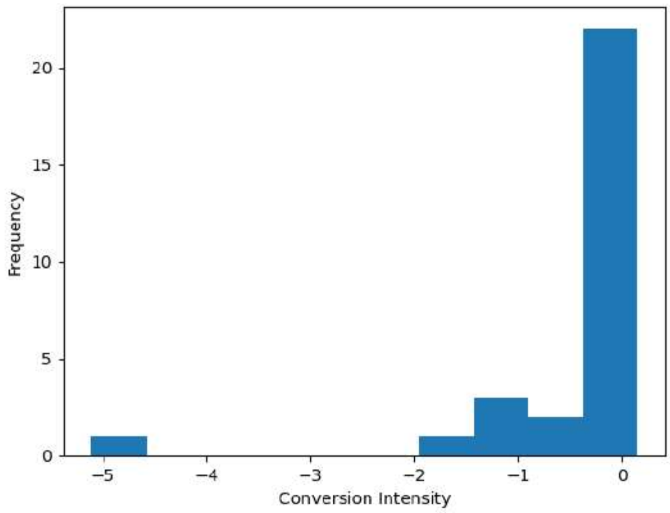

Figure 2. Distribution of conversion intensity across subdistricts.

As illustrated in Figure 2, the distribution is highly skewed with a long tail toward extreme negative values. This pattern suggests that land conversion is not only uneven but also characterized by extreme outliers. Such a distribution challenges the assumption of homogeneity in land-use change and instead indicates the presence of structural inequality across subdistricts.

Extreme Cases: Land Loss and Growth

To identify critical areas, subdistricts were ranked based on land conversion values.

Table 3. Top Subdistricts by Land Conversion

Top 5 Land Loss	
District	**Conversion (Ha)**
Cileunyi	-411
Kutawaringin	-390
Cikancung	-386
Pacet	-324
Paseh	-309
Top 2 Land Growth	
Bojongsoang	+56
Banjaran	+12

The results show that land conversion is overwhelmingly dominated by losses, with only 6.9% of subdistricts experiencing positive growth. This strongly suggests that agricultural land conversion is structurally a process of decline rather than expansion. More importantly, the concentration of extreme losses in a limited number of subdistricts reinforces the argument that land conversion is driven by localized pressures rather than evenly distributed processes.

Relationship Between Land Availability and Conversion

The correlation analysis indicates a weak negative relationship between land availability and land conversion ($r = -0.299$, $p = 0.115$), suggesting that larger agricultural areas are not significantly associated with higher levels of conversion.

This finding is further supported by the regression analysis.

Table 4. Regression Results

Variable	Coefficient	p-value
Intercept	-82.461	0.038
Land Area	-0.082	0.115
R^2	0.090	—

The regression results show that land size has a negative but statistically insignificant effect on land conversion. Moreover, the low R^2 value (0.090) indicates that only 9% of the variation in land conversion can be explained by land availability.

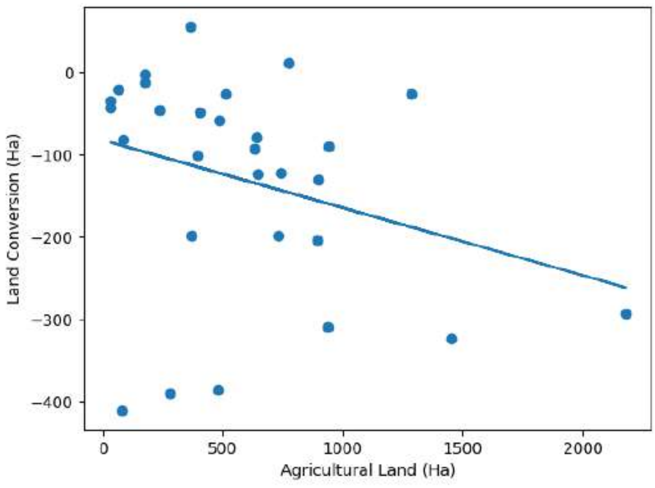

Figure 3. Relationship between land availability and land conversion

As shown in Figure 3, the scatter plot reveals a dispersed pattern with no clear linear trend. This empirical evidence directly challenges the conventional assumption that land conversion is primarily driven by land availability. Instead, the findings suggest that conversion dynamics are more strongly influenced by structural and institutional factors, such as development pressure, governance capacity, and land market dynamics.

