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Multidimensional Effects of Urban Expansion Patterns: An Empirical Study on Spatial Heterogeneity, Population Dynamics, and Economy-space Synergy in Texas

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Abstract: *This study analyzes 254 Texan cities to explore how urban expansion patterns (enclave, infill, and sprawl) correlate with population change (ΔPop), economic growth (ΔGDP), and green space dynamics (ΔGreen). Results show: (1) Infill development positively correlates with GDP growth ($r = 0.29$, $p < 0.001$), indicating compact development enhances economic performance; (2) Urban sprawl negatively associates with green space preservation ($\rho = -0.69$, $p < 0.001$), suggesting low-density expansion worsens ecological fragmentation; (3) Both enclave and sprawl patterns hinder population agglomeration ($\beta = -4.23\times10^5$, -6.10×10^5, $p < 0.001$), implying disordered expansion may cause residential dispersion. The findings offer quantitative insights for balancing spatial efficiency, economic vitality, and ecological sustainability in urban planning.*

Keywords: *Urban Expansion Patterns; Spatial Heterogeneity; Economy-Space Synergy; Compact City; Ecological Resilience; Sustainable Development*

1. Introduction

1.1 Research Background and Problem

Global urbanization has driven significant differentiation in urban spatial forms. Urban expansion patterns, as core manifestations of spatial growth, profoundly influence regional sustainable development[1][2][3]. These patterns are typically categorized into three types based on patch distribution: enclave, infill, and sprawl[4]. Enclave expansion refers to discontinuous development isolated from existing built-up areas, infill emphasizes intensive use of gaps within built-up areas, and sprawl denotes low-density, continuous outward expansion [5]. These patterns affect regional development through multidimensional "economy-ecology-society" coupling mechanisms. Economy-space synergy highlights the synergy between urban spatial structure and economic activities,driven by agglomeration effects and land-use efficiency[6]. Environmental conflicts arise from the stress effects of expansion patterns on green spaces, particularly habitat fragmentation and carbon sink degradation caused by low-density sprawl[7].

The compact city theory supports the economic benefits of high-density development[8], while landscape ecology frameworks reveal ecological risks associated with sprawl [9] Technologically, remote sensing and GIS enable quantitative identification of expansion patterns through land-use transition matrices[11] and landscape expansion indices[4]. However, existing studies have three limitations: (1) They often focus on single-dimensional effects, lacking systemic analysis of "economy-ecology-population" interactions, especially the coupling mechanisms between expansion patterns and GDP growth, green space dynamics, and population change; (2) Insufficient exploration of spatial heterogeneity, such as threshold effects of sprawl on green spaces; (3) Traditional regression models struggle to integrate multi-source heterogeneous data (e.g., high-resolution remote sensing and socio-economic panels), limiting policy evaluation (e.g., urban growth boundaries)[10].

As a rapidly urbanizing region(Figure 1), Texas exemplifies these dynamics. Its economy ranks second in the U.S., driven by energy, technology, healthcare, and agriculture. Over 90% of its population resides in metropolitan areas, with the Dallas-Fort Worth, Houston, and Austin regions

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contributing 90% of economic activity. From 2001 to 2016, urban expansion in the Texas Triangle declined, with 95% of new urban land located in metropolitan fringes, while non-metropolitan areas showed dispersed expansion[12]. Notably, the Texas Triangle exhibited increased compactness and development intensity, driven by population and economic growth.

Figure 1: Location map of Texas

1.2 Research Objectives and Innovations

This study aims to: (1) Analyze spatial coupling between expansion patterns and GDP growth; (2) Assess the impact of sprawl on green spaces; (3) Reveal population responses to expansion patterns. Innovations include integrating multi-source data to construct expansion indices and employing Winsorized outlier treatment and mixed regression models to overcome single-dimensional limitations.

