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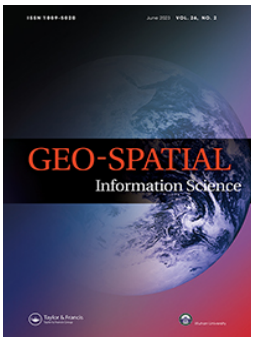

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Assessing multi-spatial driving factors of urban land use transformation in megacities: a case study of Guangdong–Hong Kong–Macao Greater Bay Area from 2000 to 2018

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ABSTRACT
Rapid morphological and socioeconomic changes have accelerated the urbanization process and urban land use transformation in China. Megacities comprise clusters of urban cities and exhibit both newly formed and well-developed urban land use development beyond administrative boundaries. It is necessary to distinguish the changing effects of spatial-varying driving factors on newly formed urban land uses from well-developed built-up areas in megacities. This study proposed a multi-spatial urbanization framework to quantify region-level socioeconomics, cluster-level ecological morphologies, and grid-level urban functional morphologies. A three-level Bayesian hierarchical model was developed to investigate the impacts of multi-spatial driving factors on urban land use transformation in megacities. The study period focused on the urbanization process between 2000 and 2018 in Guangdong–Hong Kong–Macao Greater Bay Area (GBA). Results revealed that compared with well-developed urban built-up land, changing impacts of three-level driving factors in urban land use transformation could be captured based on the proposed Bayesian hierarchical model. The region-level total population was associated with increasing possibilities in forming new residential land than the well-developed ones in 35 districts/counties/cities in GBA. Cluster-level ecological attributes with higher proportion, lower edge density of urban built areas, and lower-degree ecological complexity showed increasing probability on newly formed industrial and public land. Grid-level urban functional factors including public transportation density and shopping/dining distribution exhibited significantly decreasing probability (coefficients: −2.12 to −0.51) on contributing newly formed land uses compared with the well-developed areas, whereas business/industry distribution represented higher (coefficients: 0.99 and 0.15) and lower probabilities (coefficient: −0.22) of forming industrial/public land and residential land separately. This research shows a new attempt to distinguish multi-spatial morphological and socioeconomic effects in urban land use transformation in megacities.

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Urban function; ecological morphology; socioeconomics; megacities; Bayesian hierarchical model; Guangdong–Hong Kong–Macao Greater Bay Area (GBA)

1. Introduction

Megacities comprise highly connected urban settlements and have involved rapid urbanization processes accompanied by morphological and socioeconomic environment transformation (Kidokoro, Matsuyuki, and Shima 2022; Yeh and Chen 2020). Compared to individual cities, megacities formed as economic zones have linked up with multiple major cities and represent multi-scale patterns of economic transition and urbanization with complex state–market relations (Chakraborty et al. 2022; Yu et al. 2021). The rapid growth of megacities led to urban expansion, reduction of cultivated land, and drastic growth of urban population (Chang et al. 2020; Hui et al. 2020). Many studies have investigated the urbanization process and its driving factors such as urban morphological and socioeconomic characteristics in cities' and megacities' evolution (Naikoo et al. 2022; You and Yang 2017), which provide insights into distinguishing different urbanization levels and evaluating various urban land use transformation processes.

Megacities strengthened region-wide urban functions, which serve the basic social resources that are closely associated with the urbanization process (Liu and Su 2021; Pandey, Brelsford, and Seto 2022), by improving the spatial allocation of different places and facilities. For instance, the development of local commercial firms is associated with the concentration of specific commercial functions (Taylor and Derudder 2015). The transportation morphologies, as the major connection to transfer labor, resources, and social

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interactions among urban settlements, have been depicted by connectivity, nodes, and hierarchical structures to reflect urbanizing trends with various land uses (Chong and Pan 2020; Liu and Duan 2020). In addition, the distribution of public services such as green spaces was considered as a vital morphological component contributed by land use policies for megacity sustainable development (Huai and Van de Voorde 2022; Song et al. 2021). Such morphologies of urban functions reflect the composition and configuration of the built environment and are therefore required to be investigated based on fine-spatial scales, such as neighborhood level. The effects of neighborhood-level urban morphologies have been discussed in previous studies (Chen et al. 2021; Li et al. 2021), which provide evidence on quantifying fine-spatial urban functional facilities and distinguish their varying effects during urban land use transformation.

Meanwhile, the rapid urban growth has drastically altered land cover and ecological patterns as a response to the increasing urban population and land demand (Wang and Zhang 2022). The impacts of land cover changes on urbanization and urban land use transformation could be explained by the policy urbanization (Miao and Phelps 2021). Such changes in megacities have been heightened concerning the potential inequality of resource allocation, economic growth, and sustainable development (Wei and Ye 2014). Research has measured the unbalanced land cover dynamics during urban land use transformation: built-up land in megacities has reshaped other land cover patterns, such as the transformation of traditional to industrial and technological agriculture (Aznar-Sánchez et al. 2019), deforestation (Lin et al. 2019), and the decline in freshwater resources (Rashid, Manzoor, and Mukhtar 2018). Generally, changing landscape patterns were assessed using ecological characteristics such as the land fragmentation and expansion in previous studies (Atasoy 2018; Deng et al. 2021). Compared with urban functional patterns, ecological morphologies are beyond neighborhood and administrative restriction and often share similar distribution patterns with short distances (Taubenböck et al. 2014).

Moreover, demographic and economic processes including Gross Domestic Product (GDP) and population density have addressed the inequality among administrative regions (Liu, Wu, and Cao 2022; Liu and Li 2017; Long and Qu 2018). Particularly, fast population growth has led to the significant shrinkage of agricultural land and the heterogeneity of ecological patterns (Liu et al. 2011). Meanwhile, the drastic increase in GDP has contributed to the new waves of industrial development from labor-intensive to technology-driven industry (Yeh and Chen 2020). These studies indicated the influences of GDP and population growing among areas in newly formed urban land uses compared with well-developed ones in the development of megacities.