This weak relationship motivates further investigation into whether land conversion follows underlying structural groupings rather than continuous linear patterns.

Cluster Structure of Land Conversion

To explore this possibility, K-Means clustering was applied based on conversion intensity and absolute conversion.

Table 5. Cluster Summary

Cluster	Count	Conversion Intensity	Abs Conversion	Interpretation
0	20	-0.268	60.20	Moderate/Low Pressure
1	8	-0.490	287.75	High Pressure
2	1	-5.108	411.00	Extreme Loss

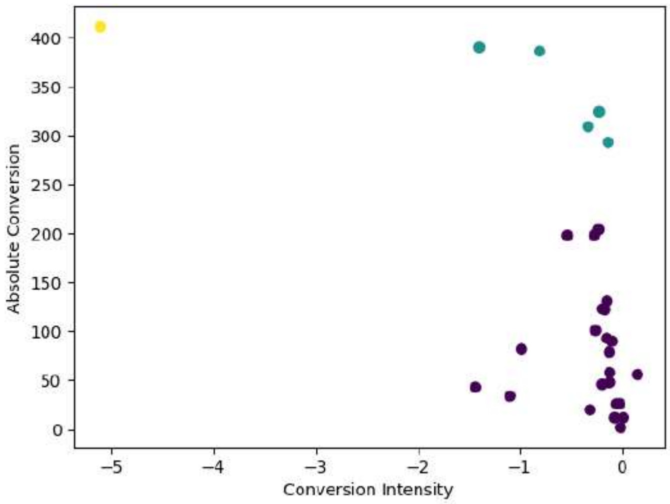

Figure 4. Cluster distribution based on conversion intensity and absolute conversion

The clustering results reveal a clear structural differentiation in land conversion patterns. The majority of subdistricts fall into a moderate/low-pressure group, while a smaller subset experiences significantly higher conversion pressure. More importantly, one subdistrict forms a distinct cluster characterized by extreme land loss.

This finding indicates that land conversion is not randomly distributed but follows a clustered pattern. The presence of a single-member extreme cluster suggests that certain areas experience disproportionately severe pressures, likely reflecting localized breakdowns in land governance or intense development pressures.

Synthesis: Non-Proportional and Clustered Land Conversion

By integrating the findings, three key patterns emerge. First, land conversion is not proportional to land availability. The regression results show no statistically significant relationship between land size and conversion, contradicting the assumption that larger land areas are inherently more vulnerable. Second, land conversion is not randomly distributed. The skewed distribution and concentration of extreme values indicate systematic inequality across subdistricts.

Third, land conversion is structurally clustered. The cluster analysis reveals distinct groups of subdistricts characterized by different levels of land-use pressure. Taken together, these findings redefine agricultural land conversion as a structurally uneven and clustered phenomenon rather than a proportional or random process. This implies that land-use change is shaped by localized dynamics and institutional conditions rather than scale alone.

From a policy perspective, this also indicates that evaluating agricultural land protection solely based on total land area is insufficient. Instead, attention must be directed toward localized dynamics and high-risk clusters where conversion pressure is concentrated.

Theoretical Contribution

This study contributes to the contemporary literature on agricultural land conversion by advancing a structurally grounded and non-spatial analytical perspective. While recent studies have increasingly relied on geospatial and remote sensing approaches to map land-use change (e.g., Petrovszki et al., 2024) global urban land expansion; Tan et al. (2010) land use change remote sensing analysis), these approaches tend to prioritize spatial visualization over statistical characterization. As a result, the internal structure, inequality, and distributional dynamics of land conversion often remain underexplored.