2. Materials and Methods

This flowchart outlines the study's methodology(Figure 2), beginning with data collection (land use, socioeconomic indicators, and green space dynamics) and preprocessing, followed by three core analytical approaches: (1) quantifying urban expansion patterns (enclave, infill, sprawl) using the Landscape Expansion Index (LEI), (2) assessing economic-ecological relationships through Pearson/Spearman correlations, and (3) modeling population responses via multivariate regression. Results are integrated to derive policy recommendations, systematically linking spatial patterns to their multidimensional impacts.

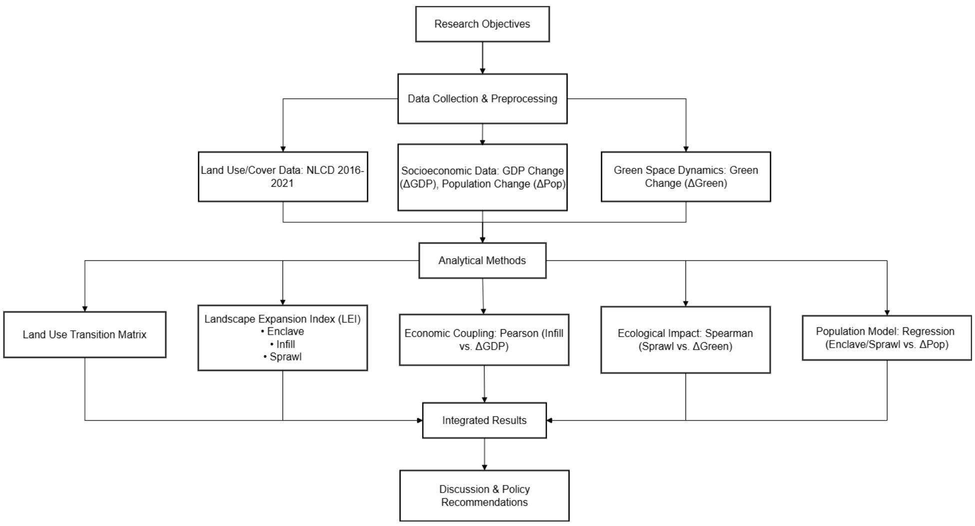

Figure 2: Research workflow diagram

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2.1 Data Sources and Preprocessing

Land Use/Cover Data:

The study utilizes the National Land Cover Database (NLCD) 2016 and 2021 editions from the U.S. Geological Survey (USGS). Derived from Landsat 8 OLI/TIRS imagery (30m resolution), the NLCD achieves over 85% classification accuracy[17] Landsat 8's improved radiometric resolution (12-bit) and additional shortwave infrared band (SWIR-2) enhance urban land identification [13].

Land Classification: Based on NLCD's 11-category system (e.g., forest, grassland, wetland, built-up areas), green spaces (forest + grassland + wetland) and urban land were extracted to analyze spatiotemporal changes from 2011 to 2021.

2.2 Research Methods

2.2.1 Land Use Transition Matrix

A Markov chain model quantifies land-use transitions [11]. The transition probability P_{ij} is calculated as:

$$P_{ij} = \frac{A_{ij}}{\sum_{k=1}^{n} A_{ik}} \tag{1}$$

In Equation (1), P_{ij} represents the percentage of total land area that transitioned from category i to category j between time T1 (baseline year) and T2 (end year), where A_{ij} denotes the area converted from initial land class i to final class j, and n indicates the total number of land categories (n=11 in this study).

Using the Raster Calculator tool in ArcGIS Pro 3.0, we conducted pixel-by-pixel comparisons of NLCD data from 2011 to 2021 to generate land-use change rasters. The Tabulate Area tool was then employed to quantify the areal transitions between land categories, enabling the construction of transition matrices for all 254 county-level units. Special emphasis was placed on analyzing both the magnitude and spatial patterns of green space conversion to built-up areas.

