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Modeling built-up land dynamics to support spatial resilience and national defense planning in Lampung province

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Abstract

Background: The expansion of built-up areas in Lampung Province has continued alongside population growth and economic development. This expansion has the potential to reduce productive land, intensify environmental pressure, and create significant challenges for spatial planning. Consequently, understanding the factors that influence built-up land expansion is essential to supporting sustainable regional planning and development.
Aims: This study investigates the dynamics of built-up land expansion in Lampung Province through an integrated analysis of remote sensing data and panel data.
Method: The study employed a panel data approach combining time-series observations spanning 2014 to 2024 with cross-sectional data drawn from 15 regencies and municipalities in Lampung Province. The dependent variable was the extent of built-up land (Y), derived from remote sensing image classification. The explanatory variables consisted of the number of schools (X_1), the Human Development Index (HDI) (X_2), and road length (X_3). The school variable encompassed educational institutions across all levels. Data on HDI and the number of schools were obtained from BPS-Statistics Indonesia for Lampung Province. Road length was estimated from Landsat and Sentinel-2 satellite imagery through road digitization and geometric attribute analysis conducted within a Geographic Information System (GIS)-based analytical framework.
Result: The results demonstrate that remote sensing provides comprehensive information on built-up areas and road networks, which can be effectively incorporated into panel data analysis. FEM produced an R-squared value of 0.984050, suggesting that the explanatory variables collectively explain approximately 98.41% of the variation in built-up land area.
Conclusion: The findings indicate that built-up land expansion is associated with socioeconomic and infrastructure-related factors. The Fixed Effects Model reveals that HDI and road length have significant positive effects on built-up area, while the number of schools exhibits a negative effect. These results suggest that improvements in human development and regional accessibility are associated with the expansion of built-up areas, whereas the negative relationship with the number of schools may reflect prevailing patterns in the distribution of educational facilities and regional service provision.

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INTRODUCTION

Regional growth is closely linked to changes in population and economic activities. Among the key indicators of this development is the transformation of land use, particularly the increasing extent of built-up areas (Chen et al., 2020). Built-up land reflects increasingly intensive human activities, including the development of residential areas, industrial zones, infrastructure, and other public facilities (Jin et al., 2023; Zhang et al., 2025). In the context of a rapidly developing region such as Lampung Province, changes in built-up land have become a critical issue that requires comprehensive investigation due to their direct impacts on environmental, social, and economic conditions.

Lampung Province, as one of the main gateways to the island of Sumatra, occupies a strategic position within Indonesia's national transportation network. This strategic location has accelerated regional development, particularly in urban areas such as Bandar Lampung City and its surrounding regions (Widayanti et al., 2025). Continuous population growth has increased the demand for land to accommodate residential development and economic activities (Ariani & Susilo, 2022; Mahtta et al., 2022). As a result, land previously used for agriculture, plantations, and other open spaces has increasingly been transformed into built-up areas. If left unmanaged, this land conversion may lead to various challenges, including the loss of productive land, increased flood risk, and environmental degradation (Rehman & Khan, 2022).

Changes in built-up land in Lampung Province warrant study due to their close links to national defense, regional resilience, the protection of strategic infrastructure, and national disaster mitigation. Rapid expansion of built-up areas can alter spatial structures and characteristics, including settlement, transportation networks (Rezvani et al., 2024), industrial zones, and economic activity hubs. In the context of national defense and security, such changes require monitoring as they can impact strategic spatial use, accessibility, inter-regional connectivity, and a region's capacity to support defense and security functions (Botezatu et al., 2023; Shi et al., 2022). Meanwhile, from the perspective of regional resilience, uncontrolled expansion of built-up land can strain resources such as land, water, energy, transportation, and basic services, potentially diminishing the region's carrying capacity(Ji et al., 2026; Seifollahi-Aghmiuni et al., 2022). Furthermore, changes in built-up land have implications for the protection of strategic infrastructure, including road networks, bridges, ports, airports, energy facilities, dams, and public service facilities. The growth of built-up areas surrounding such infrastructure can intensify activity and increase the risk of disruption to its functionality and accessibility; consequently, information regarding land-use dynamics is essential for strategic regional planning and management (Giofandi et al., 2025; Koskivaara & Lähtinen, 2023; Prados et al., 2026). Thus, monitoring changes in built-up land serves as a vital tool for identifying regional growth, evaluating increased exposure risks, supporting the protection of strategic infrastructure, and strengthening regional planning to ensure resilience against security threats and disasters.