However, limitations still exist in previous studies. First, the varying effects of morphological and socioeconomic factors contributing to newly formed urban built-up land distinguished from well-developed areas have seldom been discussed, which could lead to biases in assessing the urbanization process among different urban spaces (Chen et al. 2021). For instance, research has revealed that neighborhoods in well-developed areas with high-density mixed urban functions exhibited a greater impact on urban vitality compared with newly formed areas (Xia, Yeh, and Zhang 2020). Second, ambiguity in selecting spatial units for depicting urban environments exists, as the varying spatial effects could cause uncertainties in measuring the homogeneity of urban morphologies and socioeconomics (Schmitt et al. 2023). In other words, the depiction of urban environments should be explainable on a proper spatial scale. Neighborhoods could reflect the basic configuration of urban morphologies (Masoumi, Terzi, and Serag 2019), while ecological patches are clustered by urban built-up land with continuously homogeneous distribution (Wang et al. 2019). Socioeconomics, on the other hand, are usually reported within administrative boundaries (Li, Zhang, and Sun 2020).

Moreover, integrating morphological and socioeconomic changes as driving factors in assessing newly formed urban built-up land is always challenging. Two major approaches including frequentist and Bayesian models could be used. Frequentist framework only provides fixed parameters, which accept or reject the hypothesis of the estimation. Bayesian framework, on the other hand, involves conditional probabilities of model parameters, showing the merits of more flexible multi-layer structures and more interpretable results (Post et al. 2022; Sadeghirad et al. 2022; Wang et al. 2021). By applying Bayesian hierarchical models, the varying effects of multi-level driving factors could be flexibly modeled and effectively quantified. Previous studies have utilized Bayesian hierarchical models in assessing driving factors of land cover ecosystem (Han et al. 2023; Yang et al. 2022). It provides insights to apply such models in assessing newly formed urban built-up land in megacities.

As one of the largest megacities in China, the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) serves as the major platform of China's globalization and leads the significant growth of the global economy (Cao et al. 2019). It is therefore essential to understand land use restructuring and its driving factors during the urbanization process in GBA. Against this background, this study aimed to evaluate the impact of urban morphologies and socioeconomics on megacity evolution in GBA. A multi-spatial urbanization framework was designed to quantify grid-level urban functional characteristics, cluster-level ecological morphologies, and region-level socioeconomics. Then, a Bayesian hierarchical model was built to evaluate multi-spatial factors to distinguish newly transformed land uses from a well-developed urbanized area. Particularly, coefficients of transformed land uses, including dominant industrial, public, and residential land, were quantified. The findings of this study can contribute to understanding the dynamic process of megacities and existing urban planning policies to guide, improve, and promote long-term urbanization evaluation and land use transformation.

2. Data and methods

A research workflow investigating multi-spatial morphological and socioeconomic impacts on newly formed urban built-up land in megacity evolution was proposed (Figure 1). We first extracted both well-developed urban built-up land and changes from other land uses to urban built-up land from 2000 to 2018 and identified dominant land uses from changed areas. Then, multi-spatial urbanization factors involving region-level socioeconomic, cluster-level ecological, and grid-level functional factors were proposed. Finally, a three-level Bayesian hierarchical model was proposed to investigate the impacts of multi-spatial factors on forming different land uses during urban evolution.

2.1. Data

Data used in this study are listed in Table 1. This study focused on the period of fast economic growth in this area, which is from the proposed Pan-Pearl River Delta (Pan-PRD) that promotes economic cooperation in 2004 to the released GBA 3-year action plan

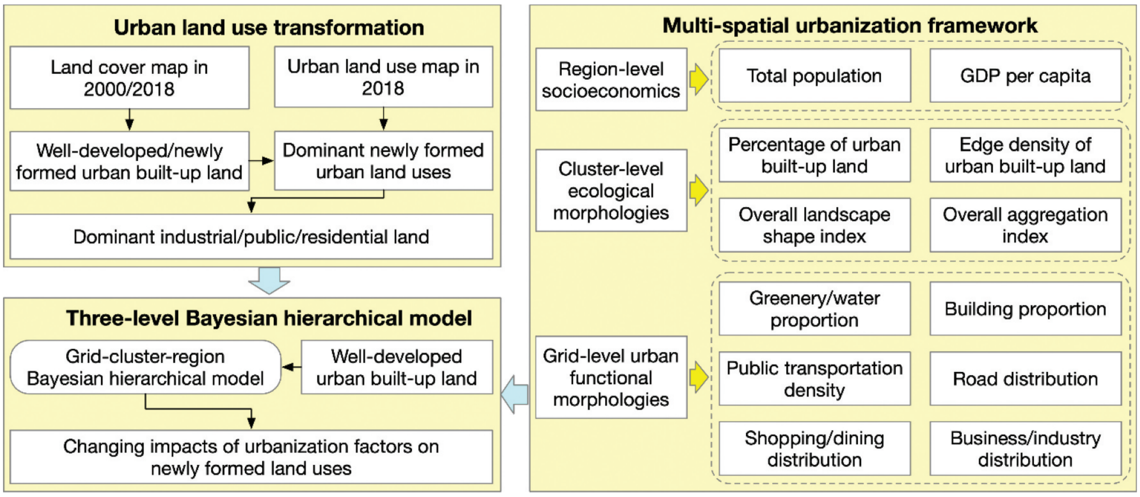


Figure 1. The research workflow, including (1) data processing to extract newly formed urban land uses, (2) a multi-spatial urbanization framework to depict morphologies and socioeconomics in megacities, and (3) a three-level Bayesian hierarchical model to distinguish the impacts of multi-spatial factors on urban land use transformation from the well-developed areas.