2.2.2 Urban Expansion Pattern Analysis

To quantitatively characterize urban spatial expansion processes, this study employs the Landscape Expansion Index (LEI) to analyze urban built-up land expansion patterns. As a landscape ecology-based metric, LEI effectively discriminates three primary urban expansion modes: enclave, infill, and sprawl. The index calculation relies on spatial relationships between urban expansion patches and existing built-up areas, determining expansion types by quantifying the proportional contact area between new patches and established urban zones [4]. The LEI is computed as follows:

$$LEI = \frac{A_o}{A_o + A_v} \times 100 \tag{2}$$

In Equation (2), (A_o) represents the contact area between expansion patches and existing built-up areas, while (A_v) denotes the contact area between expansion patches and undeveloped areas. Based on LEI values, urban expansion types can be classified into three categories:

Enclave Expansion (LEI < 50%): Characterized by minimal contact with existing built-up areas, typically occurring in isolated peripheral zones of cities.

Infill Expansion (LEI ≥ 50%): Features substantial contact with built-up areas, predominantly filling interstitial spaces within urban cores.

Urban Sprawl (LEI ≈ 50%): Exhibits balanced contact with both built-up and undeveloped areas, usually manifesting as contiguous outward growth at urban fringes.

The LEI enables quantitative identification of expansion patterns across Texas cities (Figure 3), facilitating subsequent analysis of their relationships with demographic, economic, and environmental changes. This methodology establishes a scientific foundation for quantitative urban expansion research, advancing understanding of spatial heterogeneity in urban growth and its multidimensional impacts.

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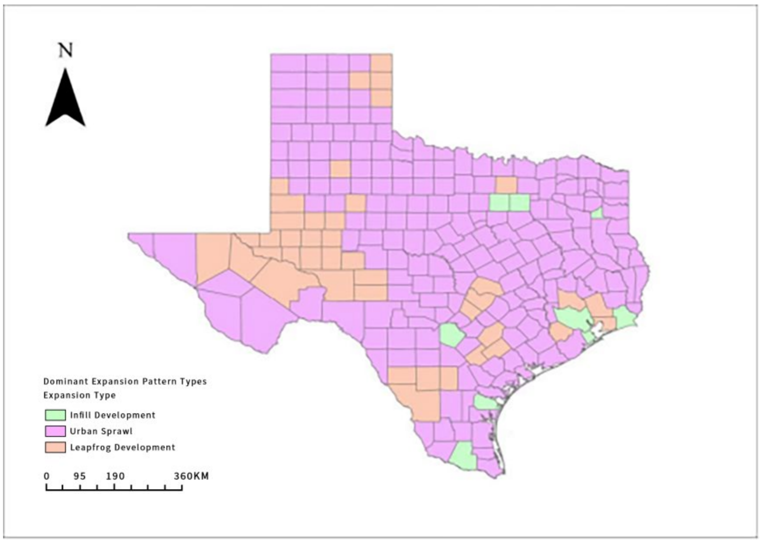

Figure 3: Spatial distribution of urban expansion patterns in Texas

2.2.3 Analysis of Economy-space Synergy

To evaluate the linear relationship between infill development patterns (Infill) and GDP change (ΔGDP), this study employs Pearson correlation analysis. The Pearson correlation coefficient is a statistical measure that quantifies the linear association between two variables, ranging from -1 to 1. A positive value indicates a positive correlation, while a negative value signifies an inverse relationship, with the absolute value reflecting the strength of the correlation [14]. By calculating the Pearson correlation coefficient between Infill and ΔGDP, this study quantitatively assesses the contribution of infill expansion to economic growth. The formula is as follows:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{3}$$

In Equation (3), X_i and Y_i represent the observed values of Infill and ΔGDP, respectively, while $\bar{X}$ and $\bar{Y}$denote their mean values.

2.2.4 Analysis of Environmental Conflicts

To assess the nonlinear relationship between urban sprawl patterns (Sprawl) and green space changes (ΔGreen), this study employs Spearman's rank correlation coefficient for analysis. As a nonparametric statistical method, Spearman correlation is particularly suitable for evaluating monotonic relationships between variables, especially when data violate normality assumptions or exhibit nonlinear associations[15]. By computing the Spearman correlation coefficient between Sprawl and ΔGreen, this approach can reveal the potential impacts of sprawling expansion on green space dynamics. The calculation formula is as follows:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{4}$$

In Equation (4),d_i denotes the rank difference between Sprawl and ΔGreen, whilen represents the sample size.

