

Understanding built-up land supply-demand coordination in China: A local and tele-coupling perspective

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Abstract: Built-up land demand in one region is increasingly met by land supplied elsewhere, forming a production–consumption system that couples local and distant places. Understanding this pattern is crucial for optimizing land resource allocation, alleviating supply–demand mismatches, and addressing regional inequality. Based on the Environmentally Extended Multi-Regional Input-Output (EE-MRIO) model and the Local and Tele-Coupling Coordination Degree (LTCCD) model, this study analyzes the local and tele-coupling patterns of built-up land supply and demand across China. It further identifies the underlying driving factors using the HistGradientBoosting (HGB) machine learning method. The results show that, from 2012 to 2020, the total supply and demand of built-up land in China continued to expand. The supply structure shifted from being dominated by local supply to being dominated by telecoupled supply, whose share increased from 33.8% to 55.1%. The LTCCD of built-up land supply and demand increased overall, albeit with fluctuations. Spatially, it exhibited a clear east–west gradient, with higher values in the east and lower values in the west. High-value areas gradually expanded from coastal to inland regions. Improvements in LTCCD depended on mutually compatible combinations of mechanisms spanning demand formation on the consumption side, supply response on the production side, telecoupling transmission, and institutional allocation. The findings provide empirical support for consumption-based land governance and interregional coordination, and for shifting land allocation from incremental expansion toward stock optimization and the human–land linkage mechanism.

Keywords: Built-up land; Regional coordination; Local and tele-coupling; China

Introduction

Built-up land, as the fundamental spatial instrument for socioeconomic activities, accounts for only 3% of the world's land area while supporting over half of the global population and approximately 80% of economic output (Massaro et al., 2023; Fang et al., 2017). Contemporary economic systems rely heavily on finite spatial resources (Wang et al., 2024b). The increasing concentration of production and population activities, coupled with the finite nature of land supply, has made built-up land a critical and sensitive resource for regional competitiveness, environmental protection, and sustainable land management (Zheng et al., 2023; Mao & Jiao, 2024). However, with the continuous deepening regional division of labor, built-up land is not merely a spatial carrier serving local development, but is also embedded into larger-scale supply-demand relationships through cross-regional trade and supply systems (Guo et al., 2020; Song et al., 2025). Despite the fact that built-up land is physically developed in specific regions, its final service recipients are often located in other regions (Chuai et al., 2021). Consequently, the development benefits and physical land use are spatially separated. This spatial separation challenges land management approaches confined to individual administrative regions. Against this backdrop, it is imperative to clarify how the built-up land supply and demand system is reshaped at the local-remote scale, and what spatial patterns and evolutionary characteristics it presents.

Traditional studies of built-up land mainly focus on human-land relationships at the local scale (Zhao et al., 2025b; Zhang et al., 2020). They underscored the supply-demand equilibrium and intensive utilization within a specific region. These studies tended to view cities or specific administrative units as relatively independent systems. Based on local population growth and economic trends, they employed models such as CA, PLUS, or neural networks to make unidimensional predictions of built-up land demand or to conduct carrying capacity assessments (Chen et al., 2020; Wang et al., 2022; Xu et al., 2022). Such studies implicitly assume that local demand is primarily met by local supply, playing a significant role in supporting micro-scale land management and scenario simulations.

However, the hypothesis cannot adequately explain the structural impacts of cross-regional factor flows and industrial relocations on local land-use systems, as regional economic linkages continue to tighten (Fu et al., 2023). If we continue to measure the built-up land supply and demand using only the physical scale from a local perspective, the true land use pressure on different regions within the macro-economic system is difficult to identify. Moreover, it is difficult to uncover the structural imbalances as well as their subsequent evolution resulting from local and remote supply and demand shifts.

The EE-MRIO model can effectively track resource flows in cross-regional production and trade, providing a foundation for quantifying resource occupation and supply relationships among different regions (Chen et al., 2015; Wang & Wang, 2023). However, current studies rarely incorporate local entities and remote trade supply into a unified analytical perspective, lacking attempts to measure the effects of both factors on regional coordination within a closed-loop system. In addition, they focus on “flow” accounting, which makes it hard to reveal the imbalances in cross-regional supply and demand, underlying pressures, and dynamic changes stemming from systemic structures (Qi et al., 2025). The telecoupling framework proposed by Liu et al. (2013) underscores the interactions of socioeconomic and environmental processes across distant systems, offering a new perspective in comprehending cross-regional flows of elements. Built-up land supply and demand at the local-remote scale form a complex coupled system. Relationships between different regions transcend simple summation; instead, they are mutually constrained through economic ties and spatial connections (Liu, 2023). Such coupling relationships may result in localized shortages or surpluses, thereby influencing the overall stability and coordination of the regional system. Therefore, quantifying the extent of coordination between land supply and demand and identifying the matching status becomes necessary. Nevertheless, a mere description of the state of coordination is inadequate for guiding the optimal allocation of land resources. It is necessary to identify the key drivers influencing the evolution of the pattern to understand the formation mechanism behind supply-demand coordination. Previous studies frequently employed

linear regression models (e.g., OLS or GWR) to examine the influencing factors under the supposition of a simple linear relationship between independent and dependent variables (Doan et al., 2025; Tang et al., 2025; Wang et al., 2025). However, such approaches fail to capture the potential nonlinear effects inherent in the supply-demand local and tele-coupling process which will lead to a biased understanding of the mechanisms underlying the coordination and imbalance of inter-regional built-up land supply and demand.

Since the Reform and Opening-up, China has experienced the world's most extensive and rapid urbanization process with the issue of land-population mismatch becoming increasingly acute (Li et al., 2020). In the face of competing pressures imposed by constrained land resources and the rigid demands of economic development (Chen et al., 2024), China's built-up land supply and demand dynamics exhibit a pronounced imbalance. Eastern coastal regions with high population density and industrial concentration face a shortage of built-up land quotas (Zhuang et al., 2023; Zhou et al., 2020). Conversely, some northeastern and less-developed regions are characterized by idle land quotas and extensive land use, resulting in low resource-use efficiency (Fan et al., 2021; Wen et al., 2022). Quotas for newly added built-up land have been tightened year by year, while the demands from new-type urbanization, infrastructure improvement, and the development of emerging industries continue to require substantial spatial support (Fang & Tian, 2020). As a result, supply-demand tensions evolve continuously over time and space, exhibiting pronounced characteristics of mismatch (Xia et al., 2024; Yuan et al., 2023). The coexistence of localized scarcity and land idleness, together with the misalignment between demand and supply (Gao et al., 2022; Zhou et al., 2023), provides a typical case for analyzing the local and tele-coupling supply-demand patterns and coupling coordination of built-up land, and underscores the necessity of quantifying supply-demand matching conditions and uncovering influencing mechanisms from a cross-regional systems perspective.

Drawing on a consistent time series of MRIO tables and provincial built-up land data, this study measures built-up land use in each province from both production- and consumption-based perspectives. It develops a LTCCD model

that explicitly accounts for interregional flows to quantify the overall coordination of provincial built-up land supply and demand. It further employs the HGB–SHAP approach to construct a nonlinear attribution model and identify the key factors affecting supply–demand coordination. The main contribution of this study is to examine local and tele-coupled built-up land supply and demand from a unified cross-regional systems perspective and to establish an integrated “flow–state–driver” analytical framework. This framework enables the systematic quantification of the evolution of supply–demand coordination and the effects of multiple factors, providing a scientific basis for sustainable land-resource management and cross-regional coordination.

Methods and data

Research framework

Fig. 1 shows the research framework. First, this study introduces the telecoupling framework. Since its inception, the framework has been applied extensively in the field of environmental sustainability research (Hull & Liu, 2018; Cotta et al., 2022). As an extension of the human-nature coupling system, it enables the capture of effects from long-distance, cross-regional flows of elements (Liu et al., 2015; Chen et al., 2023b). On this theoretical foundation, the study develops an integrated “flow-state-driver” analytical framework. Leveraging MRIO data, land conveyance data, and yearbook statistical data, it reveals the dynamic evolution characteristics and driving factors of provincial built-up land LTCCD in China. Specifically, this study first constructs a consistent annual time series of MRIO tables and then estimates provincial built-up land demand using an EE-MRIO model, thereby revealing provincial-level mismatches between built-up land supply and demand. In this study, the built-up land used to support production activities within a region is defined as built-up land supply, whereas the built-up land induced by the region’s consumption activities is defined as built-up land demand. Second, the LTCCD model is employed to quantify the coupling coordination degree between provincial built-up land supply and demand, thereby exposing spatial

disparities and developmental inequalities in regional built-up land supply-demand relationships. Third, the study applies the HGB machine learning model together with SHAP analysis to identify key influencing factors on coordination degree. Finally, based on the salient research findings, practical and feasible policy recommendations are proposed.

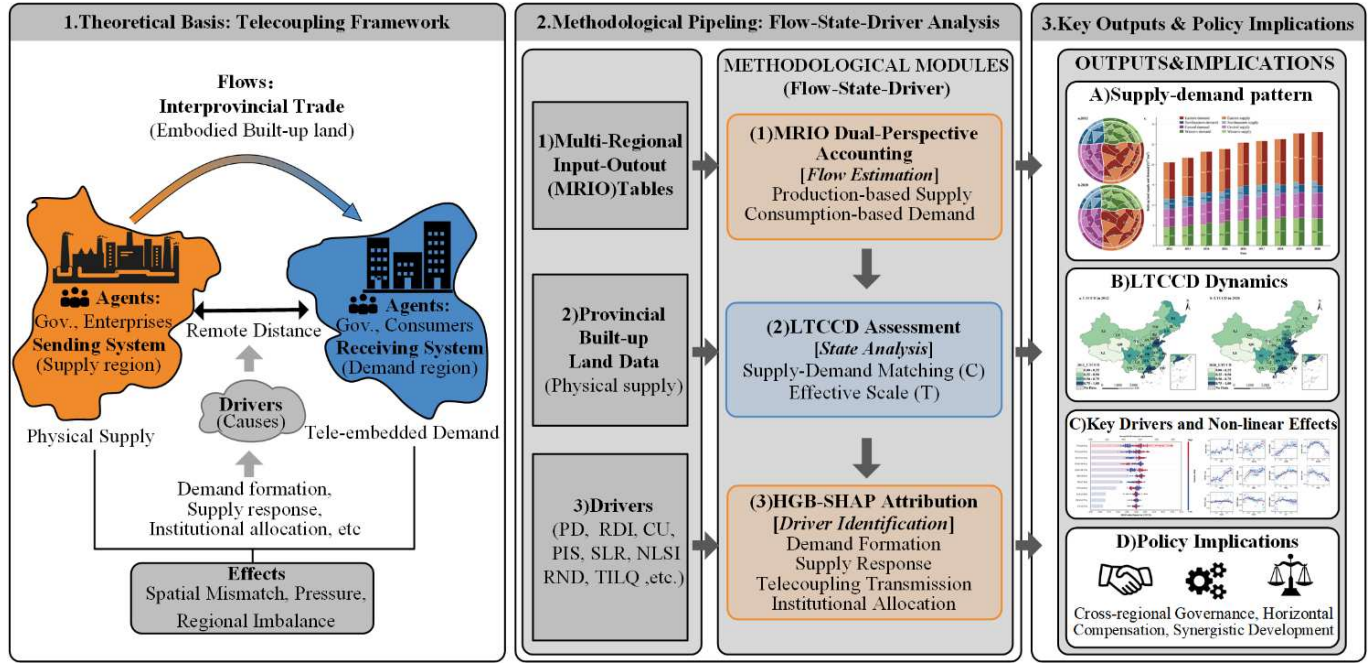


Fig. 1. Research framework.