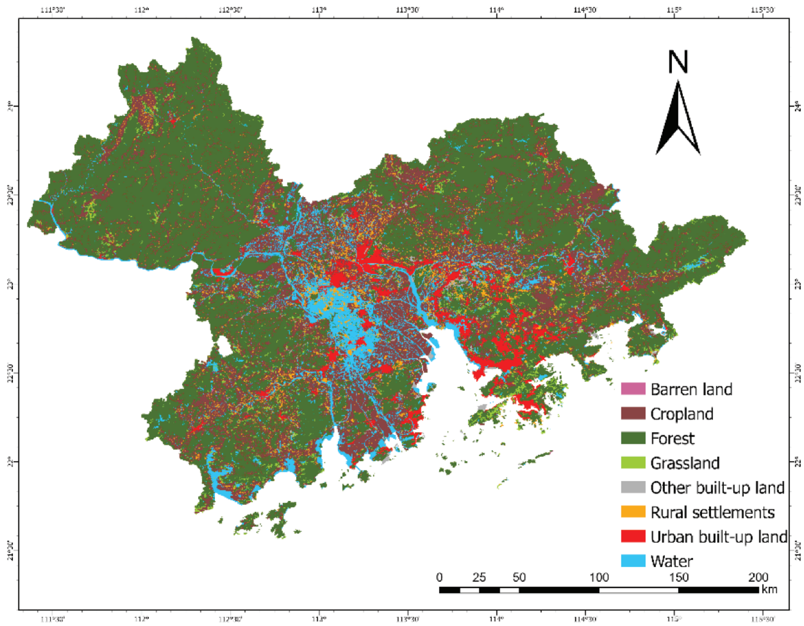
Table 1. The list of data sources, including provided datasets, representation years, spatial resolution, estimated accuracy, and source agencies.

Dataset	Year	Spatial resolution	Accuracy	Source
Land cover maps	2000 2018	30 m	Above 93% (Ning et al. 2018)	Data Center for Resources Environmental Sciences, Chinese Academy of Sciences
Urban land use map	2018	Vector data	61.2%	Gong et al. (2020)
Points of interest (POIs)	2018	Vector data	–	AutoNavi
Road networks	2018			
Landsat 8 collection 1 tier 1	2018	30 m	–	United States Geological Survey
DSM	2020	30 m	1.387 to 4.894 RMSE (Zhao et al. 2021)	ALOS World 3D
NDVI	2018	.05	–	NOAA Climate Data Record (CDR) Program
OSM data	2018	Vector data	82.2% in China (Wang, Zhou, and Tian 2020)	OSM
GDP	2018	–	–	Guangdong Statistical Yearbook The World Bank
Population	2018	.01	County-level R^2 of 0.88 in China (Ma et al. 2021)	LandScan

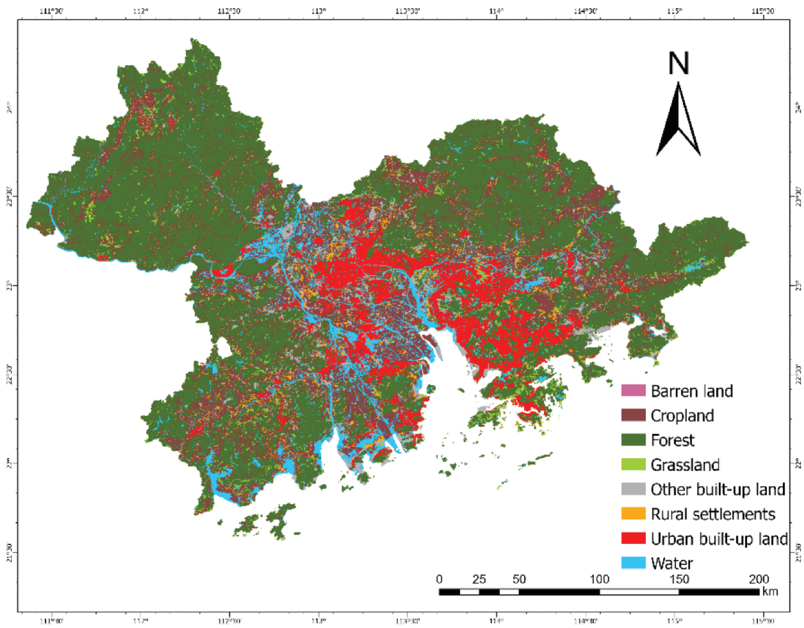
in 2019 (Tang and Ellison 2019). Due to the data availability, the period from 2000 to 2018, which approximately covers the fast-economic-development stage, was selected.

Particularly, land cover classes including barren land, cropland, forest, grassland, urban built-up land, rural settlements, and other built-up land (Figure 2) were used to (1) extract urbanization changes between 2000 and 2018 and (2) quantify ecological characteristics. Particularly, land cover changes from other classes to urban built-up land from 2000 to 2018 were delineated as newly formed urban built-up land. Since 1-km resolution has been frequently used in models of mapping the changes of large-scale land cover and land uses (Han, Champeaux, and Roujean 2004; Liu et al. 2010; Luo et al. 2022), areas were resampled from 30 m to 1 km grids as basic spatial units.

The urban land use map was used to identify dominant land uses, including residential land, industrial land (commercial land included), and public land, based on the resampled 1 km grids. Dominant land uses were identified based on three steps: (1) dominant land use was classified based on the area



(a) Land cover classification in 2000



(b) Land cover map in 2018

Figure 2. Land cover maps of the GBA in 2000 and 2018 (urban built-up land is depicted in red). (a) Land cover classification in 2000 and (b) land cover map in 2018.

occupation higher than 60%; (2) for the grids not fitting the first step, land use was classified with the highest proportion of distribution edges among all classes; and (3) well-developed urban built-up land during 2000–2018 remained unclassified.

OpenStreetMap (OSM), road networks, Landsat 8, Digital Surface Model (DSM), and Normalized Difference Vegetation Index (NDVI) data were adopted to extract buildings, greenery, water, and public spaces (roads are included) within urban built-up land using a random forest classifier. OSM data and road networks were used as classification labels for model training. Random forest parameters, including the number of trees and the number of variables per split, were determined using 10-fold cross-validation, and an overall classification accuracy of 97.74% was obtained. It should be noted that the DSM data in 2020 were utilized due to the lack of available data in 2018. And the potential inconsistency between DSM data in 2018 and 2020 may lead to the misclassification of objects within urban built-up land. However, as the classification process has been proposed based on multi-source data (OSM, DSM, and NDVI), the biases caused by inconsistent DSM data could be reduced.