Previous research has shown that built-up land in The city of Bandar Lampung, which serves as the capital of Lampung Province, has experienced a significant increase over time (Dewi et al., 2026). This growth has occurred not only in terms of the total built-up area but also in its spatial distribution, which exhibits a clustered pattern. These findings suggest that built-up land expansion does not occur randomly but follows distinct spatial patterns influenced by factors such as accessibility, economic activity centers, and spatial planning policies (Soltani et al., 2025; Zhao et al., 2024). Studies that simultaneously integrate spatial and temporal dimensions at the provincial scale remain relatively limited. In examining built-up land dynamics, a data-driven approach is essential for producing an accurate and comprehensive analysis (Alawode et al., 2025). Remote sensing imagery is among the most widely utilized sources of spatial data, particularly satellite imagery. Remote sensing data offer significant advantages by providing extensive, consistent, and regularly updated spatial information (Li et al., 2025; Ursu et al., 2025). Using image processing techniques, land-use changes can be identified and analyzed in detail over time. Remote sensing provides an effective means of monitoring changes in built-up land over time (Arif & Toersilowati, 2024; Pickens et al., 2025), particularly across large regions such as Lampung Province.

Nevertheless, remote sensing-based analysis alone is insufficient to explain the factors driving these changes quantitatively. Therefore, an additional analytical approach is required to accommodate both the temporal dimension and the heterogeneity among regions (Firozjaei et al., 2025; Mei et al., 2025). Panel data analysis provides an appropriate methodological approach by integrating cross-sectional and time-series observations, thereby allowing researchers to examine temporal dynamics while simultaneously capturing heterogeneity across spatial units (Fang et al., 2025; Ziesemer, 2024), such as regencies and municipalities. Through the use of panel data analysis, the associations between built-up land development and the factors that influence its dynamics can be systematically examined, such as population size, population density, and economic variables, can be examined more comprehensively.

The integration of remote sensing data and panel data provides a more comprehensive framework for understanding built-up land dynamics. Remote sensing identifies where land use changes occur by capturing their spatial distribution (Ennouri et al., 2021; Zhu et al., 2022). Whereas panel data analysis explains why these changes occur by quantifying the effects of socioeconomic and infrastructure-related factors. Integrating these two approaches allows the analysis to extend beyond descriptive assessment and incorporate inferential perspectives, thereby providing a robust scientific basis for evidence-based policy formulation and sustainable regional planning. This integrated approach enables researchers to examine patterns of change across both space and time simultaneously. In the context of built-up land development in Lampung Province, it provides valuable insights into how urban expansion has evolved over time and across different regions. Such information is essential for local governments in formulating sustainable spatial planning and land management policies. Advances in technology and the increasing availability of geospatial and statistical data have created significant opportunities to conduct more comprehensive and accurate analyses. Today various remote sensing platforms provide high-resolution satellite imagery with improved temporal coverage (Gámez García et al., 2025), while the statistical data required for panel data analysis have become increasingly accessible. These developments offer researchers greater opportunities to develop innovative and integrated analytical approaches. Despite these advantages, several challenges remain in integrating remote sensing and panel data, including differences in data scale, temporal consistency, and the complexity of data processing and analysis. Therefore, an appropriate methodological framework is required to ensure that these two types of data can be effectively integrated and produce reliable and valid results.

Considering these aspects, the present study focuses on analyzing the expansion of built-up areas in Lampung Province through a spatial analytical framework that integrates remote sensing data with panel data analysis. This study is intended to provide an in-depth assessment of the temporal trends and dynamics of built-up land transformation, while also identifying the factors that contribute to these changes. Such information is vital not only for supporting sustainable regional development planning but also for informing strategic regional planning, strengthening regional resilience, and guiding decision-making regarding the development and protection of strategic infrastructure in Lampung Province. Furthermore, the analysis is expected to facilitate the provision of geospatial information that can be integrated into spatial information systems to support national defense and security planning, particularly concerning regional planning and strategic spatial management. Accordingly, this research contributes to the development of knowledge in remote sensing, regional spatial analysis, and panel data modeling, while also offering practical value for supporting evidence-based decision-making in regional planning and development. The findings are expected to serve as a valuable information resource for strategic spatial planning, infrastructure development, enhancing regional resilience, disaster risk mitigation, and the development of geospatial information systems that support national development and defense interests in an integrated and sustainable manner.

METHOD

This study adopts a spatiotemporal analytical framework that integrates remote sensing data with panel data to investigate the dynamics of built-up land development in Lampung Province. The research procedure is structured into three sequential stages, comprising the preparatory stage, the implementation stage, and the final stage. The detailed research procedures are described as follows.

The research begins with a comprehensive literature review and preliminary information gathering. At this stage, relevant scientific publications, government regulations, and prior studies on land-use change, remote sensing, and panel data analysis are reviewed. This phase is primarily intended to develop a sound theoretical and conceptual basis that underpins the research. The expected outcome is a comprehensive literature review that supports the research framework.