Estimation of supply and demand for built-up land

Because China's provincial MRIO tables are not released annually, this study uses the CEADs provincial MRIO tables for 2012, 2015, 2017, 2018, and 2020 as benchmarks (Zheng et al., 2021; Li et al., 2026). For a missing target year located between two adjacent benchmark years, t_L and t_R , the two bounding MRIO tables are geometrically interpolated using the corresponding temporal weights, w_L and w_R . Provincial GDP, sectoral value added, final demand, and other target-year statistics are then used as control totals to determine the account scales (Wang et al., 2017; Ye et al., 2023). Non-negative transaction blocks are then rebalanced using the RAS procedure, whereas accounts containing negative entries, such as changes in inventories and the error item (ERR), are treated using a

modified GRAS procedure (Lenzen et al., 2007; Junius et al., 2003).

$$w_L = \frac{t_R - t}{t_R - t_L} \quad (1)$$

$$w_R = 1 - w_L \quad (2)$$

In this study, built-up land occupation on the production side and built-up land footprints on the consumption side are defined as the “supply” and “demand” of built-up land, respectively. To quantify built-up land demand in each province, built-up land intensity is incorporated into the multi-regional input–output (MRIO) model as an environmental extension. The Leontief inverse is then used to trace and quantify built-up land consumption across regions.

The core of input-output analysis lies in constructing an interregional, intersectoral technical coefficient matrix, which makes it possible to quantify how a unit change in final demand translates into changes in output. For sector i in region r , the technical coefficient linking it to sector j in region s , denoted a_{ij}^{rs} , is defined as:

$$a_{ij}^{rs} = \frac{z_{ij}^{rs}}{x_j^s} \quad (3)$$

where z_{ij}^{rs} denotes the intermediate input supplied by sector i in region r to sector j in region s ; x_j^s denotes the total output of sector j in region s .

Therefore, the interregional and intersectoral input-output relationships can be expressed by the following balance equation:

$$x_i^r = \sum_{s=1}^m \sum_{j=1}^n a_{ij}^{rs} x_j^s + \sum_{s=1}^m y_i^{rs} \quad (4)$$

where x_i^r denotes the total output of sector i in region r ; y_i^{rs} denotes the final demand in region s for the output of sector i produced in region r . Extending Eq. (4) to all regions and all sectors yields the matrix form:

$$\mathbf{X} = \mathbf{AX} + \mathbf{Y} \quad (5)$$

where $\mathbf{X}$ is the column vector stacking x_i^r , represents the total output for each region and each sector; $\mathbf{A}$ is the technical coefficient matrix composed of a_{ij}^{rs} , capturing the direct intermediate input required per unit of output; $\mathbf{Y}$ is the final-demand matrix composed of y_i^{rs} , represents the final demand for goods and services by each sector in

each region.

By solving the above system, the total built-up land requirements induced by final demand can be expressed as:

$$\mathbf{B} = \mathbf{L}(\mathbf{I} - \mathbf{A})^{-1} \mathbf{Y} \quad (6)$$

where $\mathbf{B}$ is the matrix composed of b_{ij} , representing the total built-up land requirements—both direct and indirect—for final demand across various regions; $\mathbf{L}$ is the diagonal matrix of built-up land use intensity for each region-sector, with each diagonal element calculated by dividing the built-up land occupation of a sector in a given region by the total output of that sector in the same region.

Therefore, the built-up land supply in region i can be represented as S_i , and the demand can be represented as D_i :

$$S_i = \sum_{j=1}^n b_{ij} \quad (7)$$

$$D_i = \sum_{j=1}^n b_{ji} \quad (8)$$

Measurement of the local and tele-coupling coordination degree

The LTCCD model, namely the local and tele-coupling coordination degree model, extends the traditional coupling coordination degree (CCD) model by incorporating telecoupling into the measurement framework. This enables a more comprehensive and refined assessment of spatial interactions and coordination between systems across both local and distant spaces (Tang et al., 2021; Xie et al., 2025). Unlike previous studies, this study applies distance weights to interprovincial built-up land flows and then calculates the coupling coordination degree based on effective supply and effective demand. The specific procedures are as follows:

$$w_{ij} = (1 + \frac{d_{ij}}{d_0})^{-\rho} \quad (9)$$

where w_{ij} is the distance weight, d_{ij} is the distance between provinces i and j , d_0 is the median of all off-diagonal interprovincial distances, and ρ is the distance-decay parameter, which is set to 1 in this study.

$$S_{i,t}^e = \sum_j^n w_{ij} b_{ij,t} \quad (10)$$

$$D_{ij}^e = \sum_{j=1}^n w_{ji} b_{ji,t} \quad (11)$$

where $S_{i,t}^e$ and $D_{i,t}^e$ denote the effective supply and effective demand of province i in year t , respectively.

To ensure data comparability, this study adopts the Max-Min normalization method to standardize the supply and demand data. Simultaneously, to prevent standardized data from being zero, a small offset was applied (Wang et al., 2024a).

$$U(x_{ij}) = \frac{(x_{ij} - \min x_{ij})(1 - \varepsilon)}{\max x_{ij} - \min x_{ij}} + \varepsilon \quad (12)$$

where $U(x_{ij})$ is the normalized value, x_{ij} is the original indicator value, $\max x_{ij}$ and $\min x_{ij}$ are the maximum and minimum values of x_{ij} , respectively, and ε is set to 0.001.

$$C_{i,t} = [1 - (U_{i,t}^S - U_{i,t}^D)^2] \times \frac{\min(U_{i,t}^S, U_{i,t}^D)}{\max(U_{i,t}^S, U_{i,t}^D)} \quad (13)$$

where $C_{i,t}$ denotes the supply–demand matching degree, and $U_{i,t}^S$ and $U_{i,t}^D$ are the standardized effective supply and effective demand, respectively. The closer $C_{i,t}$ is to 1, the better the match between effective supply and effective demand.

The effective supply–demand scale $T_{i,t}$ is measured as the mean of effective supply and effective demand:

$$T_{i,t} = \frac{U_{i,t}^S + U_{i,t}^D}{2} \quad (14)$$

The local and tele-coupling coordination degree of built-up land supply and demand is jointly determined by the supply–demand matching degree and the effective supply–demand scale:

$$LTCCD_{i,t} = \sqrt{C_{i,t} \times T_{i,t}} \quad (15)$$

Methods for influencing factors

To identify the most appropriate model for analyzing the influencing factors of LTCCD, this study compared four widely used machine learning models: RF, XGBoost, LightGBM, and HGB (Xie et al., 2025). Among these models, HGB achieved the highest predictive accuracy and was therefore selected as the primary model for the subsequent analysis of driving factors.

HGB is an efficient tree-based ensemble method that incorporates histogram-based acceleration into the gradient boosting decision tree (GBDT) framework. It first discretizes continuous features into bins and accumulates gradient statistics to construct histograms, allowing the best split thresholds to be identified at substantially lower computational cost than exact split-finding algorithms. Native handling of missing values, leaf-wise tree growth, and automatic early stopping further help control model complexity and reduce memory consumption, enabling HGB to balance training efficiency and predictive accuracy (Nhat-Duc & Van-Duc, 2023). This study selected 11 potential factors influencing the LTCCD of provincial built-up land supply and demand in China. Table 1 lists the data sources and descriptions of the variables used, while Table 2 presents their descriptive statistics.

Table 1. Data sources of the variables used in this study

Variables	Description	Unit	Data Sources
LTCCD	Local and tele-coupling coordination degree	Dimensionless	Input–output data
PD	Population density	persons/km ²	China Statistical Yearbook
RDI	Resident income level	CNY/person	National Bureau of Statistics of China
CU	Consumption structure upgrading	Dimensionless	National Bureau of Statistics of China
PIS	Productive investment	Dimensionless	China Statistical Yearbook on Investment in Fixed Assets
SLR	Stock land redevelopment ratio	Dimensionless	China Land Market Network
NLSI	Incremental land supply intensity	ha/10,000 km ²	China Land Market Network
TILQ	Tradable industry specialization	Dimensionless	China Statistical Yearbook
RND	Road network density	km/100 km ²	China Statistical Yearbook
ILSB	Industrial land supply bias	Dimensionless	China Land Market Network
CTS	Marketization of land supply	Dimensionless	China Land Market Network
LFD	Land finance dependence	Dimensionless	National Bureau of Statistics of China

Table 2. Descriptive statistics of the variables

Variables	N	Mean	SD	P50	P25	P75	Min	Max
LTCCD	270	0.50	0.19	0.48	0.39	0.60	0.08	0.95
PD	270	471.66	710.63	286.89	137.59	569.77	7.91	3949.21
RDI	270	22328.92	9578.16	19914.42	16169.15	24475.28	9768.00	60401.04
CU	270	0.41	0.03	0.41	0.39	0.44	0.33	0.49
PIS	270	0.57	0.10	0.59	0.53	0.64	0.29	0.73
SLR	270	0.34	0.13	0.32	0.24	0.42	0.10	0.70
NLSI	270	1002.52	923.98	784.01	446.68	1211.34	53.71	5978.14
TILQ	270	0.87	0.29	0.85	0.67	1.04	0.28	1.67
RND	270	95.67	50.78	92.26	55.48	133.99	9.14	219.42
ILSB	270	0.54	0.11	0.56	0.49	0.61	0.17	0.78
CTS	270	0.90	0.09	0.93	0.88	0.96	0.35	1.00
LFD	270	0.50	0.27	0.44	0.29	0.66	0.05	1.42

Given that the provincial panel exhibits both temporal dependence and regional clustering, we adopted an expanding-window walk-forward validation scheme. Specifically, observations from 2012–2014 were first used as the training set to predict 2015. The training window was then expanded annually by incorporating each newly observed year, with predictions generated sequentially through 2020, yielding a total of 180 out-of-sample predictions across temporal folds. The objective function at each stage is expressed as:

$$L^m = \sum_{i=1}^n \ell(y_i, \hat{y}_i^{m-1} + f_{m(x_i)}) + \Omega(f_m) \quad (16)$$

where y_i denotes the observed LTCCD value of the sample i , $\hat{y}_i^{m-1}$ is the predicted value after the first $m-1$ boosting iterations, $f_{m(x_i)}$ represents the incremental prediction generated by the m -th regression tree for sample i , $\ell(\cdot)$ is the loss function, and $\Omega(f_m)$ is the regularization term controlling model complexity.

The SHAP method introduced to improve the interpretability of the results can quantify the marginal contribution of each factor. The method is derived from cooperative game theory and uses Shapley values to quantitatively evaluate the influence of each feature. It provides a ranking of feature importance and reveals whether a feature contributes positively or negatively.

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [v(S \cup \{i\}) - v(S)] \quad (17)$$

where ϕ_i is the SHAP value of feature i ; N denotes the set of all features; S denotes a feature subset.

By employing SHAP, this study determined the relative importance of the factors and improved the interpretability of the results.

Study area and data sources

To empirically examine interprovincial built-up land supply and demand in China, we first constructed a continuous provincial multi-regional input–output (MRIO) dataset for 2012–2020 based on the CEADs MRIO database. The dataset records monetary flows of goods and services among 42 sectors across 31 provinces in mainland China, excluding Hong Kong, Macao, and Taiwan because of data unavailability. For regional comparison, the provinces were grouped into four regions (Eastern, Central, Western, and Northeastern); the province membership is provided in Supplementary Table S1. The 42 economic sectors were classified into different land-use categories (see Supplementary Table S2). Built-up land data were obtained from the China Urban Construction Statistical Yearbook.

The data used to analyze the drivers of LTCCD of built-up land supply and demand in China comprise indicators across four dimensions: demand formation, supply response, telecoupling transmission, and institutional allocation. Population density was calculated as the ratio of the year-end permanent resident population to the administrative area (Huang & Lin, 2025). Resident income level was measured by per capita disposable income (Wu & Zhang, 2012). Consumption structure upgrading was measured as the share of development- and enjoyment-oriented consumption in total household consumption expenditure (Qi et al., 2026). Productive investment was measured as the share of fixed-asset investment in productive sectors in total fixed-asset investment (Liu et al., 2019). The stock land redevelopment ratio was measured as the share of existing built-up land and new built-up land from the stock pool in the effective land supply area under the four land supply modes of agreement, tender, auction, and listing (Sun et al., 2026). Incremental land supply intensity was measured as the area of newly added built-up land supplied

divided by the administrative area (Jin et al., 2018). Tradable-industry specialization was measured using the location quotient (LQ), calculated as the ratio of the provincial employment share in mining and manufacturing to the corresponding national employment share (Pi & Wang, 2025; Daymard, 2025). Road network density was measured as total road mileage divided by the administrative area (Ji et al., 2025). Industrial land supply bias was measured as the share of industrial, mining, and warehousing land supply area in the total supply area of industrial, mining, and warehousing, commercial and service, and residential land during the same period under the four land supply modes of agreement, tender, auction, and listing (Cheng et al., 2024). Marketization of land supply methods was measured as the share of land supplied through tender, auction, and listing in the total land supply area (Xu et al., 2025). Land finance dependence was measured as the ratio of revenue from the transfer of state-owned land-use rights to local general public budget revenue (Cai et al., 2025).