2.2. Depicting three-level urbanization factors

Considering the spatial heterogeneity of urban environments, urbanization factors including region-level socioeconomic factors, cluster-level ecological factors, and grid-level urban functional factors were proposed.

Socioeconomic characteristics including population and GDP per capita are usually measured based on administrative regions. With the selected 1 km grids that represent newly formed urban land uses, the total population and GDP per capita were included in socioeconomic factors. Specifically, the 1 km grids were grouped according to districts and counties (grids were grouped in cities in Hong Kong and Macao), in which grids share the same region-level socioeconomic factors.

Ecological patterns exhibit homogenous land cover distribution within a specific area. To identify these areas, ecological patterns were first measured based on grid level and then clustered according to the characteristic similarity. Each cluster, representing the similar characteristics, was considered as the basic spatial level for ecological assessment. Particularly, the ecological factors were focused on the distribution patterns of built-up land during the urban evolution including the occupation and complexity features. Note that although 1 km grids mainly contain urban built-up land in 2018, the resampling process from 30 m to 1 km grids has involved other land cover classes within grids. On the basis of this, four ecological factors were proposed, including Percentage of Urban Built-up Land (PUBL), Edge Density of Urban Built-up Land (EDUBL), Overall Landscape Shape Index (OLSI), and Overall Aggregation Index (OAI) (Table 2). Ecological clusters based on grids were extracted using a Gaussian Mixture Models (GMM). Specifically, the Expectation Maximization (EM) algorithm is implemented to fit the GMM, which estimates the probabilities of the grids with varying ecological morphologies. Grids with high probabilities were clustered as ecological patches. In particular, the number of clusters was determined based on Bayesian Information Criterion (BIC), with lower-value BIC representing better model performance.

Urban functional factors reflect basic urban functions that serve the daily activities of citizens, such as greenery open space, shopping and business places, and public transportation. The spatial distributions of such features are usually represented in the neighborhood level. Considering the continuous large-scale areas in GBA, this study followed 1 km × 1 km grids to capture urban functional characteristics. On the basis of this, six factors were proposed for depicting grid-level urban functional characteristics, including Greenery/Water Proportion (GWP), Building Proportion (BP), Public Transportation Density (PTD), Road Distribution (RD), Shopping/Dining Distribution (SDD), and Business/Industry Distribution (BID) (Table 3).

Table 2. Cluster-level ecological factors (factors are illustrated with equations, output units and value ranges, and brief factor descriptions).

Factor	Equation	Unit	Range	Description
Percentage of Urban Built-up Land (PUBL)	$PUBL_i = \frac{A_{b,i}}{A_{g,i}} * 100$	Percent	$0 \leq PUBL_i \leq 100$	$A_{b,i}$ and $A_{g,i}$ refer to the total area of urban built-up land in the ith grid and total grid area, respectively.
Edge Density of Urban Built-up Land (EDUBL)	$EDUBL_i = \frac{E_{b,i}}{A_{g,i}} * 10000$	Meters per hectare	$EDUBL_i \geq 0$	$E_{b,i}$ represents the total length of edge involving urban built-up land in the ith grid.
Overall Landscape Shape Index (OLSI)	$OLSI_i = 0.25 * \frac{E_i}{\sqrt{A_{g,i}}}$	None	$OLSI_i \geq 0$	E_i refers to the total length of edge involving all reclassified land cover types of CNLUCC dataset in 2018.
Overall Aggregation Index (OAI)	$OAI_i = \left[\sum_{j=1}^{m}\left(\frac{g_{jj,i}}{max(g_{jj,i})}\right)P_{j,i}\right] \cdot (100)$	Percent	$0 \leq OAI_i \leq 100$	g_{jj} refers to the number of like adjacencies involving all reclassified land cover types. max ($g_{jj,i}$) represents the maximum number of g_{jj}. $P_{j,i}$ indicates the proportion of the jth land cover class.

Table 3. Grid-level urban functional factors (factors are illustrated with equations, output units and value ranges, and brief factor descriptions).

Factor	Equation	Unit	Range	Description
Greenery/Water Proportion (GWP)	$GWP_i = \frac{A_{g,i}+A_{w,i}}{A_{grid,i}}$	Ratio	$0\leq GWP_i \leq 1$	$A_{g,i}$, $A_{w,i}$ and $A_{grid,i}$ represent the total area of greenery, water, and grid-level unit in the ith grid. The areas of greenery and water were obtained from the classification of Landsat 8 imagery.
Building Proportion (BP)	$BP_i = \frac{A_{b,i}}{A_{grid,i}}$	Ratio	$0\leq BP_i \leq 1$	$A_{b,i}$ represents the total building area in the ith grid, which was obtained from the classification of Landsat 8 imagery.
Public Transportation Density (PTD)	$PTD_i = \frac{N_{s,i}}{L_{road,i}}$	Number of bus and subway stations per meter of road length	$PTD_i \geq 0$	$N_{s,i}$ and $L_{road,i}$ refer to the number of bus and subway stations and the length of roads, which were adopted from POIs and road networks of AutoNavi, respectively.
Road Distribution (RD) Shopping/Dining Distribution (SDD) Business/Industry Distribution (BID)	RD_i or SDD_i or BID_i $= \frac{1}{n_i h_i}\sum_{j=1}^{n_i} K\left(\frac{x_i - x_{ij}}{h_i}\right)$	Number of points per square kilometer	$RD_i \geq 0$ $SDD_i \geq 0$ $BID_i \geq 0$	K refers to the kernel function with h_i as the bandwidth. x_{ij} indicates distributed roads, shopping/dining, and business/industry points, while x_i refers to any given points. Bandwidths were calculated based on Silverman's Rule-of-thumb estimator. Specifically, RD_i was calculated within public space class, while SSD_i, and BID_i were calculated within both public space and building classes, which were obtained from the classification of Landsat 8 imagery.

2.3. Evaluating urban land use transformation using a Bayesian hierarchical model

The Bayesian hierarchical model was considered to distinguish the impacts of multi-spatial factors on newly formed urban built-up land than well-developed ones. Generally, the Bayesian hierarchical model utilizes the Bayesian approach to estimate the parameters of the posterior distribution based on several levels (Baio and Blangiardo 2010). Regarding the grid-cluster-region-level characteristics, this study designed a three-level Bayesian hierarchical model with categorical distribution and varying distribution priors.