The research problem, objectives, and significance are then established based on the gaps identified through a comprehensive review of the relevant literature. The research objectives are formulated in a clear and measurable manner to ensure that they directly address the identified research problems. The expected outcome of this stage is a well-defined research problem and a set of objectives that are consistent with the research background. The subsequent stage involves data collection, which includes the acquisition of satellite imagery as the primary source of remote sensing data. The image data are then processed through several stages, beginning with image classification, in which each pixel is assigned to a specific land-cover class according to its spectral characteristics (Lou et al., 2025). For studies examining built-up areas, the classification scheme may consist of several land-cover categories, such as built-up land, vegetation, water bodies, open land, and agricultural land. The selection of these classes should reflect the characteristics of the study area and align with the objectives of the research. Among the available classification approaches, the Random Forest method is well suited for analyzing patterns of built-up area expansion (Ali A. Shohan et al., 2024; Frimpong & Molkenthin, 2021). Random Forest is an ensemble learning algorithm that generates predictions by combining the outputs of multiple decision trees. During the training process, the algorithm generates an ensemble of decision trees by using different subsets of the training data. For each pixel, the final land-cover class is then determined based on the majority decision produced by these individual trees. This characteristic makes the method well suited to land-cover classification, as it is capable of modeling complex and non-linear relationships between spectral information and different land-cover categories. In addition, the algorithm can effectively handle datasets containing a large number of predictor variables.

Following image classification, the extraction of built-up areas is performed. This extraction aims to generate classes or polygons that specifically represent built-up areas derived from the land cover classification results. The subsequent step is validation, which assesses how accurately the classification results reflect actual ground conditions. This stage is crucial because classification results cannot be assumed correct simply because an algorithm has produced a map. Validation is conducted by comparing the classified classes against reference data (Foody, 2017; García-Álvarez, 2022). Validation samples are spatially distributed across the entire study area, ensuring that the sampling accounts for all classes particularly built-up land to guarantee adequate representation for each category. The validation results are then organized into a confusion matrix (Xu et al., 2024). A confusion matrix is a table that compares the classified classes with the actual reference classes that can yield an overall accuracy value. In multispectral classification involving multiple classes (Be et al., 2025), the confusion matrix helps identify which classes are most prone to misclassification. For instance, open land often shares spectral characteristics with built-up surfaces, potentially leading to misclassification between these two categories.

Overall Accuracy (OA) shows the proportion of all validation samples that were correctly classified compared to all validation samples (Farhadpour et al., 2024). The formula for overall accuracy is as follows:

$$OA = \frac{\sum_{i=1}^{k} x_{ii}}{N} \times 100\%$$

OA : Overall Accuracy
x_{ii} : the number of samples correctly assigned to the corresponding class i
k : the total number of class
N : the overall validation sample size

Overall Accuracy (OA) has a limitation, the OA value can appear high if one class has a significantly larger number of samples compared to the others. Therefore, classification performance should be assessed not only through Overall Accuracy (OA), but also by examining the accuracy of individual classes and the Kappa coefficient (Farhadpour et al., 2024; Yi et al., 2024).

The Kappa coefficient provides an assessment of the consistency between the classified results and the reference dataset (Tang et al., 2015), accounting for the likelihood of agreement occurring by chance. The general formula for Kappa is as follows:

$$K = \frac{p_0 - p_e}{1 - p_e}$$

K : Kappa Accuracy
p_0 : Observed Agreement
p_e : Expected Agreement
The Kappa coefficient typically ranges from −1 to 1, where values closer to 1 indicate stronger agreement between the classification results and the reference data. In contrast, values near 0 imply that the observed level of agreement is largely consistent with what would be expected by chance.

Once the image data has been obtained with the expected OA and Kappa values, it can be used for further analysis. This study applies a panel data approach using time-series observations from 15 regencies and municipalities, complemented by supporting spatial datasets. Satellite imagery is used to identify changes in built-up land, while panel data are used to analyze the factors influencing these changes. The expected outcome is the availability of a complete and well-organized dataset, with the performance indicator being the successful collection of 100% of the required data. The final step in the preparation phase is determining the study area and analytical units.

The study covers all regencies and municipalities in Lampung Province, which are treated as the cross-sectional units in the panel data framework. The expected outcome is the establishment of clearly defined study boundaries and analytical units, with the performance indicator being the identification and preparation of all 15 administrative units for subsequent analysis. The panel data analysis is conducted in the subsequent stage, beginning with the construction of a panel dataset that integrates time-series observations with cross-sectional data. The appropriate regression specification is then identified by evaluating the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) (Ioan et al., 2020; Ratnasari et al., 2023). CEM is estimated using the Ordinary Least Squares (OLS) approach (Pillai N., 2017). Under this specification, observations across cross-sectional units and time periods are combined into a single pooled dataset without accounting for differences among individual units or periods. A key assumption of the model is that the relationship between the dependent variable and its explanatory factors does not vary across observational units or over time. The mathematical formulation of the CEM is given as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \varepsilon_{it} \tag{1}$$

where:
Y_{it} : dependent variable observed for cross-sectional unit (i) during period (t)
X_{it} : independent variable associated with cross-sectional unit (i) at time (t)
β_0 : intercept
β_1 : regression coefficient
ε_{it} : error

The Least Squares Dummy Variable (LSDV) approach is employed to estimate FEM, where dummy variables are included to reflect differences in intercepts among cross-sectional units. By incorporating these unit-specific effects, the model can account for unobserved characteristics that differ across units but remain unchanged over time. The FEM is formulated as:

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{2}$$

where:
Y_{it} : dependent variable observed for cross-sectional unit (i) during period (t)
X_{it} : independent variable associated with cross-sectional unit (i) at time (t)
α_i : individual-specific intercept (fixed effect)
β : regression coefficient
ε_{it} : error

In this model, α_i represents the fixed effect, capturing the characteristics specific to each cross-sectional unit that remain unchanged throughout the observation period.