Results

Built-up land supply–demand patterns from a local and tele-coupling perspective

From 2012 to 2020, built-up land demand in China continued to expand, while the supply structure gradually shifted from being dominated by local supply to being dominated by telecoupled supply. National built-up land demand increased from $20.58 \times 10^3 \text{ km}^2$ in 2012 to $28.01 \times 10^3 \text{ km}^2$ in 2020, representing a cumulative increase of 36.1% (Fig. 2a). Over the same period, telecoupled supply increased from $6.95 \times 10^3 \text{ km}^2$ to $15.43 \times 10^3 \text{ km}^2$, an increase of 122.1%, while its share of total demand rose from 33.8% to 55.1%. In contrast, local supply decreased from $13.63 \times 10^3 \text{ km}^2$ to $12.58 \times 10^3 \text{ km}^2$, with its share declining from 66.2% to 44.9%. Despite fluctuations in individual years, the share of telecoupled supply showed an overall upward trend and exceeded that of local supply by 2020.

In terms of land-use composition, demand growth was increasingly concentrated in industrial land and

transportation, logistics, and warehousing land. Industrial land remained the largest category of demand throughout the study period, with its share increasing slightly from 31.6% in 2012 to 32.0% in 2020 and remaining broadly stable overall (Fig. 2b). Transportation, logistics, and warehousing land experienced the most pronounced growth, with its share increasing from 25.7% to 30.8%. Together, these two land-use categories increased their combined share from 57.3% to 62.8%, accounting for the majority of demand growth. By contrast, the share of public utility land decreased from 8.6% to 5.5%, while that of public administration and public service land declined from 21.4% to 18.6%. The share of commercial and service land remained relatively stable at approximately 13%.

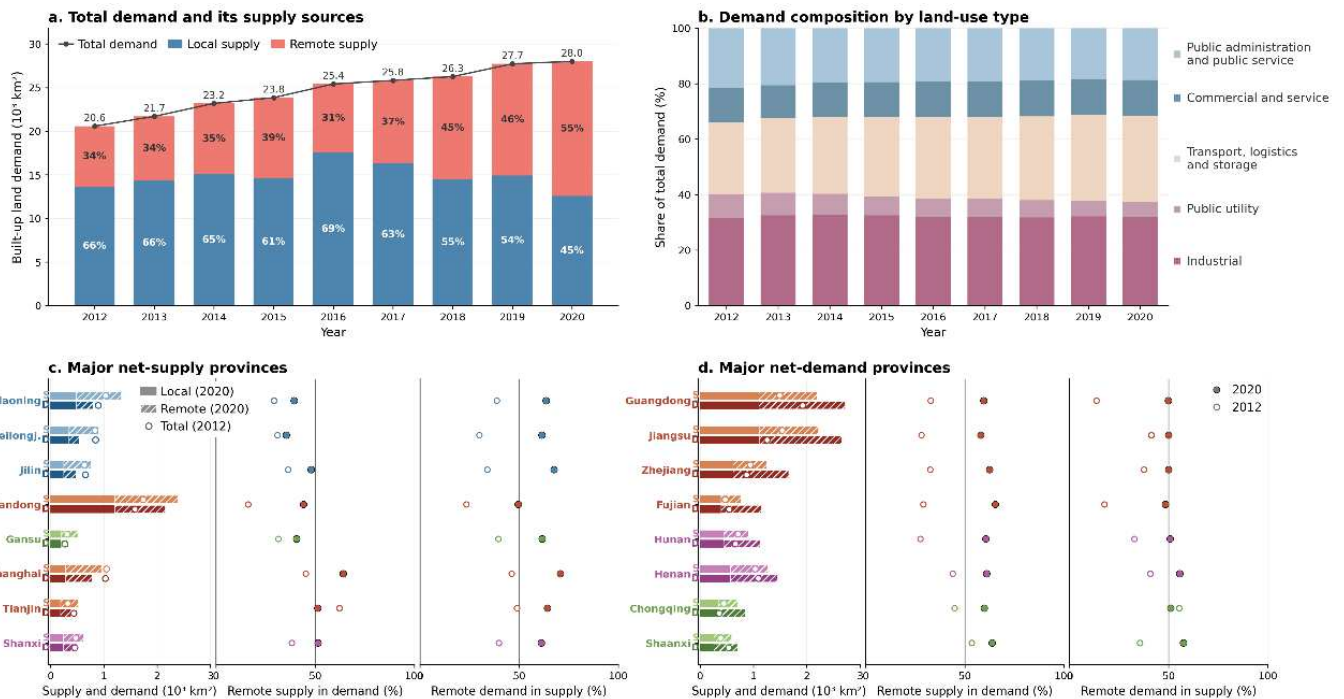


Fig. 2. Local and tele-coupled supply structure and interprovincial supply–demand differences of built-up land in China, 2012–2020. a National built-up land demand and its local and telecoupled supply sources; **b** Composition of built-up land demand by land-use type; **c** Major net-supplying provinces in 2020; **d** Major net-demanding provinces in 2020

At the regional scale, both built-up land supply and demand remained highly concentrated in eastern China, but demand grew faster than supply, resulting in a pronounced widening of the supply–demand gap. In 2012, built-up land supply and demand in eastern China were $9.01 \times 10^3 \text{ km}^2$ and $9.13 \times 10^3 \text{ km}^2$, respectively, and were broadly comparable in magnitude. By 2020, supply had increased to $12.12 \times 10^3 \text{ km}^2$, while demand had risen to $13.18 \times 10^3 \text{ km}^2$ (Fig. 3a–c). Over the same period, eastern China's share of national demand increased from 44.4% to 47.0%,

whereas its share of national supply declined slightly from 43.8% to 43.3%. Accordingly, net demand increased from $0.12 \times 10^3 \text{ km}^2$ to $1.05 \times 10^3 \text{ km}^2$. Although eastern China continued to have the largest supply of built-up land nationwide, the increase in supply was no longer sufficient to accommodate the expansion of demand, further widening the spatial mismatch between supply capacity and consumption demand. In sharp contrast, northeastern China gradually emerged as the country's most prominent net-supply region. Its built-up land supply increased from $2.49 \times 10^3 \text{ km}^2$ in 2012 to $2.99 \times 10^3 \text{ km}^2$ in 2020, while demand decreased from $2.39 \times 10^3 \text{ km}^2$ to $1.81 \times 10^3 \text{ km}^2$. Supply and demand remained relatively balanced in central and western China. Central China shifted from a net supply of approximately $0.31 \times 10^3 \text{ km}^2$ in 2012 to a net demand of approximately $0.15 \times 10^3 \text{ km}^2$ in 2020, as demand grew slightly faster than supply. Western China shifted from a net demand of approximately $0.30 \times 10^3 \text{ km}^2$ to a near balance between supply and demand. Overall, regional-scale imbalances were concentrated in the net demand of eastern China and the net supply of northeastern China, while the overall balance at the regional level partly masked the inequality of supply–demand relations within regions.

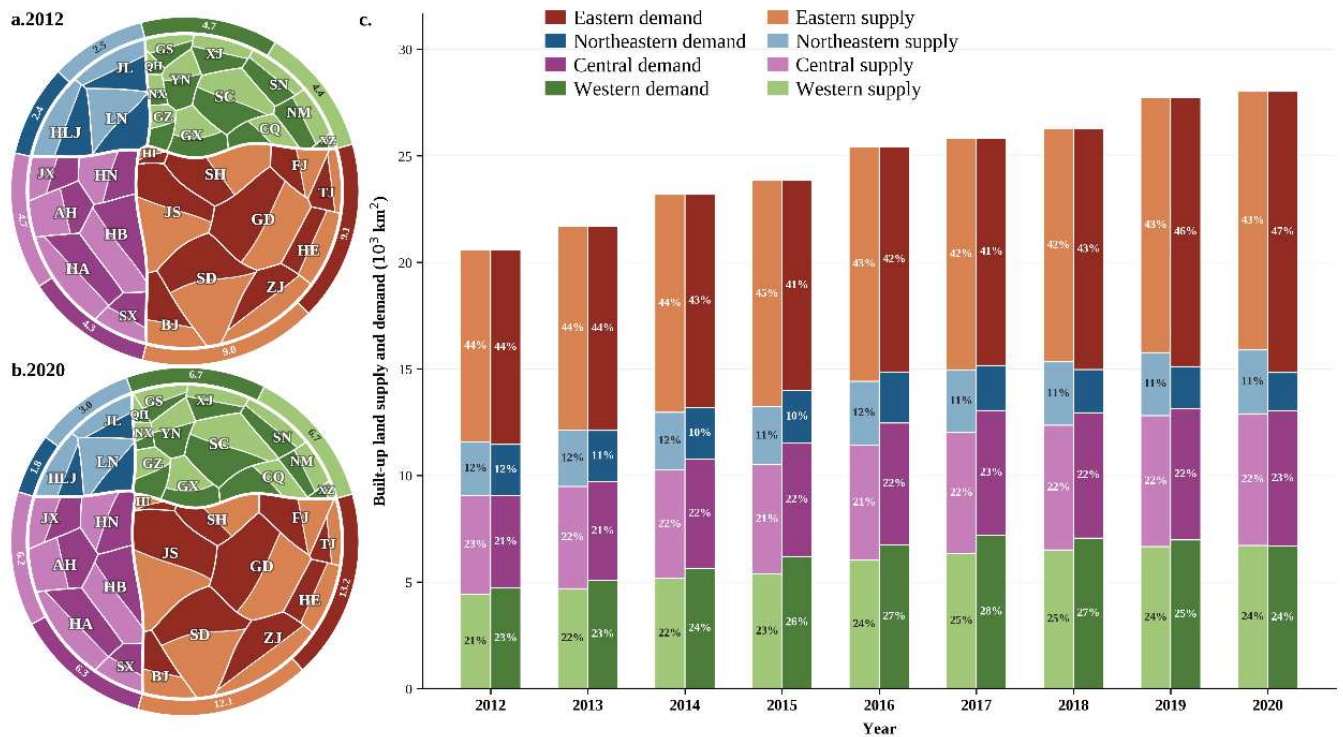


Fig. 3. Built-up land supply–demand patterns and changes in China, 2012–2020. a Regional distribution of

built-up land supply and demand in 2012; **b** Regional distribution of built-up land supply and demand in 2020; **c** Annual changes in built-up land supply and demand across Eastern, Central, Western, and Northeastern China from 2012 to 2020.

At the provincial scale, supply–demand imbalances were more pronounced. The major net-supplying provinces became increasingly concentrated in northeastern China, and the outward orientation of their supply strengthened markedly. In 2020, net supply reached 529, 363, and 288 km² in Liaoning, Heilongjiang, and Jilin, respectively, forming the most contiguous and most prominent net-supply cluster in the country (Fig. 2c). In all three provinces, more than 60% of built-up land supply was used to meet out-of-province demand, with the share reaching 67.6% in Jilin, indicating that a substantial proportion of built-up land supply in northeastern China was in fact serving economic activities outside the region. The major net-demanding provinces were concentrated in the eastern coastal region and in several population- and industry-agglomerated areas in central and western China, and generally exhibited a high dependence on telecoupled supply. In 2020, net demand reached 524, 427, 413, and 380 km² in Guangdong, Jiangsu, Zhejiang, and Fujian, respectively, making them the four provinces with the largest supply–demand gaps nationwide (Fig. 2d). In these provinces, telecoupled supply generally accounted for 58%–65% of total demand, meaning that more than half of their built-up land demand was borne by land resources outside the province. Jiangsu, Zhejiang, Hunan, and Chongqing were net-supplying provinces in 2012, but had all become net-demanding provinces by 2020, suggesting that demand expansion and increasing telecoupled inflows were continuously reshaping the provincial supply–demand pattern. Notably, while these net-demanding provinces relied heavily on built-up land from other provinces, they still maintained a certain level of telecoupled supply. Based on their respective industrial advantages, provinces assumed differentiated supply roles within the interprovincial division of labor, and interprovincial built-up land flows exhibited a pattern of bidirectional complementarity.