Before the Bayesian hierarchical model was implemented, the proposed characteristics were scaled with z-score standardization. At the first level, the relationship between dominant land uses and three-level urbanization characteristics follows a categorical distribution combined with a logit link, formulated as:

$$y_k \sim \text{Categorical}(\boldsymbol{p}) \tag{1}$$

$$\text{logit}(\text{p}_\text{k}) = \boldsymbol{\alpha}_\text{k} + \boldsymbol{\beta}_\text{grid}\boldsymbol{x}_\text{grid,k} + \boldsymbol{\beta}_\text{cluster}\boldsymbol{x}_\text{cluster,k} + \boldsymbol{\beta}_\text{region}\boldsymbol{x}_\text{region,k} \tag{2}$$

where α_k indicates the random intercepts, while $\boldsymbol{\beta}_{grid}$, $\boldsymbol{\beta}_{cluster}$, and $\boldsymbol{\beta}_{region}$ represent the coefficients of grid-level indicators $\boldsymbol{x}_{grid,k}$, cluster-level indicators $\boldsymbol{x}_{cluster,k}$, and region-level indicators $\boldsymbol{x}_{region,k}$, respectively. $\boldsymbol{\alpha}_k$, $\boldsymbol{\beta}_{grid}$, $\boldsymbol{\beta}_{cluster}$, and $\boldsymbol{\beta}_{region}$ are formulated as follows:

$$\boldsymbol{\alpha}_k = \alpha + \alpha_{cluster,k} + \alpha_{region,k} \tag{3}$$

$$\boldsymbol{\beta}_{grid}\boldsymbol{x}_{grid,k} = \beta_{GWP}x_{GWP,k} + \beta_{BP}x_{BP,k} + \beta_{PTD}x_{PTD,k} + \beta_{RD}x_{RD,k} + \beta_{SDD}x_{SDD,k} + \beta_{BID}x_{BID,k} \tag{4}$$

$$\boldsymbol{\beta}_{cluster}\boldsymbol{x}_{cluster,k} = \beta_{PUBL}x_{PUBL,k} + \beta_{EDUBL}x_{EDUBL,k} + \beta_{OLSI}x_{OLSI,k} + \beta_{OAI}x_{OAI,k} \tag{5}$$

$$\boldsymbol{\beta}_{region}\boldsymbol{x}_{region,k} = \beta_{POP}x_{POP,k} + \beta_{GDP}x_{GDP,k} \tag{6}$$

where α, $\alpha_{cluster,k}$, and $\alpha_{region,k}$ refer to the intercepts of fix effect, cluster-level random effect, and region-level random effect of the kth grid. β and x indicate the coefficients and variables of grid-level, cluster-level, and region-level indicators. At the second level, fix-effect intercept α and the coefficients of grid-level indicators include β_{GWP}, β_{BP}, β_{PTD}, β_{RD}, β_{SDD}, and β_{BID}, followed by a prior of Gaussian distribution. As variables were preprocessed based on z-score standardization, parameters' mean and variation were set as 0 and 1, shown as follows:

$$\alpha \sim \text{Normal}(0, 1) \tag{7}$$

$$\beta_{GWP}, \beta_{BP}, \beta_{PTD}, \beta_{RD}, \beta_{SDD}, \beta_{BID} \sim \text{Normal}(0, 1) \tag{8}$$

Moreover, cluster-level and region-level intercepts $\alpha_{cluster}$ and α_{region}, as well as coefficients including β_{PUBL}, β_{EDUBL}, β_{OLSI}, β_{OAI}, β_{POP}, and β_{GDP}, were drawn from the prior multivariate normal distribution:

$$\begin{bmatrix} \alpha_{cluster} \\ \beta_{PUBL} \\ \beta_{EDUBL} \\ \beta_{OLSI} \\ \beta_{OAI} \end{bmatrix} \sim \text{MVNormal}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \boldsymbol{S}_{cluster} \right) \tag{9}$$

$$\begin{bmatrix} \alpha_{region} \\ \beta_{POP} \\ \beta_{GDP} \end{bmatrix} \sim \text{MVNormal}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, S_{region} \right) \tag{10}$$

$$\boldsymbol{S}_{cluster} = \text{diag}(\tau_c)\boldsymbol{R}_{\text{cluster}}\text{diag}(\tau_c) \tag{11}$$

$$\boldsymbol{S}_{region} = \text{diag}(\tau_r)\boldsymbol{R}_{\text{region}}\text{diag}(\tau_r) \tag{12}$$

where $\boldsymbol{S}_{cluster}$ and $\boldsymbol{S}_{region}$ refer to covariance matrices. $\boldsymbol{R}_{cluster}$ and $\boldsymbol{R}_{region}$ represent the cluster-level and regional-level correlation matrix, separately, while τ_c and τ_r are the vectors of coefficient scales. At the third level, τ_c and τ_r follow a half-Cauchy distribution prior, while $\boldsymbol{R}_{cluster}$ and $\boldsymbol{S}_{region}$ were assigned to a Lewandowski–Kurowicka–Joe (LKJ) correlation distribution prior, which are formulated as follows:

$$\tau_c, \tau_r \sim \text{HalfCauchy}(0, 1) \tag{13}$$

$$\boldsymbol{R}_{cluster}, \boldsymbol{S}_{region} \sim \text{LKJcorr}(1) \tag{14}$$

Specifically, the proposed Bayesian hierarchical model considers both fixed effects and random effects of the urbanization factors. While fixed effects usually adopt Gaussian distribution as priors with the most concerned variables, multivariate distributions are often used in random effects. Grid-level indicators were implemented as fixed effects since urban functional morphologies such as transportation and different functional facilities are served as the basic roles in forming urban land use transformation (Li et al. 2019; Wu et al. 2021), whereas cluster-level and region-level factors, which were implemented as random effects, are aggregated or influenced by the basic urban configurations (Schmitt et al. 2023).