Population Association Model

To examine the effects of enclave expansion (Enclave) and urban sprawl (Sprawl) on population change (ΔPop), this study employs a multiple linear regression model. As a statistical approach, multiple linear regression evaluates the linear influence of multiple independent variables on a single dependent variable [18]. In the specified model, ΔPop serves as the dependent variable, while Enclave and Sprawl function as independent variables. Regression coefficients are estimated using ordinary least squares (OLS), with the model expressed as follows:

$$\Delta Pop = \beta_0 + \beta_1 \cdot Enclave + \beta_2 \cdot Sprawl + \epsilon \tag{5}$$

In Equation (5), β_0 represents the intercept term,$\beta_1$and β_2 denote the regression coefficients for Enclave and Sprawl respectively, while ϵ signifies the random error term.

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3. Results and Analysis

3.1 Land Transition Matrix

Analysis of the 2001-2021 land transition matrix (Table 1) reveals core characteristics of urban expansion in Texas. The built-up area increased from 18,618 km² in 2001 to 24,957 km² in 2021, with a net growth of 6,339 km². This expansion primarily resulted from conversion of green spaces (4,085 km², 64.5% of new built-up area) and farmland (506 km², 8.0%). Notably, the built-up area exhibited a 99.9% retention rate (18,617 km² unchanged), indicating exceptional stability of urbanized zones[16].

Table 1 Land use transition matrix of Texas (2001-2021).

		2021(T_2)							
	Land Use Type	Others	Green Space	Farmland	Desert	Water Body	Wetland	Built-up Area	Total
2001 (T_1)	Others	14872	0	0	0	0	0	1461	16333
	Green Space	1672	520150	7225	618	756	487	4085	534993
	Farmland	182	3237	75824	85	51	13	506	79898
	Desert	52	135	3	1645	253	102	116	2306
	Water Body	6	170	27	52	6981	319	16	7572
	Wetland	48	85	17	28	401	25751	156	26486
	Built-up Area	0	1	0	0	0	0	18617	18618
	Total	16832	523778	83097	2429	8443	26671	24957	686207

3.2 Economy-space Synergy of Expansion Patterns

Pearson correlation analysis demonstrates a statistically significant positive correlation between infill development (Infill) and GDP change (ΔGDP) ($r = 0.29$, $p < 0.001$), thereby confirming Hypothesis H1 (Figure 4).

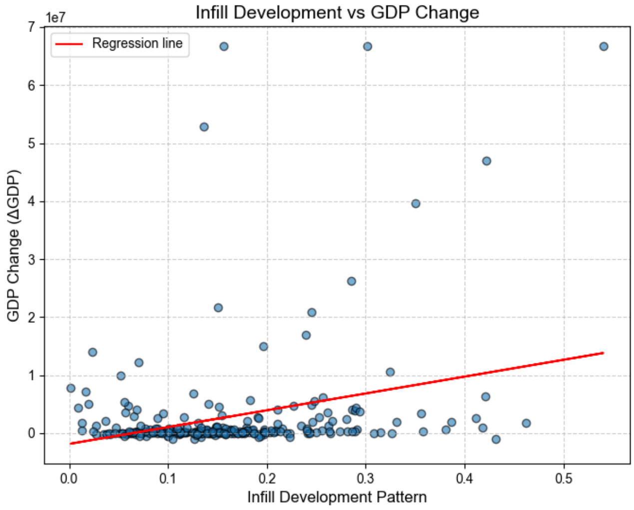

Figure 4: Analysis of infill development patterns and GDP change

These findings align with the core postulates of compact city theory [6], demonstrating that high-density development significantly stimulates economic growth through agglomeration effects and enhanced land-use efficiency. Specifically, infill development optimizes the utilization of interstitial spaces within existing built-up areas, thereby increasing GDP output per unit of land.