Overall, from 2012 to 2020, both built-up land supply and demand in China continued to expand, while the

supply structure shifted from local to telecoupled supply and supply–demand imbalances became increasingly pronounced at the provincial scale. The locations of built-up land supply and consumption became increasingly separated, gradually forming a spatial coupling pattern characterized by net-demand provinces along the eastern coast as major demand centers and net-supplying provinces in northeastern China and parts of central and western China as supporting hinterlands. Driven by their large final demand, the former externalized substantial built-up land occupation to other provinces through interprovincial production linkages. The latter, in turn, supported economic activities outside their own provinces through sustained local land inputs, with an increasingly outward-oriented supply structure. Accordingly, land-use statistics confined to administrative boundaries cannot fully capture the actual land demand of individual provinces. In addition to local land development, embodied interprovincial land flows should therefore be incorporated into land-use planning and coordination, providing a basis for differentiated land-use quota allocation and cross-regional coordination mechanisms.

Evolution of the local and tele-coupling coordination degree

The LTCCD of built-up land supply and demand in China exhibited an overall fluctuating upward trend, with the national mean increasing from 0.447 to 0.486. This evolution was broadly consistent with the concurrent deepening of regional industrial specialization and the enhanced capacity for cross-regional allocation of land resources, accompanied by improved spatial matching between built-up land supply and demand. However, by 2020, the national mean had still not exceeded 0.5 (Fig. 4c), and most provinces remained at relatively low levels of coordination, indicating that the supply–demand mismatch had not been substantially alleviated. As the telecoupling of built-up land flows intensified, the supply–demand relationship shifted from local balancing toward cross-regional coordination. While this shift enhanced spatial allocation capacity, it also entailed higher spatial transfer costs, thereby constraining further improvements in the coupling coordination degree.

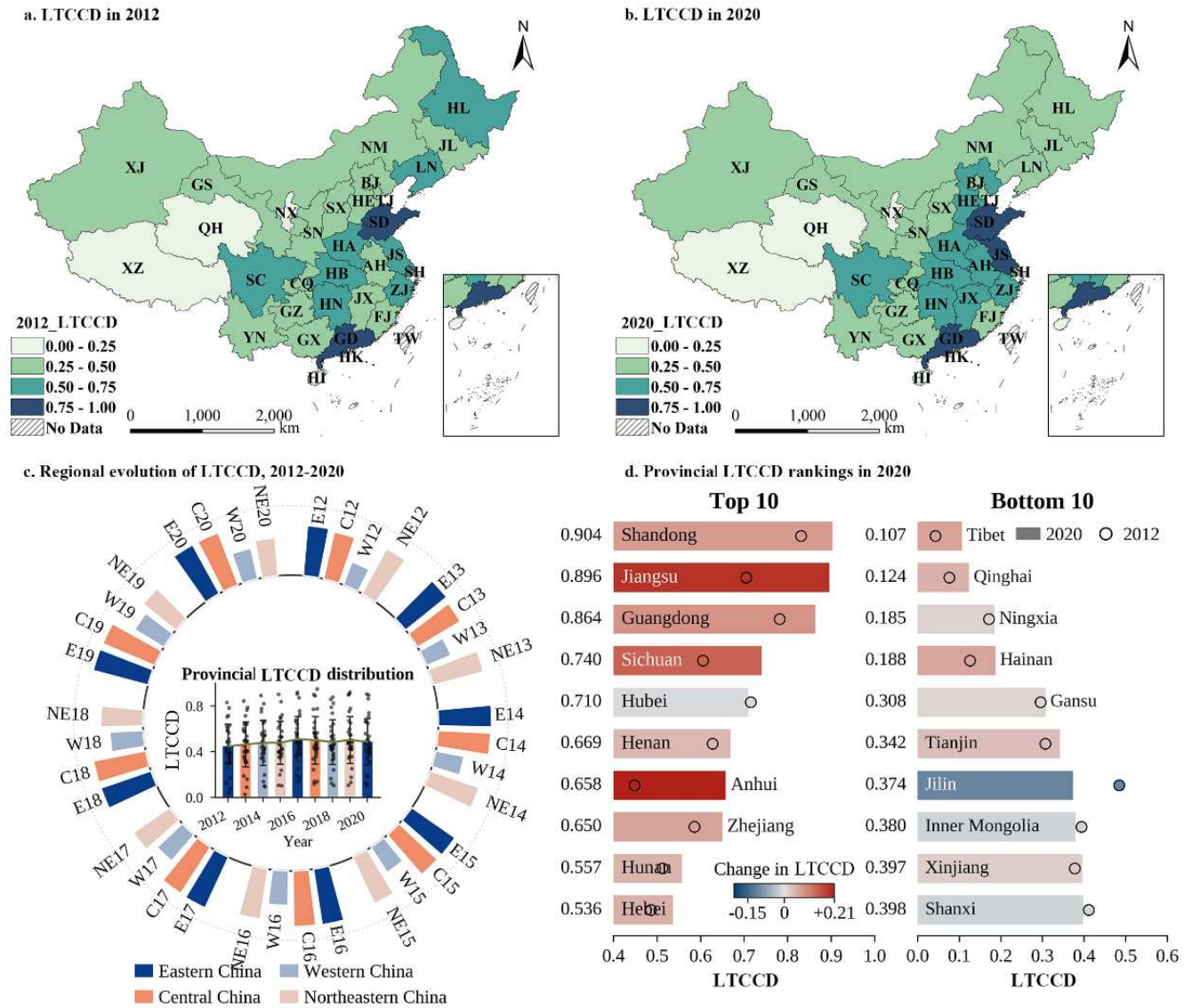


Fig. 4. Spatiotemporal evolution and regional disparities of provincial LTCCD in China, 2012–2020. **a** Spatial distribution of provincial LTCCD in 2012; **b** Spatial distribution of provincial LTCCD in 2020; **c** Regional evolution of LTCCD from 2012 to 2020, the inset shows the provincial distributions and national mean by year; **d** Provincial LTCCD rankings in 2020, showing the top and bottom ten provinces; bars indicate 2020 values, circles indicate 2012 values, and bar colours represent changes from 2012 to 2020.

Spatially, LTCCD exhibited a pronounced gradient pattern, with high-value areas progressively extending from coastal to inland regions. In 2012, high LTCCD values were concentrated in the eastern coastal and northeastern regions, with Shandong, Jiangsu, Guangdong, and Liaoning ranking among the most coordinated provinces nationwide (Fig. 4a). By 2020, high-value areas had extended into central China, with Anhui, Hunan, and Hubei successively reaching relatively high levels of coordination, forming a progressive coastal-to-inland expansion pattern (Fig. 4b). This evolution broadly coincided with the strengthening of regional economic linkages and ongoing

industrial spatial restructuring during the study period. Accordingly, inland provinces became increasingly capable of accommodating external demand and adjusting built-up land supply–demand relations. Although LTCCD in western China improved to some extent, its overall level remained relatively low. Tibet, Qinghai, Ningxia, and Xinjiang remained at low levels of coordination throughout the study period. Limited population agglomeration and weak industrial bases kept both supply and demand relatively small in these provinces, while their greater distances from major economic regions increased the costs of cross-regional built-up land flows, leaving many western provinces in peripheral positions within the supply–demand network. Notably, interprovincial disparities did not converge as the national mean increased. In 2020, Shandong ranked first with an LTCCD of 0.904, whereas Tibet ranked last at 0.107, yielding a range of 0.797 (Fig. 4d). The mean LTCCD of the top ten provinces was 0.718, compared with only 0.280 for the bottom ten, a difference of 0.438. These results indicate pronounced interprovincial differentiation in LTCCD.

In terms of its components, LTCCD is primarily determined by the degree of supply–demand matching (C) and the effective supply–demand scale (T). C reflects the degree of matching between effective supply and effective demand, whereas T represents the effective scale of supply and demand involved in cross-regional allocation. Accordingly, improvements in LTCCD can follow two pathways: improving supply–demand matching or expanding the effective supply–demand scale. The increases in Shandong and Jiangsu were driven mainly by T. During the study period, Shandong's LTCCD increased from 0.831 to 0.904, with T rising by 0.154 even as C declined by 0.021. Jiangsu's LTCCD increased from 0.705 to 0.896, with T rising by 0.359 while C declined by 0.008 (Fig. 5a–f). Thus, the improvements in both provinces were primarily attributable to increases in the effective supply–demand scale. Sichuan followed a similar T-driven pathway. Its T increased by 0.162, whereas C increased by only 0.050, raising LTCCD from 0.606 to 0.740. Anhui, by contrast, benefited from simultaneous improvements in C and T. Its C and T increased by 0.207 and 0.179, respectively, raising LTCCD from 0.448 to 0.658, the largest increase nationwide.

These results suggest that jointly improving supply–demand matching and the effective supply–demand scale provides a more effective pathway for achieving substantial gains in LTCCD. In contrast to the overall increase in the national mean, all three northeastern provinces experienced declines in LTCCD. From 2012 to 2020, LTCCD in Heilongjiang, Jilin, and Liaoning decreased by 0.153, 0.111, and 0.085, respectively, with their national rankings falling from 10th, 13th, and 9th to 21st, 25th, and 12th. In terms of their components, these declines were driven primarily by deterioration in supply–demand matching. C decreased by 0.247, 0.238, and 0.220 in Heilongjiang, Jilin, and Liaoning, respectively, whereas the corresponding declines in T were relatively modest, at 0.094, 0.051, and 0.014. The three northeastern provinces provided substantial built-up land supply through cross-regional allocation, supporting land demand in other regions at the expense of their own supply–demand matching. Cross-regional compensation mechanisms are therefore needed to provide reasonable compensation to provinces that undertake remote supply responsibilities and to balance regional interests in the allocation of built-up land.

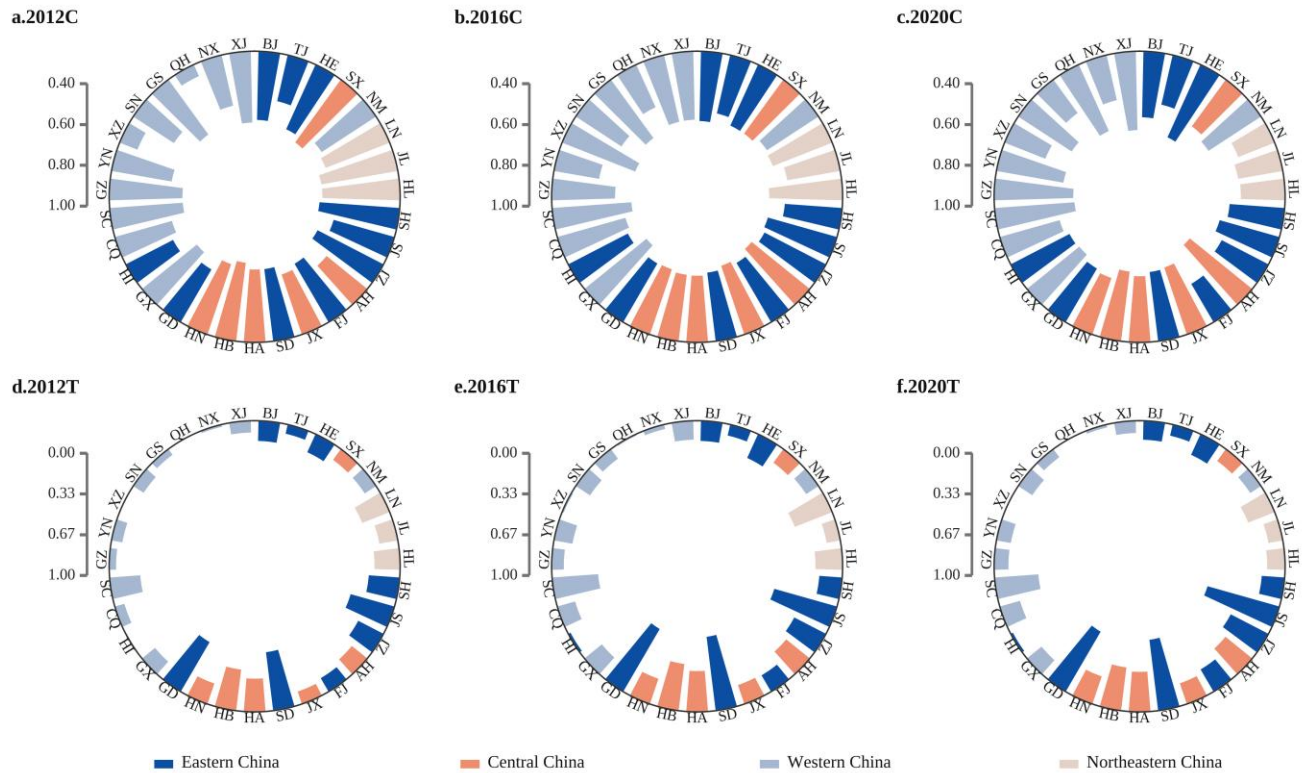


Fig. 5. Provincial distributions of coupling degree (C) and effective supply–demand level (T) across China, 2012–2020. a–c Provincial distributions of C in 2012, 2016, and 2020, respectively; **d–f** Provincial distributions of

T in 2012, 2016, and 2020, respectively.