REM, in this estimation, it is assumed that differences between individuals are not fixed, but are random and follow a certain distribution, the equation for this model is:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

where:
Y_{it} : dependent variable observed for cross-sectional unit (i) during period (t)
X_{it} : independent variable associated with cross-sectional unit (i) at time (t)
β_0 : intercept
β_1 : regression coefficient
μ_i : individual effect
ε_{it} : error (Putri, 2023).
Once the alternative panel regression models have been estimated, the appropriate model must be identified to produce reliable and consistent estimates of the model parameters. Two statistical tests, the Chow test and the Hausman test, are applied in this study to determine the most appropriate model specification.

The Chow test is used to assess whether CEM or FEM is more suitable for the panel dataset. The corresponding hypotheses are stated as follows:

H_0: CEM is considered the more appropriate model.
H_1: FEM is considered the more appropriate model.

The Chow test is assessed using the F-statistic. If the p-value is below 0.05, $H_0$is rejected, indicating that the FEM is preferred to the CEM. Conversely, a p-value above 0.05 suggests that the CEM is more appropriate. The F-statistic is calculated as follows:

$$Chow\ test\ (F) = \frac{RSS_1 - RSS_2/(N-1)}{RSS_2/(NT-N-k)} \tag{4}$$

where the residual sum of squares is denoted by RSS, while N represents the number of cross-sectional units, T indicates the number of observation periods, and K denotes the number of independent variables. H_0 is rejected when the calculated F-statistic is greater than the corresponding critical value. Subsequently, the Hausman test is performed to determine whether the FEM or REM provides the more appropriate specification. The hypotheses for this test are formulated as follows:

H_0: REM is considered the more appropriate specification.
H_1: FEM is considered the more appropriate specification.

The Hausman test statistic is based on the chi-square distribution and can be formulated as follows:

$$\chi^2(K) = (b-\beta)'[var(b-\beta]^{-1}(b-\beta) \tag{5}$$

where;
b : random effect coefficient
β : fixed effect coefficient
H_0 is rejected when the calculated chi-square statistic exceeds its corresponding critical value.

Another model selection procedure used in panel data analysis is the Lagrange Multiplier (LM) test (Büscher & Bauer, 2025), this test is applied to determine whether REM or CEM is more appropriate (Tores). The hypotheses are formulated as follows:

H_0: CEM is the appropriate model.
H_1: REM is the appropriate model.

The Breusch–Pagan statistic serves as the basis for the LM test and is calculated using the following formula:

$$LM = \frac{T}{2}\sum_{i=1}^{N}\left(\frac{\sum_{t=1}^{T} e_{it}}{T}\right)^2 \tag{6}$$

A test statistic exceeding the chi-square critical value leads to rejection of the H_0 is rejected, suggesting that FEM is more suitable than REM (Ratnasari et al., 2023).

After obtaining the best model among the three, assumption testing is conducted. This aims to obtain a reliable model estimate. This assumption test includes:

1. Normality Test: The normality assumption of the model residuals is evaluated using the Jarque–Bera (JB) test. The corresponding test statistic is calculated using the following equation: (Glinskiy et al., 2024):

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{7}$$

where S represents the skewness coefficient and K denotes the kurtosis coefficient. If the resulting p-value exceeds 0.05, there is insufficient evidence to reject the normality assumption, suggesting that the residuals are consistent with a normal distribution.

2. Multicollinearity Test: The multicollinearity assessment is conducted to identify potential linear relationships among the independent variables in the regression model. This condition can be evaluated based on the correlation coefficients between explanatory variables or by examining their Variance Inflation Factor (VIF) values. (Daoud, 2017).

$$VIF = \frac{1}{1-R^2} \tag{8}$$

If the VIF is greater than 10, there is multicollinearity.

3. Heteroscedasticity Test: This assessment examines whether the residual variance is consistent across the observations. Heteroscedasticity can be detected by applying either the Breusch–Pagan test or the Glejser test (Ilori & Tanimowo, 2022). The Breusch-Pagan test follows the following equation:

$$LM = nR^2 \tag{9}$$

p-value below 0.05 indicates the presence of heteroscedasticity in the model. The Glejser test can be formulated as follows:

$$|e_i| = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i \tag{10}$$

Heteroscedasticity is indicated when the estimated coefficient of an independent variable is statistically significant.