Moreover, among dominant land uses, the proposed three-level Bayesian hierarchical model takes the well-developed land uses as a reference class. As a result, the estimated coefficients of factors corresponding to dominant residential land, industrial land, and public land indicate the probabilities of how urbanization characteristics link to the identified classes in newly formed land uses when compared to the linkage between urbanization characteristics and well-developed land uses. Positive and negative coefficients represent increasing and decreasing probabilities to identify a specific dominant land use type, respectively.

3. Results

3.1. Region-level socioeconomic impacts

Compared with well-developed urban built-up land, the region-level total population exhibited higher probabilities on forming new residential land than the well-developed ones in 35 districts/counties/cities in GBA (Figure 3). Moreover, the impacts of the total population on newly formed industrial and public land significantly varied (coefficients: −0.38 to 0.55 and – 0.24 to 0.3, respectively). And GDP per capita showed both increasing and decreasing effects on urban land use transformation compared with the well-developed regions in GBA (coefficients for dominant industrial, public, and residential land: −1.66 to 0.87, −0.24 to 0.19, −0.88 to 0.77). In summary, the total population played a vital role in contributing residential land compared with industrial and public land during the urban transformation process. The increasing population has contributed to higher housing demand, which serves the basic needs of inhabitants and thus exhibits close linkage with the residential land growth (Overman, Puga, and Turner 2008). On the other hand, inconsistent association was shown between the increasing GDP and the development of newly formed urban built-up land. The potential reasons include different economic foundation and directions, as well as the governments' intervention in the land market (Yu, Zhou, and Yang 2019).

3.2. Cluster-level ecological morphological impacts

Grids were classified into 146 clusters that share similar ecological patterns using GMM. Five clusters with different characteristics, which were depicted based on relatively high-, mid-, and low-degree ecological factors, were selected to further assess the impacts on newly formed urban land uses (Table 4). Changing impacts of ecological factors on forming urban land uses compared with well-developed ones in GBA varied among these clusters (Figure 4). Regarding industrial land, PUBL in Cluster 12 exhibited the highest probability in urban land use transformation (coefficient: over 0.02). EDUBL and OLSI in Cluster 15 showed increasing probabilities (coefficients: over 0.04 and 0.05), whereas OAI in Cluster 15 reported decreasing probability (coefficient: −0.05) in forming dominant industrial land. For dominant public land, EDUBL and OLSI in Cluster 15 represented the highest probabilities (coefficients: 0.16 and 0.09), while PUBL and OAI showed the lowest probabilities (coefficients: −0.1 and – 0.04) of urban land use transformation. For dominant residential land, highest probabilities (coefficients: 0.18 and 0.13) were revealed in EDUBL and OLSI in Cluster 94, while lowest probabilities (coefficients: −0.1 and – 0.05) were found in PUBL and OAI in Cluster 94.

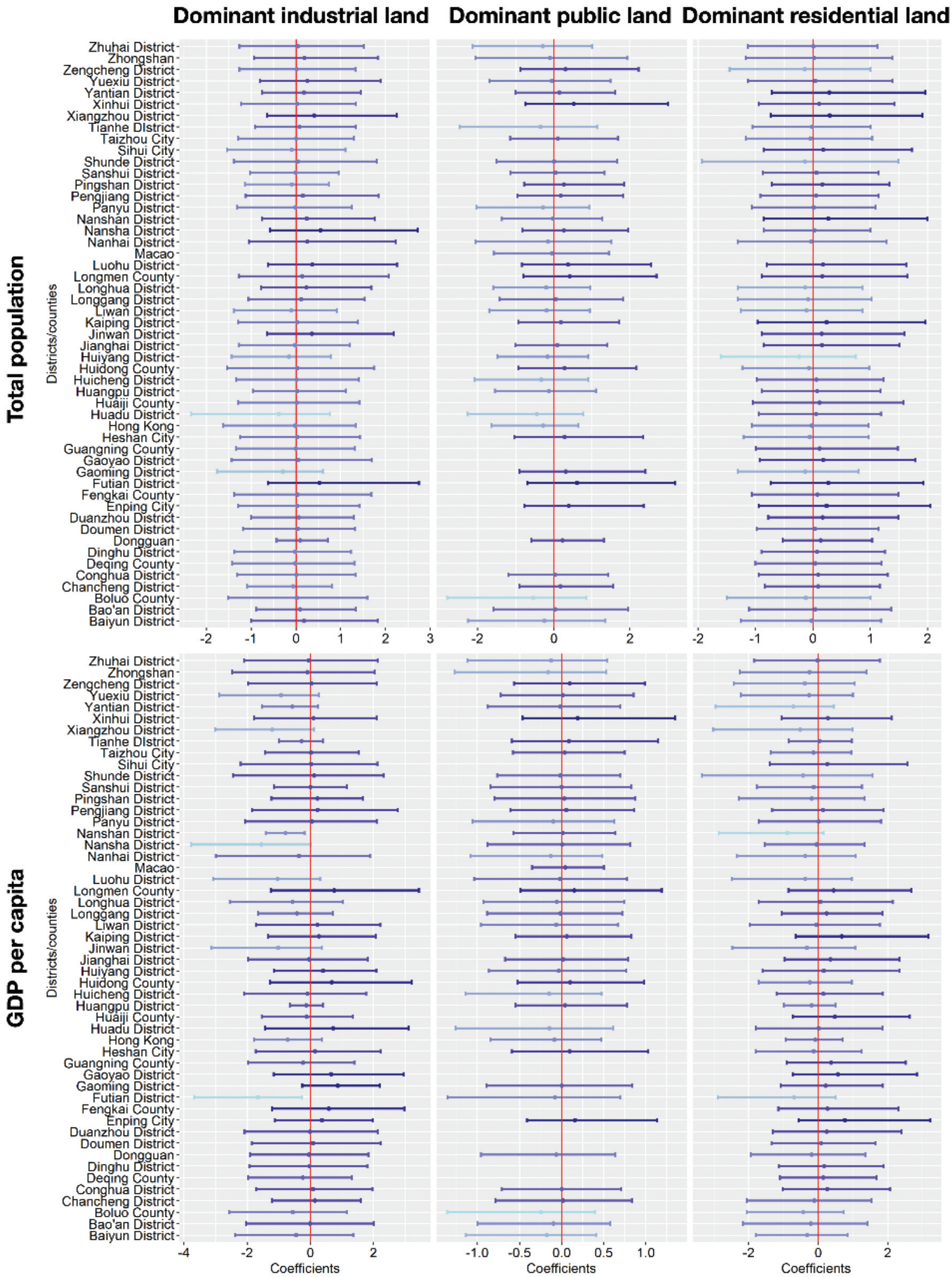


Figure 3. The random effects of region-level socioeconomic factors on industrial, public, and residential land. The *x*-axis represents coefficient values of the total population and GDP per capita, and *y*-axis represents counties/districts/cities in GBA.