Western provinces such as Qinghai and Tibet remained at low levels of coordination over the long term, primarily due to their limited effective supply–demand scale (T). During the study period, Qinghai's supply–demand matching degree (C) increased from 0.499 to 0.943, whereas T rose only from 0.012 to 0.016, leaving its LTCCD at only 0.124 and ranking 30th nationwide. In 2020, Tibet had a C value of 0.729, but its T was only 0.016, and it remained at the bottom of the national ranking. Xinjiang, Hainan, and Ningxia also had relatively high levels of supply–demand matching, with C values of 0.987, 0.894, and 0.747, respectively. However, their limited effective supply–demand scales kept LTCCD at low coordination levels over the long term. For such provinces, appropriately increasing built-up land development could leverage land resources to foster industrial and population agglomeration, promote the endogenous growth of T, and thereby improve LTCCD.

Influencing factors of the local and tele-coupling coordination degree

This study employed the HGB–SHAP approach to conduct a nonlinear attribution analysis of the factors influencing the LTCCD of built-up land supply and demand. Based on panel data for 30 Chinese provinces (excluding Tibet) from 2012 to 2020, the training and test sets were divided using a year-by-year forward-chaining scheme. The HGB model demonstrated strong explanatory power and stable performance, with an R^2 of 0.776, an MSE of 0.0079, an RMSE of 0.089, and an MAE of 0.067, indicating that the model can effectively capture the combined effects of these factors on the cross-regional coordination of built-up land supply and demand.

Fig. 6 presents the relative contributions and directions of effect of the factors influencing LTCCD. The color intensity of each point reflects the magnitude of its feature value, while the sign indicates whether the corresponding variable promotes ($SHAP > 0$) or inhibits ($SHAP < 0$) coupling coordination. The results show that Population Density (PD) is the most important factor influencing LTCCD, with a mean absolute SHAP value of 0.050 and a contribution share of 20.58%. Low PD values are predominantly associated with negative SHAP values, whereas

high values are associated with positive SHAP values. Tradable-industry specialization (TILQ) contributes 12.29% and exhibits an overall positive effect. Land Finance Dependence (LFD) and Industrial Land Supply Bias (ILSB) contribute 11.10% and 10.85%, respectively. The former shows an overall positive effect, whereas the effect of the latter shifts from positive to negative as its value increases. Road Network Density (RND) contributes 10.73% and shows an overall positive effect. Together, these five factors account for 65.55% of the total contribution and constitute the primary factors influencing LTCCD. Resident Income Level (RDI) and Productive Investment (PIS) contribute 9.63% and 7.80%, respectively, both showing overall positive effects. Market-oriented Land Conveyance (CTS) contributes 6.39% and exhibits an overall negative effect. Stock Land Redevelopment (SLR), New Land Supply Intensity (NLSI), and Consumption Upgrading (CU) contribute 3.79%, 3.69%, and 3.14%, respectively, indicating relatively limited effects. Among them, SLR shows a weak overall positive effect, whereas NLSI and CU show overall negative effects.

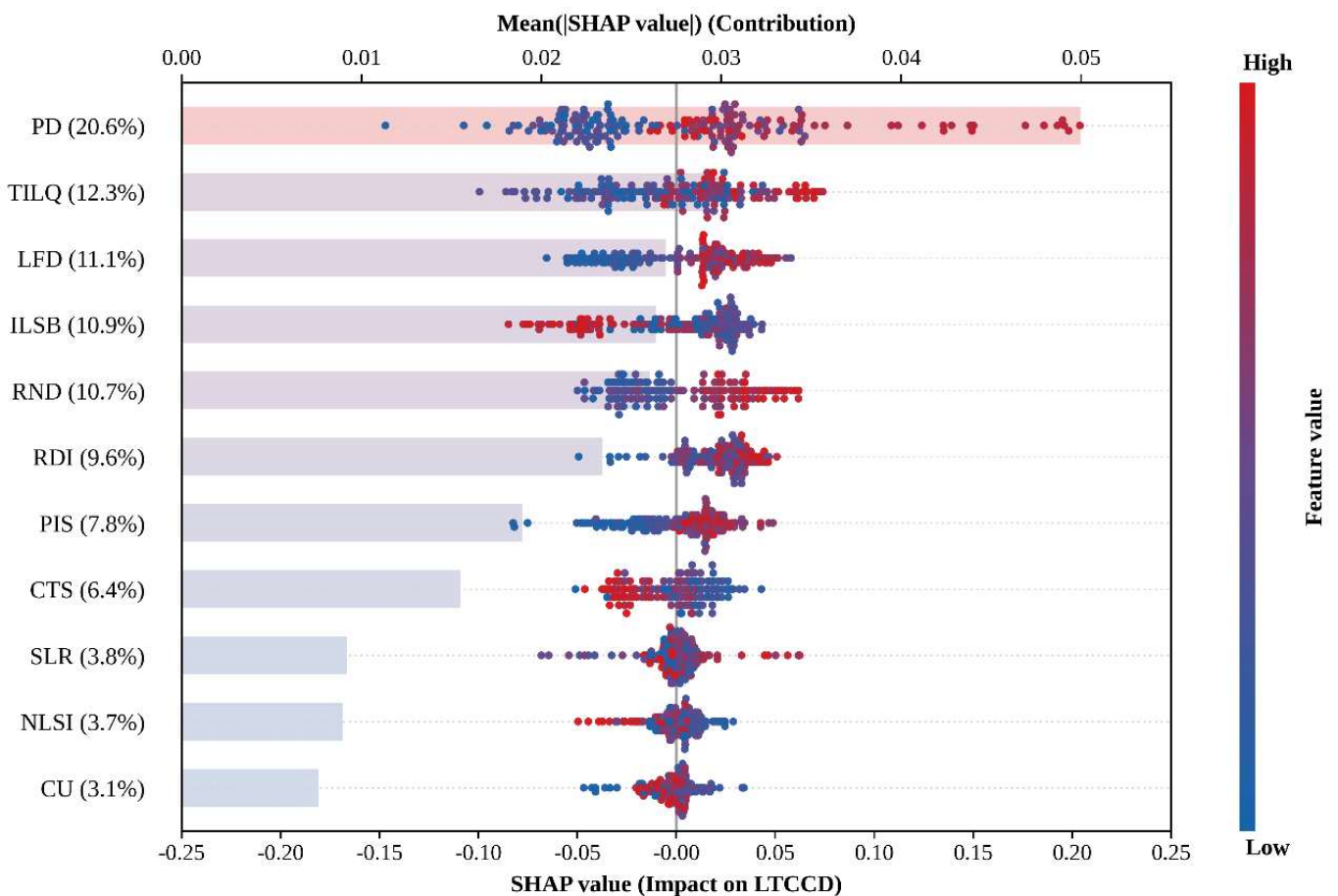


Fig. 6. Influencing factors of LTCCD. Mean absolute SHAP values indicate the relative importance of each factor, while the SHAP value distributions show the direction and magnitude of their contributions to LTCCD.

To reveal the nonlinear effects of different factors on the LTCCD of built-up land supply and demand, SHAP dependence plots were further used to examine how the effects of each variable vary across different value ranges (Fig. 7). The SHAP value of PD increases steadily as PD rises, shifting from negative to positive in the intermediate range and leveling off at higher values, indicating a stable positive relationship between PD and LTCCD. The SHAP value of TILQ remains negative in the low-to-medium range, but turns rapidly positive after crossing a critical level and continues to increase, exhibiting a pronounced threshold effect. The SHAP value of LFD shifts from negative at low levels to positive and remains relatively stable in the medium-to-high range. ILSB exhibits an inverted U-shaped relationship, with moderate levels corresponding to positive effects and high levels shifting to negative effects. The SHAP value of RND is negative in the low and medium-to-low ranges, but rises rapidly and turns positive at high levels, showing a pronounced threshold effect. The SHAP value of RDI rises rapidly from negative to positive at low levels and subsequently maintains a stable positive effect. The SHAP value of PIS shifts from negative at low levels to positive and remains stable in the medium-to-high range. CTS also exhibits an inverted U-shaped relationship, with moderate values corresponding to positive effects and high values shifting to negative effects. The SHAP value of SLR fluctuates slightly around zero, with no stable direction of effect. NLSI has a positive effect in the medium-to-low range, but turns negative thereafter. The SHAP value of CU shows relatively small fluctuations, remaining slightly positive in the medium-to-low range before turning negative at high levels, and thus exhibits a weak overall negative effect. Overall, the local and tele-coupling coordination of built-up land supply and demand is a nonlinear outcome shaped by multiple factors, and its formation depends on the matching among demand agglomeration, telecoupling transmission, and institutional regulation.

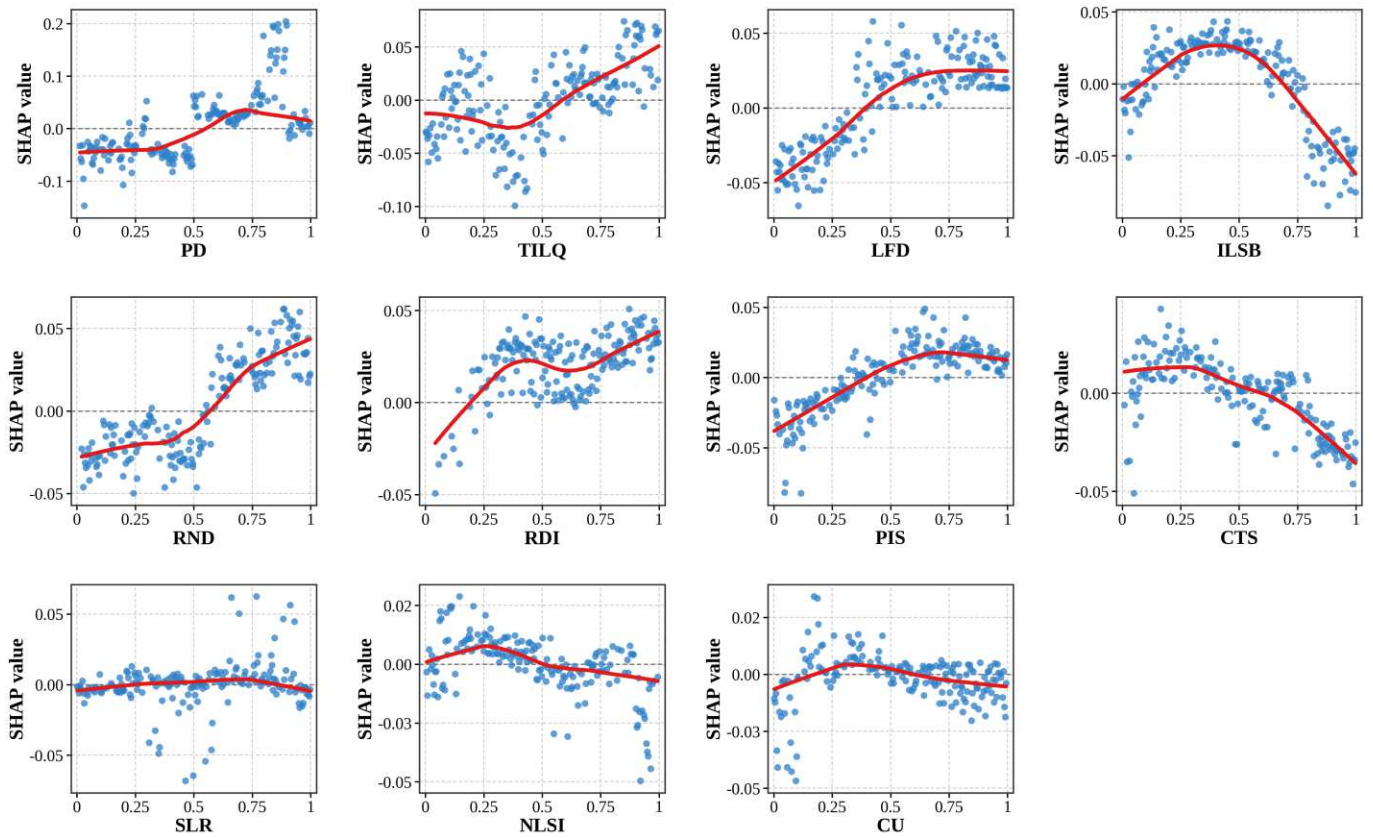


Fig. 7. Nonlinear associations between variables and LTCCD. Each panel shows the relationship between the feature value and its SHAP contribution to LTCCD, with the fitted curve indicating the overall association.