First, this study challenges the widely held assumption that land conversion is primarily driven by land availability. Recent empirical research suggests that land-use change is increasingly shaped by institutional arrangements, governance quality, and speculative pressures rather than purely by land endowment (Suriadikusumah et al., 2022) global land use displacement; Fathololoumi et al. (2024) land system transformations). The findings of this study—showing a weak and statistically insignificant relationship between land size and conversion—provide empirical support for this emerging perspective.

Second, this study advances the concept of conversion intensity as a key analytical variable, emphasizing proportional land-use pressure rather than absolute change. This approach aligns with recent developments in land system science that highlight the importance of relative pressure, vulnerability, and resilience in understanding land-use dynamics (Han et al., 2023) land system intensity metrics; Deng et al. (2024) global land use intensity mapping). By revealing substantial variation in conversion intensity across subdistricts, this study demonstrates that land conversion is characterized by structural inequality rather than uniform processes.

Third, the application of cluster analysis provides evidence that land conversion follows non-random and structurally differentiated patterns. This finding is consistent with recent urban and regional studies emphasizing spatial inequality, uneven development, and localized vulnerability as central features of land-use change (Christiawan & Lai Nguyen, 2024) urban expansion patterns; Zhong et al. (2022) urban-rural land transition inequality). The identification of high-pressure clusters and extreme outliers suggests that land conversion is concentrated in specific areas rather than distributed evenly.

Taken together, these contributions support a conceptual shift from viewing agricultural land conversion as a scale-dependent phenomenon toward understanding it as a structurally uneven and institutionally mediated process. This shift is particularly relevant in rapidly urbanizing regions, where land-use change is driven by complex interactions between governance systems, economic incentives, and development pressures.

Policy Implications

The findings of this study have important implications for agricultural land protection policies, particularly within the LP2B (*Lahan Pertanian Pangan Berkelanjutan*) framework in Indonesia. While LP2B represents a formal regulatory commitment to preserving agricultural land, the empirical evidence presented here highlights critical gaps between policy design and actual outcomes.

First, the absence of a significant relationship between land availability and conversion exposes a fundamental limitation of area-based protection policies. LP2B primarily relies on land designation, assuming that formal classification ensures protection. However, recent policy studies indicate that land designation alone is insufficient without effective enforcement, monitoring, and institutional coordination (Xia et al. (2024) land governance effectiveness; FAO (2023) land governance and tenure report). The persistence of land conversion within designated areas suggests a classic case of policy–implementation gap.

Second, the identification of clustered land conversion patterns indicates that policy impacts are spatially uneven. Recent research emphasizes that uniform policy approaches often fail in heterogeneous socio-economic contexts, leading to inefficiencies and unintended consequences (Hidayat, 2022) place-based policy framework; Christiawan & Lai Nguyen (2024) spatial inequality and development). In the context of

LP2B, this implies that a one-size-fits-all approach is inadequate, and more localized, adaptive strategies are required.

Third, the presence of extreme outliers suggests potential cases of policy failure, where regulatory mechanisms are unable to counteract strong development pressures. Recent studies on land governance highlight how rapid urbanization, speculative land markets, and weak institutional enforcement can undermine formal land protection frameworks (Rondhi et al., 2018; Tateishi et al., 2021). These conditions are likely contributing to the observed concentration of extreme land conversion in specific subdistricts.

Fourth, the findings underscore the need for a shift toward data-driven and risk-based policy approaches. Rather than evaluating policy success solely based on the total area of protected land, policymakers should prioritize high-risk clusters identified through empirical analysis. This aligns with recent advances in evidence-based policy design, which emphasize targeted intervention and adaptive governance (Liu & Zhu, 2025) evidence-based policymaking).