4. Autocorrelation Test: To determine whether the regression residuals are correlated across successive observations, the Breusch–Godfrey test is employed. The test statistic is defined by the following expression:

$$LM = (n-p)R^2 \tag{11}$$

p-value below 0.05 indicates the presence of autocorrelation in the residuals.

The subsequent stage integrates the findings from the spatiotemporal analysis with the panel data analysis. The results of the spatial analysis are used to describe and interpret the observed patterns of change, whereas the panel analysis is employed to identify the factors associated with these changes. By combining the two analytical perspectives, the study provides a more comprehensive understanding of the dynamics of built-up land.

RESULTS AND DISCUSSION

This study uses time-series data on built-up land area from 2014 to 2024. Additionally, it incorporates cross-sectional data from the 15 regencies and cities within Lampung Province. The study location is shown in Figure 1. These cross-sectional data are assumed to exhibit distinct characteristics across the various regional units (regencies/cities). Panel data analysis is deemed the most appropriate method, this approach integrates time-series observations with cross-sectional data within a unified analytical framework, thereby enabling the capture of both temporal dynamics and inter-regional characteristic differences.

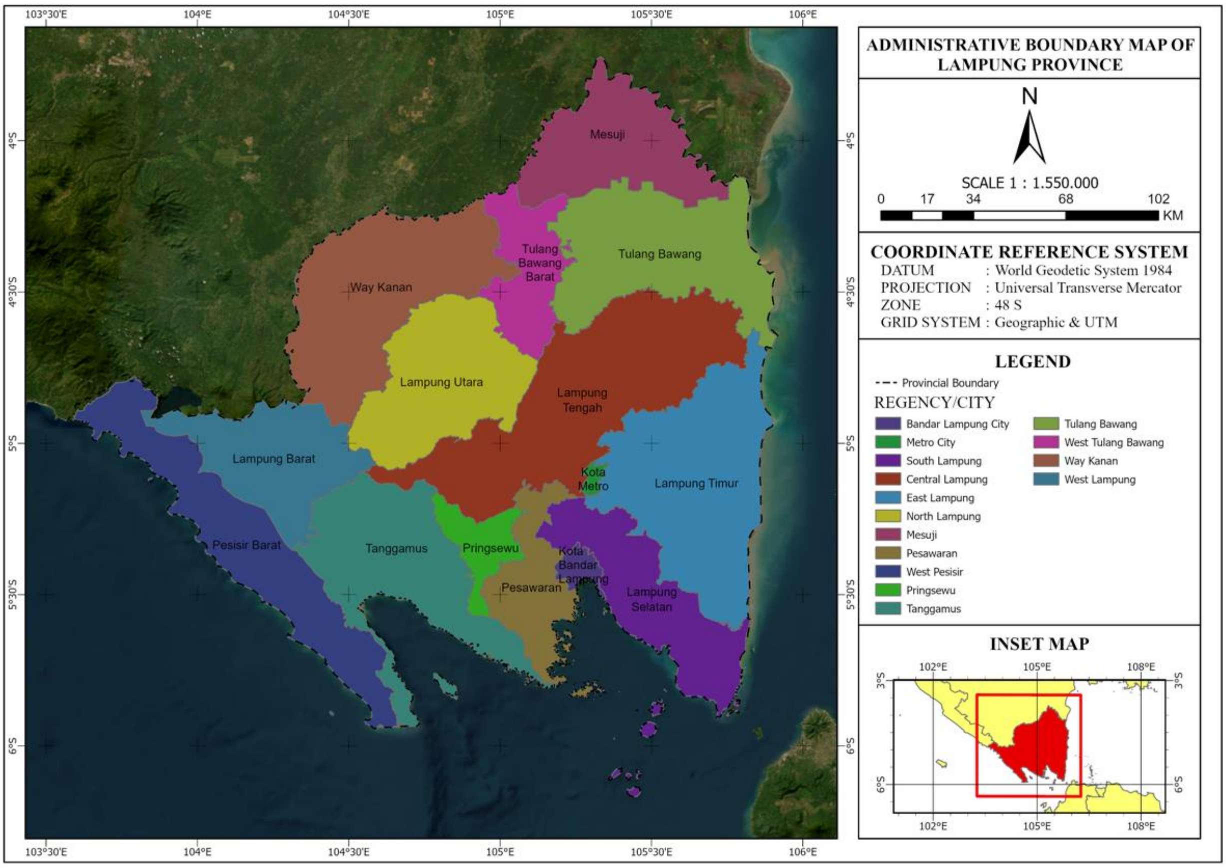

Figure 1. Location map of the 15 regencies in Lampung province.

Table 1. Descriptive analysis of each variable.