3.3 Environmental Conflicts of Expansion Patterns

Spearman's rank correlation analysis reveals a strong negative association between urban sprawl (Sprawl) and green space loss (ΔGreen) ($\rho = -0.69$, $p < 0.001$), confirming Hypothesis H2 (Figure 5). This result indicates that sprawl development patterns exert significant impacts on green space reduction, with particularly pronounced effects in low-density expansion areas where green space depletion is most severe.

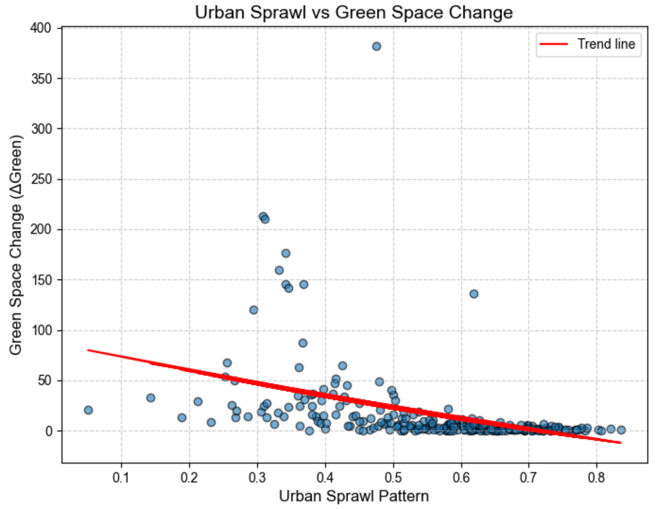

Figure 5: Analysis of urban sprawl patterns and green space change

Spatial Heterogeneity Analysis reveals distinct patterns in the green space loss-sprawl relationship: Areas with pronounced sprawl development exhibit particularly severe green space reduction. For instance, in Houston's suburban Harris County, each 0.1 increase in the Sprawl index corresponds to a 2.3 km² decrease in green space ($\beta = -2.3$, $p = 0.003$). These results strongly corroborate Forman's landscape ecology theory[7], confirming that low-density expansion threatens ecological security through habitat fragmentation and corridor disruption.

Policy Intervention Effectiveness is evidenced in counties implementing Urban Growth Boundaries (UGBs), such as Williamson County, where both sprawl indices and green space loss rates show significant reduction. This demonstrates that well-designed policy interventions can effectively mitigate sprawl-induced pressures on green infrastructure systems.

3.4 Population Dynamics of Expansion Patterns

Multiple regression analysis confirms that both enclave ($\beta = -4.23\times10^5$, $p < 0.001$) and sprawl ($\beta = -6.10\times10^5$, $p < 0.001$) expansion patterns significantly suppress population growth, thereby validating Hypothesis H3 (Figure 6).

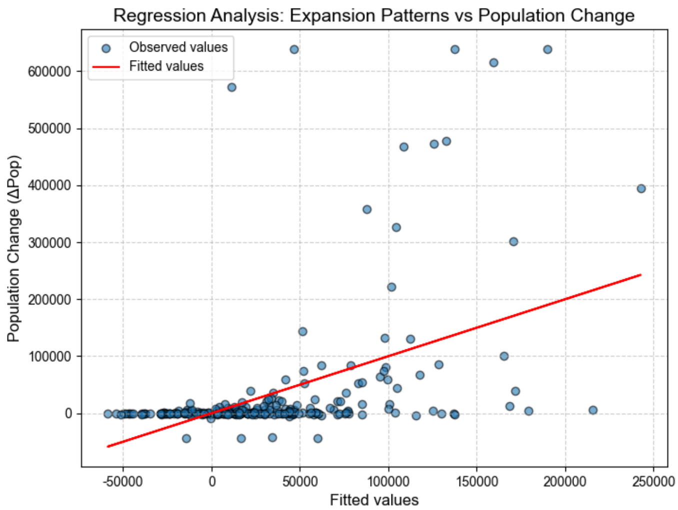

Figure 6: Regression analysis of urban expansion patterns and population change

Mechanistic Analysis reveals that enclave expansion substantially diminishes residential attractiveness by increasing commuting distances and reducing access to public services, while sprawl development further suppresses population agglomeration through inefficient infrastructure investment in low-density areas.