To sum up, results based on the selected clusters revealed the contribution of higher proportion, lower density of urban built-up land, and lower-degree ecological complexity on urban land use transformation in GBA. Such ecological patterns highlighted the aggregation trend of urban built-up land, which could be supported by the period of rapid urban expansion in GBA (Zheng et al. 2022). Moreover, the low-degree complexity of ecological morphologies revealed the dominant distribution of urban built-up land compared with other land cover classes such as green spaces, and water body, indicating the unbalanced urban configurations and further suggesting the sustainable development of physical environment.

Table 4. The selected clusters (clusters were depicted with different characteristics, including relatively high-, mid-, and low- PUBL, EDUBL, OLSI, and OAI).

Clusters	Characteristics
Cluster 12	Mid PUBL, OLSI, and OAI
Cluster 15	High PUBL Low EDUBL and OLSI
Cluster 52	Low PUBL High EDUBL, OLSI
Cluster 64	Mid PUBL, OLSI, OAI
Cluster 94	High PUBL, Low EDUBL

3.3. Grid-level urban functional morphological impacts

Grid-level urban functional factors exhibited various impacts on forming urban land uses compared with well-developed areas (Figure 5). Particularly, increasing and decreasing probabilities of GWP on industrial, public, and residential land were found on contributing to urban land uses (coefficients: 0.15, −0.13, and – 0.09). BP showed no significant changes between impacts on newly formed land uses and well-developed areas. RD exhibited less impacts on newly formed public and residential land and decreasing probabilities on contributing to dominant industrial land. Moreover, PTD and SDD showed significantly decreasing probabilities on forming dominant industrial, public, and residential lands. BID showed positive probabilities on newly formed industrial land and public land (coefficients:

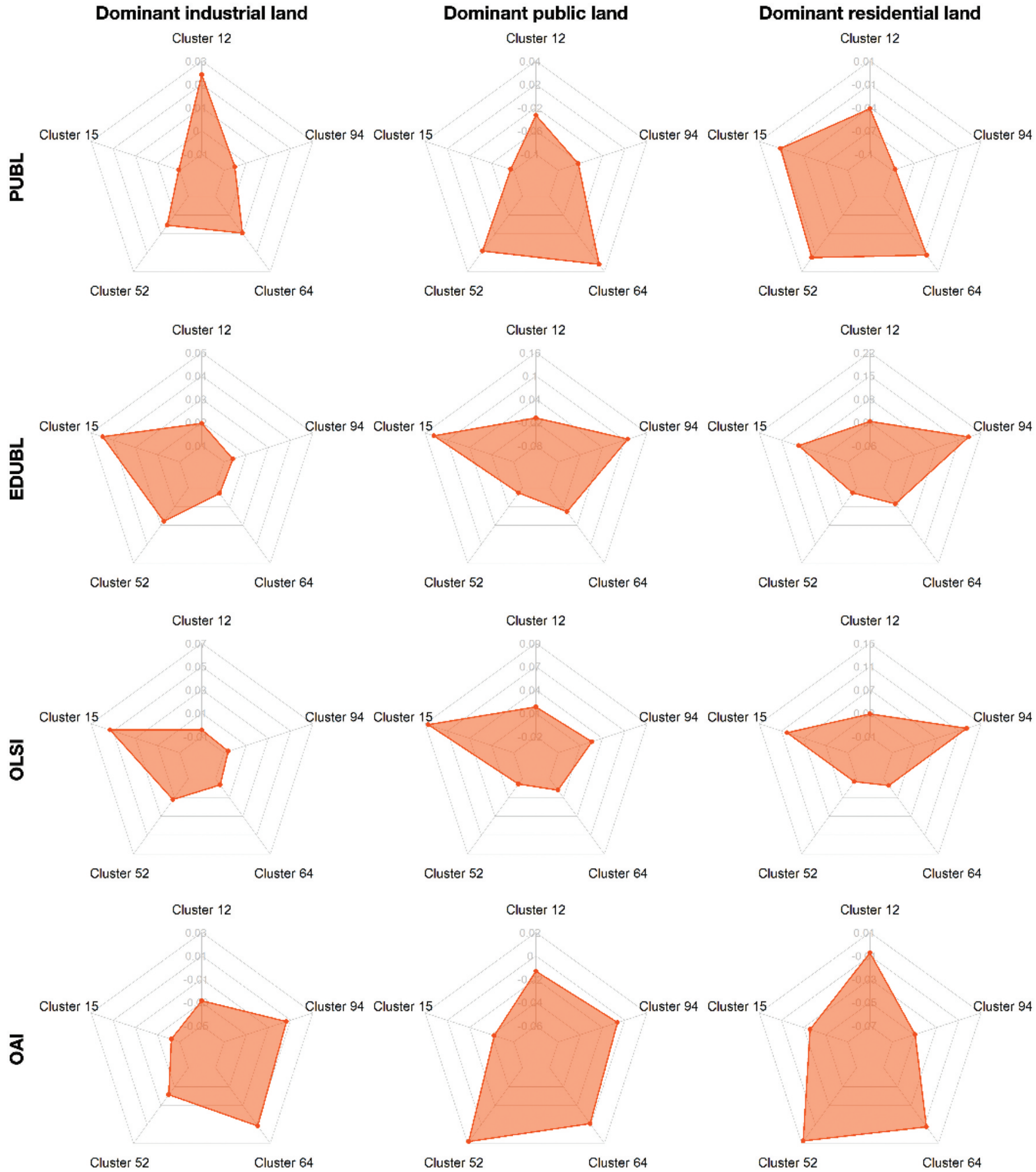


Figure 4. Radar plots of cluster-level ecological effects on industrial, public, and residential land in selected clusters. Axes represent coefficients of PUBL, EDUBL, OLSI, and OAI for each cluster.