More broadly, this study highlights a fundamental distinction between formal protection and effective protection. The existence of LP2B-designated land does not guarantee its preservation in practice. Improving policy effectiveness therefore requires not only regulatory frameworks but also institutional strengthening, incentive alignment, and continuous monitoring systems.

Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the use of cross-sectional data limits the ability to capture temporal dynamics and causal relationships. Land conversion is inherently a dynamic process influenced by long-term socio-economic and policy changes. Future research should employ longitudinal or panel data approaches to examine how land conversion evolves over time and to identify causal drivers more robustly.

Second, this study adopts a non-spatial analytical approach, which, while effective in identifying structural patterns, does not account for spatial dependencies or geographic spillover effects. Recent studies have shown that land-use change is often spatially interconnected, with developments in one area influencing neighboring regions (Deng et al., 2024). Integrating spatial econometric or GIS-based methods would provide a more comprehensive understanding of land conversion dynamics.

Third, the analytical model includes a limited set of variables, focusing primarily on land availability and conversion metrics. However, land conversion is influenced by a wide range of factors, including population growth, infrastructure development, land market dynamics, and governance capacity. Future studies should incorporate multi-dimensional datasets to better capture the complexity of land-use change processes.

Fourth, the clustering approach, while useful for identifying structural groupings, is sensitive to methodological choices such as the number of clusters and variable selection. Future research could explore alternative clustering techniques or validation methods to enhance robustness.

Finally, future research should aim to integrate statistical, spatial, and institutional perspectives into a unified analytical framework. Such an approach would enable a more holistic understanding of agricultural land conversion and provide stronger empirical support for policy design and evaluation.

CONCLUSION

This study set out to analyze the distribution and intensity of agricultural land conversion, examine the relationship between land availability and conversion dynamics, and identify structural clustering patterns at the subdistrict level in Bandung Regency within the LP2B framework. The findings provide several important conclusions that advance the understanding of agricultural land conversion beyond conventional approaches.

First, the results demonstrate that agricultural land conversion is highly uneven and disproportionately concentrated. A small number of subdistricts account for a large share of total land loss, while most areas experience relatively moderate changes. This indicates that land conversion is not a uniform process, but one characterized by distributional inequality and localized concentration.

Second, the study finds that land conversion is not significantly related to land availability. The weak and statistically insignificant relationship between designated agricultural land and conversion challenges the common assumption that larger land areas are inherently more vulnerable to conversion. Instead, this suggests that land conversion is shaped more by structural and institutional factors than by land size alone.

Third, the clustering analysis confirms that land conversion follows non-random and structurally differentiated patterns. The identification of distinct clusters—ranging from moderate pressure to extreme loss—demonstrates that subdistricts experience different levels of vulnerability. The presence of an extreme outlier further highlights that land conversion can reach critical levels in specific locations, indicating potential governance or policy failures.

Taken together, these findings suggest that agricultural land conversion should be understood as a non-proportional, non-random, and structurally clustered phenomenon. This represents a shift from traditional perspectives that emphasize spatial distribution or land availability, toward a more nuanced understanding of land conversion as a process shaped by inequality, localized pressures, and institutional dynamics.

From a broader perspective, this study advances the field by introducing a non-spatial, statistically grounded analytical framework that captures structural patterns often overlooked in spatial analyses. By integrating conversion intensity, regression analysis, and clustering techniques, the study provides a more comprehensive approach to understanding land conversion dynamics.

In terms of practical implications, the findings indicate that the effectiveness of agricultural land protection policies such as LP2B cannot be assessed solely based on the extent of designated land. Instead, policy evaluation must consider where and how conversion pressures are concentrated, emphasizing targeted and adaptive interventions rather than uniform regulatory approaches.

Despite its contributions, this study remains limited by its cross-sectional design and restricted variable scope. Future research should incorporate longitudinal data, spatial analysis, and additional socio-economic variables to further explore the drivers of land conversion and strengthen causal inference. Such efforts would provide deeper insights into the mechanisms underlying land-use change and support the development of more effective and evidence-based policy interventions.

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