4. Discussion

4.1 Economy-Space Synergy Mechanism

The significant positive correlation between infill development and GDP change ($r = 0.29$, $p < 0.001$) substantiates the central thesis of compact city theory[6]. This relationship demonstrates that high-density development enhances land-use efficiency through agglomeration economies. However, the moderate correlation strength ($r = 0.29$) suggests potential constraints from existing stock renewal costs. Future theoretical frameworks should incorporate institutional economics perspectives to develop dynamic cost-benefit models that reconcile policy incentives with market constraints[7][20].

4.2 Ecological Resilience Paradox and Threshold Effects

The strong negative association between urban sprawl and green space loss (Spearman's $\rho = -0.69$, $p < 0.001$) validates Forman's landscape fragmentation theory[7]. These findings indicate that low-density expansion critically compromises ecosystem connectivity and resilience through habitat segmentation and ecological corridor disruption. The results underscore the necessity of incorporating spatial heterogeneity adjustment mechanisms in policy design to achieve balanced ecological preservation and development needs.

4.3 Dynamic Mechanisms of Population Redistribution

The multiple regression model demonstrates that both enclave ($\beta = -4.23\times10^5$, $p < 0.001$) and sprawl ($\beta = -6.10\times10^5$, $p < 0.001$) expansion patterns significantly suppress population growth, with the model explaining 21.8% of variance ($R^2 = 0.218$). Subsequent studies will incorporate additional control variables to enhance precision. These findings align with Alonso's commuting cost model[19], confirming that low-density development reduces residential attractiveness by increasing commuting costs and diminishing access to public services. Future theoretical frameworks should integrate behavioral geography to examine heterogeneous resident preferences regarding commuting costs[21].

5. Conclusions

This study, through an empirical analysis of 254 cities in Texas, reveals the multidimensional effects of urban expansion patterns: infill development drives GDP growth ($r = 0.29, n=254$) via agglomeration economies, yet its benefits are constrained by the costs of existing-area redevelopment; urban sprawl leads to green space loss ($\rho = -0.69, n=254$) and forms a negative feedback loop with population decentralization ($\beta = -6.10 \times 10^5, n=254$). Policymaking should adopt differentiated strategies—such as delineating adjustable ecological redlines in sensitive zones and constructing mixed-use, job-housing balanced communities in leapfrog developments. Future research should integrate multi-source heterogeneous data to develop an "economic-ecological-social" comprehensive assessment model, providing scientific support for climate-adaptive urban planning.

6. Research Limitations and Future Directions

While this study systematically demonstrates the multidimensional effects of urban expansion patterns in Texas, several limitations should be acknowledged. First, the temporal coverage (2011–2021) and spatial resolution (30 m) of the data may constrain the detection of long-term trends and micro-scale morphological variations, potentially leading to an underestimation of cumulative effects and local heterogeneity in expansion patterns. Second, the model does not fully incorporate external factors such as policy interventions (e.g., urban growth boundaries) and natural hazards (e.g., flood risks), which may affect the comprehensiveness of the conclusions. Additionally, the focus on Texas—a region characterized by an energy-dominated industrial structure and low-density urban form—may limit the generalizability of the findings to high-density or policy-driven regions.

Future research could integrate high-resolution remote sensing data with dynamic modeling approaches to extend the study period and simulate nonlinear evolutionary pathways of urban

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expansion. Comparative studies across regions (e.g., other U.S. states or international cases) could further elucidate the spatial heterogeneity of expansion effects. Moreover, incorporating climate change and social equity dimensions to develop a comprehensive "sustainability-resilience-equity" assessment framework would provide more universal theoretical support for global urbanization processes.

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