Discussion

Widespread imbalance between built-up land supply and demand

The imbalance between population and land resources and the mismatch in land allocation are considered key factors limiting regional sustainable development (Wang & Zhang, 2022; Zhang et al., 2022; Zhao et al., 2025a). Optimizing the alignment of supply and demand for built-up land can help alleviate regional conflicts between population and land resources and improve the efficiency of resource allocation (Yang et al., 2024). Although land use management has long emphasized achieving supply-demand balance at the administrative district level (Chen et al., 2023a; Cao et al., 2020; Hu et al., 2025), empirical results show that in contexts of high population concentration, deepening industrial specialization, and intensifying regional connectivity, local supply and local demand struggle to

achieve stable alignment, which is consistent with prior research (Das et al., 2024). Estimates based on the EE-MRIO model show that the eastern coastal developed region and the less-developed western region have developed a long-term and stable telecoupled dependence on built-up land in the central and northeastern regions. Resource-exporting regions, despite facing relatively modest local demand pressure, bear substantial built-up land development as well as the associated environmental and spatial costs through their product outflows (Zhang et al., 2018). Over the study period, the provincial-level LTCCD of built-up land supply and demand increased overall, suggesting that regulatory policies, including binding land-use planning, quota controls, and related intensification-oriented measures, have begun to take effect. However, persistent interregional disparities in resource endowments and socioeconomic development still lead less-developed regions to shoulder disproportionate land pressures, producing a form of “environmental inequality” in which development opportunities and ecological burdens are unevenly allocated across space (Althouse et al., 2023; Chuai et al., 2023). Taken together, these findings provide empirical evidence that built-up land supply and demand are not confined within administrative boundaries but are embedded in an interregional economic system. Accordingly, discussing land supply-demand relations solely from a local perspective is increasingly insufficient for addressing the structural tensions that emerge in the stage of high-quality development.

Local and tele-coupling reshapes built-up land supply–demand relationships

From a cross-regional systems perspective, this study reveals the supply–demand relationships of built-up land under local and tele-coupling and their coordination characteristics. Highly developed core regions, such as the eastern coastal provinces, often rely on remote built-up land use in resource-exporting regions in central and northeastern China to meet the substantial land demand arising from the high concentration of population and industries, thereby alleviating local supply constraints. This coupling mechanism alters the way in which built-up land supply–demand relationships are formed, such that a local supply–demand balance no longer directly reflects

coordination at the system level. While satisfying demand in core regions, such remote dependence also increases the land-use pressure borne by resource-exporting regions, giving rise to structural imbalances across regions (Wang et al., 2024a).

Some economically developed regions do not meet their growth-induced land demand through large-scale expansion of local built-up land. Instead, through interregional trade and extended production chains, they transfer embodied built-up land demand to other regions. While this telecoupled embedding mechanism alleviates local supply constraints, it also weakens the self-adjustment capacity of built-up land supply and demand at the local scale. As a result, the level of coupling coordination does not necessarily improve in parallel with economic expansion.

The empirical results further reveal pronounced spatial heterogeneity in this imbalance. In central China, both the effective scale of supply and demand and the supply–demand matching degree improved as provinces accommodated production activities and demand from other regions, resulting in the most pronounced increase in LTCCD. The three northeastern provinces continued to provide large-scale remote supply, supporting built-up land demand elsewhere at the cost of a marked decline in their own supply–demand matching degree, and consequently experienced a decrease in LTCCD. Although eastern China alleviated local land constraints through telecoupled embedding, the spatial separation between demand and supply constrained further improvements in LTCCD. Western China, by contrast, remained characterized by a generally low LTCCD and pronounced interprovincial differentiation.

While telecoupling helps sustain the stable operation of the economic system, it also results in a spatial mismatch between the costs and benefits of land development. Developed regions alleviate local demand pressures through the telecoupled use of built-up land, whereas less-developed regions bear the associated development and environmental burdens, resulting in an unequal distribution of benefits across regions (Schröter et al., 2018). Therefore, the overall improvement in LTCCD may, to some extent, obscure the deeper interregional mismatch between built-up land supply and demand. This suggests that system-wide optimization cannot be achieved through local land policies or

localized regulation alone. Instead, effective allocation of built-up land resources requires cross-regional coordination and integrated spatial planning.

Nonlinear influencing factors of LTCCD

The factors influencing LTCCD generally exhibit nonlinear relationships, including threshold effects and inverted-U-shaped patterns, indicating that their effects are distinctly stage-specific and context-dependent. Sustained improvements in LTCCD are therefore not driven by any single factor, but depend on the coordinated alignment of multiple mechanisms involving demand formation, supply response, telecoupling transmission, and institutional allocation. In terms of demand formation, the continued concentration of population in urban agglomerations and metropolitan areas directly increases built-up land demand while also creating economies of scale for sharing public facilities and promoting intensive land use. However, when demand expansion is not supported by corresponding industrial capacity and supply networks, the concentration of population and consumption may also deepen regional dependence on external built-up land. The weak negative effect of consumption upgrading may arise precisely because demand upgrading has outpaced adjustments in the supply system. In terms of the regional division of labor, embodied land flows allow built-up land demand to transcend administrative boundaries and be met through interregional allocation (Guo et al., 2020), while transport infrastructure such as high-speed rail reshapes land-use patterns in cities along its routes by improving spatial accessibility and generating spillover effects (Niu et al., 2021). However, interprovincial specialization does not automatically translate into greater coordination. Our results show that only when industrial specialization and spatial accessibility jointly exceed certain thresholds can external demand generate stable flows of built-up land. The positive effect of productive investment is also released primarily through this channel.

Supply response and institutional allocation exhibit even clearer threshold effects. The effect of land-finance

dependence shifts from negative to positive and then gradually levels off, suggesting that, at certain stages, land finance can serve as a mechanism for mobilizing funds for infrastructure construction and land development. However, continuously deepening dependence may also accumulate fiscal and development risks (Wang & Zhang, 2022; Yu & Zhou, 2024). Industrial land supply bias exhibits an inverted-U-shaped relationship, reflecting a transition in its role from accommodating industrial activities to generating structural imbalance. A moderate bias toward industrial land helps accommodate productive activities, whereas excessive bias may cause land allocation to deviate from the actual demand generated by population consumption and industrial upgrading (Huang & Du, 2017). The marketization of land supply likewise exhibits stage-specific effects. Previous research has shown that land marketization in China is essentially shaped by the interplay between state and market forces (Jiang et al., 2021). Our results further indicate that, once marketization reaches a high level, excessive responsiveness of land-supply decisions to short-term price signals may weaken the alignment between the supply structure and long-term demand. As the scope for incremental built-up land expansion continues to narrow, the redevelopment of underutilized stock land is becoming an increasingly important direction of supply-side adjustment (Zhou et al., 2026). The negative effect of incremental land supply at high intensities, together with the persistently weak positive effect of stock land redevelopment, further indicates that the mode of land supply and its structural alignment with demand are more important than simply expanding the scale of supply. Therefore, improvements in supply–demand coordination do not depend on any single policy lever, but rather on a mutually aligned combination of demand, supply, telecoupling transmission, and institutional allocation mechanisms at different stages of development. This also constitutes the basic logic for advancing cross-regional collaborative governance.

Study limitations and future prospects

Although this study systematically examined the dynamic local and tele-coupling characteristics of

interprovincial built-up land supply and demand in China and their underlying driving mechanisms using the EE-MRIO model, LTCCD model, and HGB-SHAP method, several limitations remain. First, due to the inherent constraints of input–output data, this study could not fully account for the inflows of externally embodied built-up land. Consequently, built-up land demand may be underestimated in some coastal regions characterized by strong economic spillover capacity and intensive construction activities. Second, idle built-up land was not incorporated into the analysis, which may lead to some overestimation of the potential supply capacity of built-up land across provinces. Third, the study period was limited to 2012–2020 and therefore does not capture the dynamic changes in built-up land use after the COVID-19 pandemic. Nevertheless, this study provides a theoretical basis and methodological reference for understanding the mechanisms underlying the dynamic balance of provincial built-up land supply and demand in China and its spatial evolution.

Future research can be further extended in several directions. At the data level, high-resolution land-use remote-sensing data can be integrated with socioeconomic big data to construct a dynamically updated, multidimensional input–output database. This would enable a more accurate characterization of long-term interregional land-flow patterns while alleviating the within-region spatial homogeneity assumption. At the model level, spatiotemporal coupling models with time-varying weights or agent-based simulation approaches could be introduced to improve the responsiveness of the analytical framework to policy interventions and spatial interaction effects. Future studies could also incorporate factors such as the conversion of unused land, ecological impacts, and policy constraints to more comprehensively reveal the complex mechanisms underlying the coordination of built-up land supply and demand and the heterogeneity of regional responses.

Conclusion and policy implications

Conclusions

As coordinated regional development has become a core agenda of national spatial governance, identifying and quantifying spatial linkages among regions has become increasingly important for understanding the interactions between socioeconomic and land systems. Regional development does not occur in isolation; rather, complex local and tele-coupling systems are formed through multilevel and multiscale factor flows, economic linkages, and policy transmission. Local coupling primarily reflects the interactions and coordination between built-up land supply and demand within a regional system and provides a direct manifestation of adjustments in human–land relationships, whereas telecoupling reveals interactions and feedbacks between geographically distant but economically closely connected regions. As a direct material manifestation of regional development, the built-up land supply–demand system can, through its degree of coupling coordination, effectively reflect the optimization of spatial patterns and the efficiency of factor flows. Therefore, dynamically examining built-up land supply and demand from a local and tele-coupling perspective can help reveal the spatial response mechanisms and policy regulation pathways underlying coordinated regional development. The results show that:

(1) The balance between built-up land supply and demand in China has become increasingly dependent on interregional flows, with local and tele-coupling reshaping the spatial relationships of land allocation across regions. During the study period, the supply structure shifted from local dominance toward telecoupling dominance, with a growing share of additional demand being supported by built-up land in other provinces through interprovincial industrial linkages and commodity flows. Supply–demand linkages are not characterized by one-way dependence but are embedded in a bidirectional and complementary network of interprovincial flows, in which provinces play differentiated supply roles in the interprovincial division of labor based on their respective industrial advantages. Although this coupling mechanism supports the functioning of the national economy, it also creates a spatial mismatch between the costs and benefits of land development. Regions such as Northeast China, which serve as major suppliers in telecoupled flows, support built-up land demand elsewhere at the cost of a decline in their own

supply–demand matching.

(2) The local and tele-coupling coordination degree of built-up land supply and demand in China showed an overall fluctuating upward trend, yet the overall level of coordination remained relatively low, and most provinces had not achieved substantive coordination. Spatially, a clear gradient emerged, with high-value areas progressively expanding from the eastern coastal regions toward the interior. The central provinces experienced the most pronounced improvement in coordination while accommodating industrial relocation and external demand, whereas Northeast China showed a decline. The western region remained at a low level of coordination over the long term, constrained by the relatively small scale of supply and demand and the high costs of interregional flows. Provincial disparities did not narrow with the increase in the national mean, and pronounced interprovincial inequality persisted.