	Y	X_1	X_2	X_3
Mean	224,665	363.461	67.72	258,629
Median	220,990	304	67.13	239,011
Maximum	683,730	803	79.86	671,815
Minimum	10,640	101	58.16	12,289
Std. Dev.	139.898	212.545	4.50	184,362
Skewness	0.706	0.775	0.64	0.650
Kurtosis	3.671	2.363	3.19	2.352
Jarque-Bera	16.8225	19.2966	11.419	14.513
Probability	0.0002	0.0001	0.0033	0.0007
Observations	165	165	165	165

The analysis uses the number of schools (X_1) in each regency/city as the independent variable. The variable covers all major levels of formal education, covering primary, junior secondary, senior secondary, and vocational education levels. The data includes schools under the auspices of both the Ministry of Basic and Secondary Education and the Ministry of Religious Affairs, covering both public and private institutions. These data were obtained from the Lampung Province Statistics Indonesia office and cover the period from 2014 to 2024 for each regency/city. Another variable used in this study is X_2, representing the Human Development Index (HDI) for each regency/city in Lampung Province, HDI data were also sourced from Lampung Province for the 2014–2024 period. Additionally, variable X_3 represents road length in each regency/city in Lampung Province during the same 2014 - 2024 period. Road length data were derived through the processing of Landsat and Sentinel satellite imagery. The data processing involved digitizing the road network, followed by calculating road lengths using geometric attributes within Geographic Information System (GIS). The final stage of processing involved validation and correction to ensure the accuracy of the resulting data. Table 1 presents a summary of the descriptive statistics for all variables analyzed in this study. Based on these results, the average built-up area across all regencies/cities is 224,665 km^2, while the average road length is 258,629 km. Once the data had been fully collected and verified, the next step was to conduct data analysis. The data analysis procedure adopted in this study consists of several stages, beginning with the panel data analysis.

Panel regression models can be specified using three commonly applied estimation approaches, namely the Common Effects Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM). The appropriate model specification is determined by conducting a series of statistical tests to compare the suitability of these alternatives. The first step in the model selection procedure is the Chow test, which is used to determine whether the CEM or FEM provides a better fit to the data. The test yields an F-statistic of 74.6455 and a p-value of 0.0000. Since the p-value is lower than the 0.05 significance threshold, the null hypothesis is rejected. The rejection of the null hypothesis supports the alternative hypothesis, suggesting that the FEM offers a more appropriate specification than the CEM. The Hausman test is then conducted to determine the relative suitability of the FEM and REM. The test results yield a chi-square statistic of 25.0856 and a p-value of 0.0000, which is also lower than the 0.05 significance threshold. The statistical evidence supports rejection of the null hypothesis, indicating that the FEM is the more appropriate model for the analysis. The findings suggest that the unobserved individual effects associated with the regencies/cities are correlated with the explanatory variables. Consequently, the FEM is considered more appropriate for capturing the variation in the data than the REM.

The LM test is used to assess whether the REM should be preferred over the CEM in panel data estimation (Büscher & Bauer, 2025). In the present study, however, the LM test was not conducted because the results of the Chow and Hausman tests consistently identified FEM as the preferred specification. Thus, there was no need for an additional comparison between the REM and CEM. The estimation results of the selected FEM are presented in Table 2. Once the appropriate model specification had been identified, a series of classical assumption tests was conducted to verify that the regression model met the underlying statistical requirements.

Table 2. Results of the Fixed Effect (FE) model analysis.

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-252.7324	85.46798	-2.957042	0.0036
X_1	-0.714676	0.13685	-5.153214	0.0000
X_2	8.828205	1.557246	5.669115	0.0000
X_3	0.538517	0.047865	11.25071	0.0000
Effects Apecification				
Cross-section fixed (dummy variables)				
R-squared	0.965915	Mean dependent var		224.6655
Adjusted R-squared	0.961973	S.D dependent var		139.8982
S.E of regression	27.28071	Akaike info criterion		9.5530
Sum squared resid	109402.8	Schwarz criterion		9.8917
Log likelihood	-770,1147	Hannan-Quinn criterion		9.6904
F-Statistic	245.0455	Durbin-Watson stat		0.2822
Prob (F-statistic)	0.000000			

Based on the classical assumption test results, the multicollinearity assumption was met, with VIF values of 1.07, 1.05, and 1.07 for variables X_1, X_2, and X_3, respectively, indicating the absence of multicollinearity. However, the model exhibited several violations, including heteroscedasticity, non-normality of residuals, autocorrelation and cross-sectional dependence. Consequently, remedial measures were required to refine the model so that it satisfied the necessary assumptions. One applicable method is data transformation, as employed in the study by Atchadé & Tchanati (2022). Since the main issue was associated with residual variation related to the dependent variable, To alleviate this issue, a logarithmic transformation was performed on the dependent variable (Y). This transformation was expected to reduce non-constant variance, improve the distribution of residuals, and minimize autocorrelation. Following the transformation, the analysis was subsequently repeated, beginning with the selection of the appropriate panel data model and followed by classical assumption tests, to verify that the resulting model satisfied the required statistical validity criteria..

The analysis was conducted by applying a logarithmic transformation to the dependent variable ($\log Y$), with X_1, X_2, and X_3 serving as the independent variables. The results of both the Chow and Hausman tests favored the Fixed Effects Model (FEM) as the appropriate model specification. Consequently, the Lagrange Multiplier (LM) test, which is intended to distinguish between the Random Effects Model (REM) and the Common Effects Model (CEM), was not required. Following model selection, the analysis proceeded with a series of classical assumption tests. The Jarque–Bera test yielded a p-value of 0.0000, which falls below the 0.05 significance threshold, suggesting that the regression residuals depart significantly from a normal distribution.

Heteroskedasticity was subsequently assessed using the Glejser test. The analysis resulted in a p-value of 0.8976, which is higher than the 0.05 significance threshold. Therefore, H_0 was not rejected, these findings suggest that the model does not exhibit heteroskedasticity and therefore satisfies the assumption of constant error variance. The autocorrelation test was subsequently conducted using the Breusch–Godfrey test. The test yielded a p-value of 0.0000, falling below the 0.05 significance threshold. Accordingly, H_0 was rejected in favor of H_1, providing evidence of serial correlation among the residuals. Thus, the assumption of no autocorrelation is not satisfied. The analysis also examined cross-sectional dependence to determine whether the observation units exhibit interdependence. The Breusch–Pagan Lagrange Multiplier test was employed for this assessment. The analysis produced a p-value of 0.0000, which falls below the 0.05 significance threshold. Hence, H_0 was rejected and H_1 was accepted, suggesting the existence of cross-sectional dependence across the regencies and cities represented in the model.

Table 3. Results of the Fixed Effect (FE) model analysis ($\log Y$ transformation).

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.659384	0.165170	3.992144	0.0001
X_1	-0.000553	0.000268	-2.063386	0.0408
X_2	0.024257	0.003009	8.060204	0.0000
X_3	0.000478	0.000092	5.71478	0.0000
Effects Apecification				
Cross-section fixed (dummy variables)				
R-squared	0.984050	Mean dependent var		2.22486
Adjusted R-squared	0.982206	S.D dependent var		0.39522
S.E of regression	0.052721	Akaike info criterion		-2.94493
Sum squared resid	0.408589	Schwarz criterion		-2.60610
Log likelihood	260.9569	Hannan-Quinn criterion		-2.80739
F-Statistic	533.4928	Durbin-Watson stat		0.31543
Prob (F-statistic)	0.000000			

The results of the classical assumption tests, performed after expressing the dependent variable in logarithmic form (Y), the model was found to satisfy the assumptions regarding multicollinearity and heteroskedasticity. However certain assumptions specifically the normality test, autocorrelation test, and cross-section dependence test were not met. Nevertheless, in the context of panel data analysis, these three assumptions are not always strictly required, further analysis could proceed using FEM as the selected model. FEM estimation results are reported in Table 3. Based on these estimates, the panel regression equation is specified using the FEM framework. In this model, the slope coefficients are assumed to be identical across all cross-sectional units, whereas the intercept is allowed to differ between individuals. These unit-specific intercepts represent individual or cross-sectional effects (CX-F), capturing characteristics that are specific to each regency/city. Accordingly, the general specification of the panel regression model under the FEM can be written as follows:

$$Log_Y = 0.659384 - 0.000553X_1 + 0.024257X_2 + 0.000478\,X_3 + (CX - F)$$

where (CX-F) represents the individual effect for each regency/city, as shown in Table 4.

Table 4. Individual/cross-section effect values (CX-F).

Cross-section	Effect	Cross-section	Effect	Cross-section	Effect
1	0.268860	6	0.165566	11	0.182777
2	-0.048846	7	0.306677	12	0.152792
3	0.368185	8	0.088510	13	0.065872
4	0.283421	9	0.260368	14	-0.631739
5	0.337060	10	-0.546929	15	-1.252.573

The partial significance results presented in Table 3 show that the p-values associated with the t-statistics for all independent variables are below the 0.05 significance level. Thus, H_0 is rejected and H_1 is accepted, indicating that each explanatory variable has a statistically significant effect on the dependent variable, namely built-up land area. Specifically, the number of schools (X_1), the Human Development Index (HDI) (X_2), and road length (X_3) each contribute significantly to variations in built-up land area. The estimated coefficient for the number of schools (X_1) is -0.000553. Holding the other variables constant, this coefficient suggests that an increase of one school is associated with an approximately 0.06% reduction in built-up land area. The negative coefficient indicates an inverse relationship between the number of schools and built-up land area within the estimated model. However, this result requires further substantive explanation, it does not imply that constructing a school causes a reduction in built-up land area. One possibility is that the addition of schools occurs in areas with spatial constraints.