(3) The local and tele-coupling coordination of built-up land supply and demand in China is nonlinearly influenced by multiple factors. Population agglomeration is the most important driving factor, while tradable industry specialization and transportation infrastructure exert stable positive effects after crossing certain thresholds. Industrial land supply bias and the marketization of land supply both exhibit inverted U-shaped relationships: moderate levels promote coordination, whereas excessive levels exert inhibitory effects. Improvements in LTCCD therefore do not depend on a single policy lever, but rather on a mutually compatible combination of mechanisms involving demand formation, supply response, and institutional allocation at different stages of development.

5.2. Policy implications

Based on the analysis of the local and tele-coupling coordination of built-up land supply and demand across Chinese provinces, and considering the spatial heterogeneity of LTCCD and its key influencing factors, the following policy recommendations are proposed to promote efficient resource allocation and coordinated regional development:

(1) Move beyond the notion of “local balance” within individual administrative jurisdictions and incorporate

telecoupled land flows into the integrated allocation of land resources. A benefit-balancing mechanism combining vertical transfer payments with horizontal regional cooperation should be established. Net-demand regions should be encouraged to provide reasonable compensation, through regional development funds, pairing assistance programs, and other channels, to regions such as Northeast China that have long undertaken telecoupled supply responsibilities. Such compensation should account for their land development costs, ecological conservation efforts, and foregone development rights, thereby correcting the spatial mismatch whereby the benefits of land supply accrue elsewhere while the costs are borne locally.

(2) Implement region-specific, category-based, and development-stage-sensitive land management strategies.

In the eastern coastal region, where net demand is large and the spatial separation between supply and demand is pronounced, priority should be given to optimizing existing land stocks, promoting urban renewal, and upgrading the industrial structure. The expansion of new built-up land should be strictly controlled to reduce excessive dependence on telecoupled supply. For net-supply regions such as Northeast China, the land supply structure should be optimized alongside appropriate compensation to prevent further deterioration in supply–demand matching. In the central region, which is increasingly accommodating industrial relocation, improvements in supply–demand matching should be accompanied by an expansion in the effective scale of both supply and demand, thereby consolidating the recent gains in coordination. In the western region, where both supply and demand remain relatively small, adequate land provision for infrastructure and industrial development should be maintained. Land allocation should be leveraged to facilitate the agglomeration of population and industries in central cities and promote the endogenous expansion of effective supply and demand, while avoiding extensive land expansion that could generate new supply–demand mismatches.

(3) Anchor land demand in population agglomeration and strengthen demand-side management through the “people–land linkage” mechanism. Population agglomeration is the most important factor driving improvements in

coupling coordination. The allocation of built-up land quotas should therefore be more closely aligned with the permanent resident population and actual land demand. Adequate land for housing and public services should be secured in population-receiving areas, while orderly population agglomeration should be encouraged in urban agglomerations and metropolitan areas with high coordination potential. Rational agglomeration on the demand side can thereby amplify the economies of scale arising from shared public facilities and intensive land use.

(4) Promote coordination between industrial and land-supply policies and better align the structure, timing, and mode of land supply to improve the long-term matching of supply and demand. Industrial development should be integrated with infrastructure provision to simultaneously strengthen regional capacities to accommodate external demand and facilitate interregional flows. The proportions and timing of industrial, residential, and commercial land supply should be appropriately coordinated to prevent the land supply structure from becoming persistently over-biased toward industrial land. While improving market-oriented land supply mechanisms, land-supply decisions should not be unduly driven by short-term price signals at the expense of long-term actual demand.

References:

- Althouse, J., Cahen-Fourot, L., Carballa-Smichowski, B., Durand, C., & Knauss, S. (2023). Ecologically unequal exchange and uneven development patterns along global value chains. *World Development*, 170, 106308. <https://doi.org/10.1016/j.worlddev.2023.106308>
- Cai, L., Liao, Y., & Tang, H. (2025). How does land finance affect carbon emissions? Evidence from 270 Chinese cities. *International Review of Economics & Finance*, 104771. <https://doi.org/10.1016/j.iref.2025.104771>
- Cao, Y., Zhang, X., Zhang, X., & Li, H. (2020). The incremental construction land differentiated management framework: The perspective of land quota trading in China. *Land Use Policy*, 96, 104675. <https://doi.org/10.1016/j.landusepol.2020.104675>
- Chen, G., Li, X., Liu, X., Chen, Y., Liang, X., Leng, J., ... & Huang, K. (2020). Global projections of future urban land expansion under shared socioeconomic pathways. *Nature Communications*, 11(1), 537. <https://doi.org/10.1038/s41467-020-14386-x>

- Chen, G. Q., & Han, M. Y. (2015). Virtual land use change in China 2002–2010: Internal transition and trade imbalance. *Land Use Policy*, 47, 55-65. <https://doi.org/10.1016/j.landusepol.2015.03.017>
- Chen, W., Pan, S., & Ye, X. (2023a). Land-use planning in China: Past, present, and future. *Journal of Geographical Sciences*, 33(7), 1527-1552. <https://doi.org/10.1007/s11442-023-2141-7>
- Chen, X., Hou, Y., Kastner, T., Liu, L., Zhang, Y., Yin, T., ... & Li, Y. (2023b). Physical and virtual nutrient flows in global telecoupled agricultural trade networks. *Nature Communications*, 14(1), 2391. <https://doi.org/10.1038/s41467-023-38094-4>
- Chen, X., Yu, L., Li, Y., Liu, T., Liu, J., Peng, D., ... & Gong, P. (2024). China's ongoing rural to urban transformation benefits the population but is not evenly spread. *Communications Earth & Environment*, 5(1), 416. <https://doi.org/10.1038/s43247-024-01580-8>
- Cheng, J., Zhao, J., Dai, Y., & Li, Y. (2024). Land supply patterns and the Chinese low consumption puzzle. *Structural Change and Economic Dynamics*, 69, 232-245. <https://doi.org/10.1016/j.strueco.2023.12.006>
- Chuai, X., Gao, R., Huang, X., Lu, Q., & Zhao, R. (2021). The embodied flow of built-up land in China's interregional trade and its implications for regional carbon balance. *Ecological Economics*, 184, 106993. <https://doi.org/10.1016/j.ecolecon.2021.106993>
- Chuai, X., Xia, M., Zhang, M., Cai, H. H., & Ye, X. (2023). Reveal the inequality hidden in industry land use by integrating domestic trade and the industry efficiency. *Journal of Environmental Management*, 344, 118716. <https://doi.org/10.1016/j.jenvman.2023.118716>
- Cotta, B., Coenen, J., Challies, E., Newig, J., Lenschow, A., & Schilling-Vacaflor, A. (2022). Environmental governance in globally telecoupled systems: Mapping the terrain towards an integrated research agenda. *Earth System Governance*, 13, 100142. <https://doi.org/10.1016/j.esg.2022.100142>
- Das, M., Das, A., & Saikh, S. (2024). Estimating supply-demand mismatches for optimization of sustainable land use planning in a rapidly growing urban agglomeration (India). *Land Use Policy*, 139, 107061. <https://doi.org/10.1016/j.landusepol.2024.107061>
- Daymard, A. (2025). Is agricultural productivity a prerequisite for structural transformation? Evidence on the role of trade openness. *Structural Change and Economic Dynamics*. <https://doi.org/10.1016/j.strueco.2025.10.016>
- Doan, Q. C., Ma, J., Chen, S., & Zhang, X. (2025). Nonlinear and threshold effects of the built environment, road vehicles and air pollution on urban vitality. *Landscape and Urban Planning*, 253, 105204. <https://doi.org/10.1016/j.landurbplan.2024.105204>
- Fan, J., Zhou, L., Yu, X., & Zhang, Y. (2021). Impact of land quota and land supply structure on China's housing

prices: Quasi-natural experiment based on land quota policy adjustment. *Land Use Policy*, 106, 105452. <https://doi.org/10.1016/j.landusepol.2021.105452>

Fang, L., & Tian, C. (2020). Construction land quotas as a tool for managing urban expansion. *Landscape and Urban Planning*, 195, 103727. <https://doi.org/10.1016/j.landurbplan.2019.103727>

Fang, W., An, H., Li, H., Gao, X., Sun, X., & Zhong, W. (2017). Accessing on the sustainability of urban ecological-economic systems by means of a coupled energy and system dynamics model: A case study of Beijing. *Energy Policy*, 100, 326-337. <https://doi.org/10.1016/j.enpol.2016.09.044>

Fu, W., Yang, S., Hu, S., & Zhang, P. (2023). The impact of embodied land flow in interregional trade on carbon emissions in China. *Applied Geography*, 159, 103065. <https://doi.org/10.1016/j.apgeog.2023.103065>

Gao, J., Cai, Y., Liu, Y., Wen, Q., Marcouiller, D. W., & Chen, J. (2022). Understanding the underutilization of rural housing land in China: A multi-level modeling approach. *Journal of Rural Studies*, 89, 73-81. <https://doi.org/10.1016/j.jrurstud.2021.11.020>

Guo, S., Wang, Y., Shen, G. Q., Zhang, B., & Wang, H. (2020). Virtual built-up land transfers embodied in China's interregional trade. *Land Use Policy*, 94, 104536. <https://doi.org/10.1016/j.landusepol.2020.104536>

Hu, H., Wang, L., & Lu, H. (2025). Mapping land use regulation and urban characterisation in territorial spatial planning of Chinese cities. *Environment and Planning B: Urban Analytics and City Science*, 52(8), 2048-2051. <https://doi.org/10.1177/23998083251336844>

Huang, S., & Lin, Y. (2025). Research on high-quality urbanization development and optimization pathways based on the coupling coordination perspective of “population–land–economy–environment”: A case study of Jiangsu Province, China. *Land*, 14(2), 435. <https://doi.org/10.3390/land14020435>

Huang, Z., & Du, X. (2017). Government intervention and land misallocation: Evidence from China. *Cities*, 60, 323-332. <https://doi.org/10.1016/j.cities.2016.10.006>

Hull, V., & Liu, J. (2018). Telecoupling: A new frontier for global sustainability. *Ecology and Society*, 23(4). <https://doi.org/10.5751/es-10494-230441>

Ji, Y., Liu, Y., Tang, H., Li, Z., Bai, Y., & Feng, T. (2025). Stratified strategies for enhancing thermal comfort through multidimensional compactness optimization in urban built-up areas during heatwaves. *Sustainable Cities and Society*, 127, 106445. <https://doi.org/10.1016/j.scs.2025.106445>

Jiang, X., Lu, X., Liu, Q., Chang, C., & Qu, L. (2021). The effects of land transfer marketization on the urban land use efficiency: An empirical study based on 285 cities in China. *Ecological Indicators*, 132, 108296. <https://doi.org/10.1016/j.ecolind.2021.108296>