In theories regarding service facilities and regional development, the presence of a school can essentially act as a magnet for population activity (de Armas et al., 2022; Papcunová et al., 2023). Yet, in a multivariate model, a negative relationship may arise because school construction or expansion is specifically directed toward relatively underdeveloped areas or regions with lower levels of existing built-up development. This suggests that schools can serve as a public service intervention to mitigate inter-regional service disparities, rather than merely being a consequence of built-up land expansion. Furthermore, school construction does not always necessitate large-scale expansion of built-up areas; schools can be built in established residential zones or in rural areas where land remains available. Consequently, an increase in the number of schools can occur without a commensurate increase in built-up land area. In other words, the negative sign for X_1 is best understood as a conditional relationship within the model, rather than implying that school construction directly reduces the extent of built-up land.

The positive HDI (X_2) coefficient of 0.024257 aligns well with regional development and modernization theories. The HDI provides a comprehensive measure of human development by considering health conditions, educational attainment, and the standard of living. Higher HDI generally reflects improvements in human resource quality as well as broader socio-economic conditions within the population. From the perspective of regional economic growth theory, improvements in human quality boost productivity and economic activity (Luo et al., 2025; Wu & Zhang, 2021). This economic activity, in turn, drives demand for space for settlements, commerce, services, industry, and public facilities. As a result, increasing demand for land may contribute to the continued expansion of built-up areas.

For the road length variable (X_3), the estimated coefficient is 0.000478. This result implies that, ceteris paribus, an increase of one unit in road length is associated with an estimated 0.0478% rise in the built-up area. The positive association may be related to the role of transportation infrastructure in improving regional accessibility and connectivity. As the road network expands, areas surrounding transportation corridors may become more attractive for residential development, commercial activities, public services, industrial uses, and other economic activities. These findings are consistent with those reported in previous studies by Krisnanta et al. (2026), Pokharel et al. (2023), Qi et al. (2025). The joint significance test produced an F-statistic of 533.4928 and a p-value of 0.0000, which is lower than the 0.05 significance threshold. Accordingly, H_0 is rejected while H_1 is accepted. This result demonstrates that the number of schools (X_1), Human Development Index (HDI) (X_2), and road length (X_3) collectively exert a statistically significant effect on the extent of built-up area. The estimated model achieves an R-squared value of 0.984050, indicating that the number of schools, HDI, and road length jointly explain approximately 98.41% of the observed variation in built-up area (Chicco et al., 2021). The remaining 1.59% may be associated with other factors that fall outside the scope of the model.

Research findings indicate that the dynamics of built-up areas have strategic implications for regional resilience, as changes in the patterns and intensity of land use are closely linked to a region's capacity to withstand development pressures and disaster risks, as well as the need to protect strategic infrastructure. Enhanced accessibility via road networks and improvements in human resource quality can drive the expansion of built-up areas; consequently, spatial management is required that accounts for carrying capacity, vulnerability levels, and access to transport routes and infrastructure. This study contributes to the existing literature by establishing an empirical framework that examines built-up area dynamics in relation to socioeconomic conditions and infrastructure development using panel data analysis. This integration yields an analytical framework that not only explains the factors driving built-up area expansion but also provides a spatial information base to support spatial resilience, strategic infrastructure planning and protection, and regional resilience. Thus, the developed model can be expanded into a tool for spatial-based decision-making to anticipate changes in spatial structure, identify priority areas for infrastructure reinforcement and evacuation planning, and enhance regional adaptive capacity in the face of disaster risks and national security dynamics.

CONCLUSION

The findings demonstrate that remote sensing data can provide valuable information for panel data analysis of built-up land expansion in Lampung Province. The observed changes in built-up areas are associated with both socio-economic conditions and infrastructure development. The Fixed Effect Model results show that HDI and road length exert statistically significant positive effects on built-up land area, while the number of schools has a significant negative effect. These results indicate that improvements in human development and regional accessibility are associated with greater expansion of built-up areas. In contrast, the negative association with the number of schools may reflect the spatial distribution of educational facilities as part of efforts to provide public services more evenly across the region. The integration of remote sensing and panel data analysis represents a significant contribution to understanding the dynamics of spatial development. The developed model has the potential to support spatial resilience, strategic infrastructure planning, and the strengthening of regional resilience.

Future research should incorporate more complex factors influencing built-up land expansion, such as population density, Gross Regional Domestic Product (GRDP), industrial zones, strategic facilities, and defense infrastructure. Furthermore, policymakers should regulate the establishment of educational facilities and pay close attention to locations at risk of uncontrolled built-up land expansion.

AUTHOR CONTRIBUTIONS

T.W.: Conceptualization, numerical simulation, visualization, and drafting of the original manuscript. M.A.E.R.: Data curation, methodology development, validation. E.L.I.: Formal analysis, review and editing process. R.A.Y.: Investigation, formal analysis. Each author took part in interpreting the study results and contributed to the manuscript's preparation, subsequent revisions, and final approval.

CONFLICT OF INTEREST

The authors report no financial, personal, or professional conflicts of interest associated with this study.

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