- Jin, W., Zhou, C., & Luo, L. (2018). Impact of land input on economic growth at different stages of development in Chinese cities and regions. *Sustainability*, 10(8), 2847. <https://doi.org/10.3390/su10082847>
- Junius, T., & Oosterhaven, J. (2003). The solution of updating or regionalizing a matrix with both positive and negative entries. *Economic Systems Research*, 15(1), 87-96. <https://doi.org/10.1080/0953531032000056954>
- Lenzen, M., Wood, R., & Gallego, B. (2007). Some comments on the GRAS method. *Economic Systems Research*, 19(4), 461-465. <https://doi.org/10.1080/09535310701698613>
- Li, J., Zhang, Z., Liang, D., Ouyang, Q., Tian, P., Guan, D., & Zheng, H. (2026). China's provincial multi-regional input-output database for 2018 and 2020. *Scientific Data*, 13(1), 222. <https://doi.org/10.1038/s41597-025-06543-y>
- Li, Y., Kong, X., & Zhu, Z. (2020). Multiscale analysis of the correlation patterns between the urban population and construction land in China. *Sustainable Cities and Society*, 61, 102326. <https://doi.org/10.1016/j.scs.2020.102326>
- Liu, J. (2023). Leveraging the metacoupling framework for sustainability science and global sustainable development. *National Science Review*, 10(7), nwad090. <https://doi.org/10.1093/nsr/nwad090>
- Liu, J., Hull, V., Batistella, M., DeFries, R., Dietz, T., Fu, F., ... & Zhu, C. (2013). Framing sustainability in a telecoupled world. *Ecology and Society*, 18(2). <https://doi.org/10.5751/ES-05873-180226>
- Liu, J., Mooney, H., Hull, V., Davis, S. J., Gaskell, J., Hertel, T., ... & Li, S. (2015). Systems integration for global sustainability. *Science*, 347(6225), 1258832. <https://doi.org/10.1126/science.1258832>
- Liu, Y., Gao, Y., & Hao, Y. (2019). Gospel or disaster? An empirical study on the environmental influences of domestic investment in China. *Journal of Cleaner Production*, 218, 930-942. <https://doi.org/10.1016/j.jclepro.2019.01.333>
- Mao, W., & Jiao, L. (2024). Land-use intensification dominates China's land provisioning services: From the perspective of land system science. *Journal of Environmental Management*, 356, 120541. <https://doi.org/10.1016/j.jenvman.2024.120541>
- Massaro, E., Schifanella, R., Piccardo, M., Caporaso, L., Taubenböck, H., Cescatti, A., & Duveiller, G. (2023). Spatially-optimized urban greening for reduction of population exposure to land surface temperature extremes. *Nature Communications*, 14(1), 2903. <https://doi.org/10.1038/s41467-023-38596-1>
- Nhat-Duc, H., & Van-Duc, T. (2023). Comparison of histogram-based gradient boosting classification machine, random Forest, and deep convolutional neural network for pavement raveling severity classification. *Automation in Construction*, 148, 104767. <https://doi.org/10.1016/j.autcon.2023.104767>
- Niu, F., Xin, Z., & Sun, D. (2021). Urban land use effects of high-speed railway network in China: A spatial spillover perspective. *Land Use Policy*, 105, 105417. <https://doi.org/10.1016/j.landusepol.2021.105417>

- Pi, Y., & Wang, Y. (2025). Transportation infrastructure, comparative advantage, and regional specialization: Evidence from China's high-speed railway network. *Transportation Research Part A: Policy and Practice*, 191, 104334. <https://doi.org/10.1016/j.tra.2024.104334>
- Qi, F., Zhang, P., Zhang, M., & Guo, D. (2026). How does digital transformation promote residents' consumption upgrading?-Evidence from China's supply and demand restructuring. *Habitat International*, 168, 103679. <https://doi.org/10.1016/j.habitatint.2025.103679>
- Qi, L., Najam, H., Oskenbayev, Y., Alisher, S., & Hairis, K. (2025). Impact of rapid urban construction land expansion on spatial inequalities of ecosystem health in China: Evidence from national, economic regional, and urban agglomeration perspectives. *Ecological Indicators*, 172, 113196. <https://doi.org/10.1016/j.ecolind.2025.113196>
- Schröter, M., Koellner, T., Alkemade, R., Arnhold, S., Bagstad, K. J., Erb, K. H., ... & Bonn, A. (2018). Interregional flows of ecosystem services: Concepts, typology and four cases. *Ecosystem Services*, 31, 231-241. <https://doi.org/10.1016/j.ecoser.2018.02.003>
- Song, Y., Huang, X., Li, Q., Qi, X., Sun, R., & Wang, M. (2025). Unpacking China's land use and trade-driven land transfers through telecoupling. *Land Use Policy*, 158, 107709. <https://doi.org/10.1016/j.landusepol.2025.107709>
- Sun, F., Xu, H., & Niu, K. (2026). Decentralization dividends: Can expanding land approval autonomy improve the quality and scale of urban land use efficiency? *Growth and Change*, 57(1), e70115. <https://doi.org/10.1111/grow.70115>
- Tang, P., Huang, J., Zhou, H., Fang, C., Zhan, Y., & Huang, W. (2021). Local and telecoupling coordination degree model of urbanization and the eco-environment based on RS and GIS: A case study in the Wuhan urban agglomeration. *Sustainable Cities and Society*, 75, 103405. <https://doi.org/10.1016/j.scs.2021.103405>
- Tang, R., Hou, G., Chen, Y., Liu, X., Chu, S., & Li, L. (2025). Spatial and temporal characteristics and driving mechanisms of recreational ecosystem services supply-demand mismatch in rapidly urbanizing areas: Evidence from the Yangtze River Delta. *Ecological Indicators*, 171, 113153. <https://doi.org/10.1016/j.ecolind.2025.113153>
- Wang, J., & Zhang, X. (2022). Land-based urbanization in China: Mismatched land development in the post-financial crisis era. *Habitat International*, 125, 102598. <https://doi.org/10.1016/j.habitatint.2022.102598>
- Wang, S., Chen, X., Xie, R., Liu, K., Wang, J., Liu, X., ... & Fang, C. (2024a). Demand-side insights for steering human appropriation of net primary productivity within planetary boundaries. *One Earth*, 7(4), 650-662. <https://doi.org/10.1016/j.oneear.2024.02.010>
- Wang, S., Wang, A., Liu, S., Zhang, C., Qiao, L., & Li, X. (2024b). Research on the coupling coordination relationship between the digital economy and high-quality energy development: Evidence from China. *Heliyon*, 10(2).

<https://doi.org/10.1016/j.heliyon.2024.e24637>

Wang, S., & Wang, J. (2023). Embodied land in China's provinces from the perspective of regional trade. *Journal of Geographical Sciences*, 33(1), 59-75. <https://doi.org/10.1007/s11442-023-2074-1>

Wang, X., Zhang, Y., Li, C., Yin, C., & Shao, C. (2025). Investigating nonlinear and spatially heterogeneous impacts of the built environment on urban vitality. *Sustainable Cities and Society*, 107033. <https://doi.org/10.1016/j.scs.2025.107033>

Wang, Y., Geschke, A., & Lenzen, M. (2017). Constructing a time series of nested multiregion input–output tables. *International Regional Science Review*, 40(5), 476-499. <https://doi.org/10.1177/0160017615603596>

Wang, Z., Gao, Y., Wang, X., Lin, Q., & Li, L. (2022). A new approach to land use optimization and simulation considering urban development sustainability: A case study of Bortala, China. *Sustainable Cities and Society*, 87, 104135. <https://doi.org/10.1016/j.scs.2022.104135>

Wen, L., Chatalova, L., & Zhang, A. (2022). Can China's unified construction land market mitigate urban land shortage? Evidence from Deqing and Nanhai, Eastern coastal China. *Land Use Policy*, 115, 105996. <https://doi.org/10.1016/j.landusepol.2022.105996>

Wu, K. Y., & Zhang, H. (2012). Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978–2008). *Applied Geography*, 34, 137-145. <https://doi.org/10.1016/j.apgeog.2011.11.006>

Xia, Q., Tian, G., Zhao, D., Zhao, Q., & Varis, O. (2024). Effects of new-type urbanization on resource pressure: Evidence from a water-energy-food system perspective in China. *Sustainable Cities and Society*, 107, 105411. <https://doi.org/10.1016/j.scs.2024.105411>

Xie, A., Zhang, F., Ding, Y., Chen, J., Yang, P., & Peng, G. (2025). Exploring the dynamic local and tele-coupling coordination mechanism of the ecosystem services supply–demand and its driving forces: Taking China's Yangtze River Economic Belt as an example. *Land Degradation & Development*, 36(9), 3178-3193. <https://doi.org/10.1002/ldr.5559>

Xu, D., Zhang, K., Cao, L., Guan, X., & Zhang, H. (2022). Driving forces and prediction of urban land use change based on the geodetector and CA-Markov model: A case study of Zhengzhou, China. *International Journal of Digital Earth*, 15(1), 2246-2267. <https://doi.org/10.1080/17538947.2022.2147229>

Xu, F., Wang, H., & Chi, G. (2025). Does market-oriented land conveyance affect regional economic resilience? A spatial and mediation analysis based on 287 Chinese cities. *Land Use Policy*, 150, 107457. <https://doi.org/10.1016/j.landusepol.2024.107457>

- Yang, L., Chen, W., Fang, C., & Zeng, J. (2024). How does the coordinated development of population urbanization and land urbanization affect residents' living standards? Empirical evidence from China. *Cities*, 149, 104922. <https://doi.org/10.1016/j.cities.2024.104922>
- Ye, Q., Krol, M. S., Shan, Y., Schyns, J. F., Berger, M., & Hubacek, K. (2023). Allocating capital-associated CO₂ emissions along the full lifespan of capital investments helps diffuse emission responsibility. *Nature Communications*, 14(1), 2727. <https://doi.org/10.1038/s41467-023-38358-z>
- Yu, B., & Zhou, X. (2024). Land finance and urban sprawl: Evidence from prefecture-level cities in China. *Habitat International*, 148, 103074. <https://doi.org/10.1016/j.habitatint.2024.103074>
- Yuan, F., Xiao, W., & Wei, Y. D. (2023). Heterogeneous mechanisms of urban land price in China: a perspective of natural restrictions and strategic supply. *Humanities and Social Sciences Communications*, 10(1), 163. <https://doi.org/10.1057/s41599-023-01589-y>
- Zhang, B., Wang, Q., Liu, Y., Zhang, Y., Wu, X., Sun, X., & Qiao, H. (2020). Uneven development within China: Implications for interprovincial energy, water and arable land requirements. *Journal of Environmental Management*, 261, 110231. <https://doi.org/10.1016/j.jenvman.2020.110231>
- Zhang, M., Tan, S., Pan, Z., Hao, D., Zhang, X., & Chen, Z. (2022). The spatial spillover effect and nonlinear relationship analysis between land resource misallocation and environmental pollution: Evidence from China. *Journal of Environmental Management*, 321, 115873. <https://doi.org/10.1016/j.jenvman.2022.115873>
- Zhang, W., Liu, Y., Feng, K., Hubacek, K., Wang, J., Liu, M., ... & Bi, J. (2018). Revealing environmental inequality hidden in China's inter-regional trade. *Environmental Science & Technology*, 52(13), 7171-7181. <https://doi.org/10.1021/acs.est.8b00009>
- Zhao, A., Ploegmakers, H., Rouwendal, J., & Ma, X. (2025a). Land investment regulation and allocative efficiency: evidence from the Chinese manufacturing sector. *Journal of Economic Geography*, 25(2), 151-174. <https://doi.org/10.1093/jeg/lbae024>
- Zhao, X., Tan, S., Li, Y., & Khan, S. (2025b). Quantitative analysis of local coupling and telecoupling mechanism between urbanization and ecological environment quality based on multi-source remote sensing data. *Ecological Indicators*, 173, 113345. <https://doi.org/10.1016/j.ecolind.2025.113345>
- Zheng, H., Bai, Y., Wei, W., Meng, J., Zhang, Z., Song, M., & Guan, D. (2021). Chinese provincial multi-regional input-output database for 2012, 2015, and 2017. *Scientific Data* 8: 244. <https://doi.org/10.1038/s41597-021-01023-5>
- Zheng, W. (2023). Land supply and industrial agglomeration: Extension of the new economic geography model with

land elements incorporated. *Land Use Policy*, 132, 106757. <https://doi.org/10.1016/j.landusepol.2023.106757>

Zhou, D., Hu, Y., Sun, Q., & Xie, D. (2023). Land resource mismatch and energy efficiency: Evidence from 243 cities in China. *Energy Policy*, 183, 113800. <https://doi.org/10.1016/j.enpol.2023.113800>

Zhou, Y., Huang, X., Zhong, T., Chen, Y., Yang, H., Chen, Z., ... & Li, H. (2020). Can annual land use plan control and regulate construction land growth in China?. *Land Use Policy*, 99, 105026. <https://doi.org/10.1016/j.landusepol.2020.105026>

Zhou, Y., Wu, Y., Li, X., Huang, X., & Niu, L. (2026). Impact of land market on the expansion of urban construction land in Shanghai, China. *Cities*, 168, 106390. <https://doi.org/10.1016/j.cities.2025.106390>

Zhuang, L., & Ye, C. (2023). More sprawl than agglomeration: The multi-scale spatial patterns and industrial characteristics of varied development zones in China. *Cities*, 140, 104406. <https://doi.org/10.1016/j.cities.2023.104406>

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