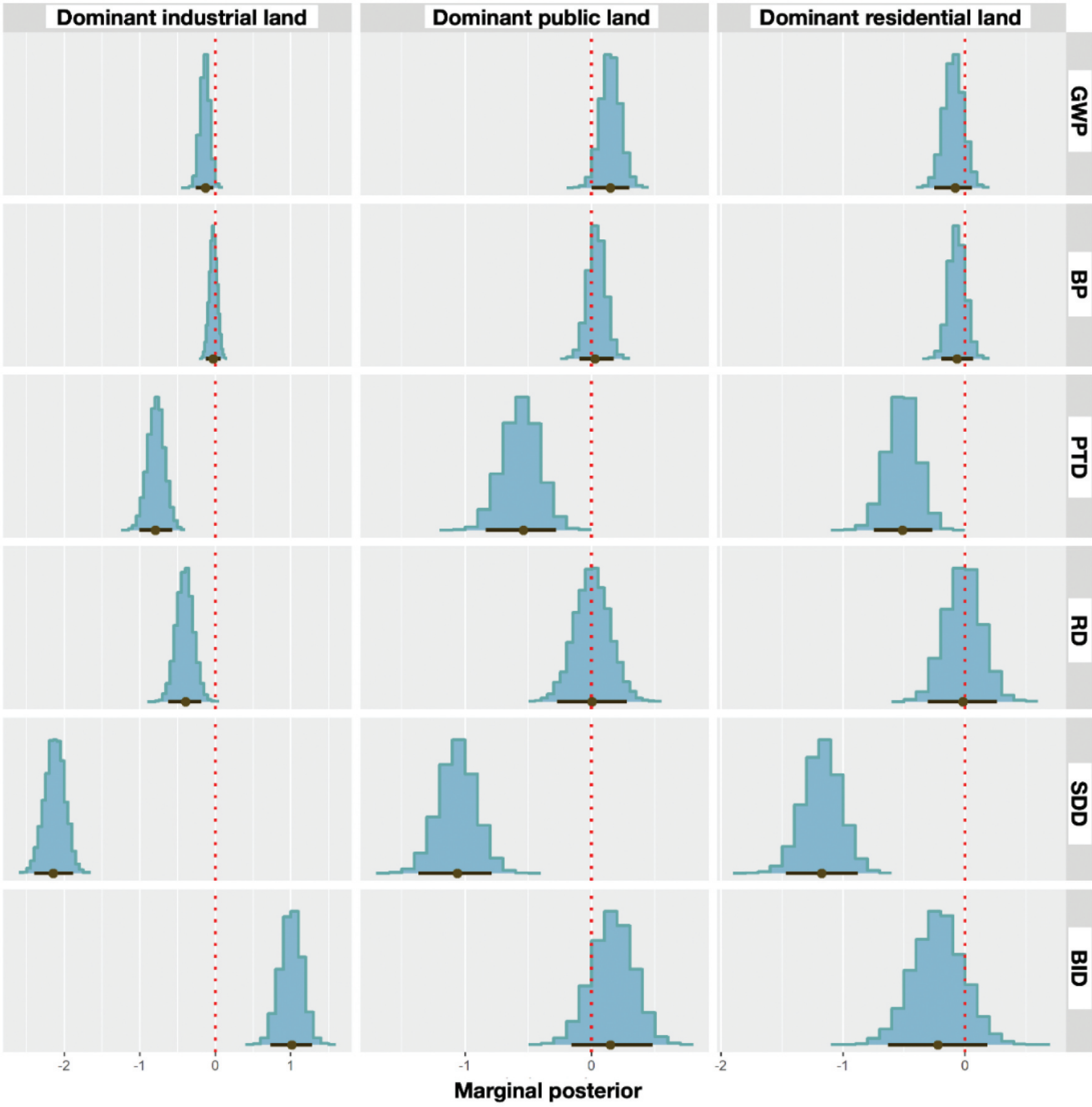


Figure 5. The impacts of grid-level urban functional factors on dominant industrial, public, and residential land in the GBA. The *x*-axis represents coefficient values and *y*-axis represents cumulative quantities of grids within the ranges of coefficients. The red-dotted lines indicate the coefficients being 0. Blue columns and brown lines represent coefficient distribution and coefficients with 95% intervals.

0.99 and 0.15) and negative probabilities on dominant residential land (coefficient: −0.22).

3.4. Multi-spatial urbanization factors in individual cities in GBA

To assess the impacts on multi-spatial urbanization factors (especially grid-level urban functional characteristics) in megacities, investigations on individual cities in GBA were proposed (Figure 6). Compared with GBA-level analyses, Dongguan has revealed the increasing probabilities based on road density of forming dominant industrial and public lands. Findings can be explained by the strategies and policies proposed by governments to develop new districts that are named "experimental zones" (Wang 2013; Wuttke 2011). Binhai Bay in Dongguan, constructed as a designated area for city planning, provided sufficient evidence on such significant linkages between urban functional construction and urbanization changes (Yang 2019). Specifically, it was designed as advanced manufacturing places that promote industrial transformation during urban sprawl and became the corridors Guangzhou-Shenzhen, as well as Shenzhen-Zhongshan, respectively. Those strategies support our findings that road structures show a higher impact on the urbanization process in Dongguan instead of the entire GBA region. Regarding the dominant public land, Hong Kong showed much less significant impacts of urban functional characteristics, especially the public transportation density, road density, and distribution of both shopping/dining and business/industry, compared with other cities. As one of the developed cities in the world, Hong Kong has the well-organized strategies of urban utilization and had formed systematic economic and public services

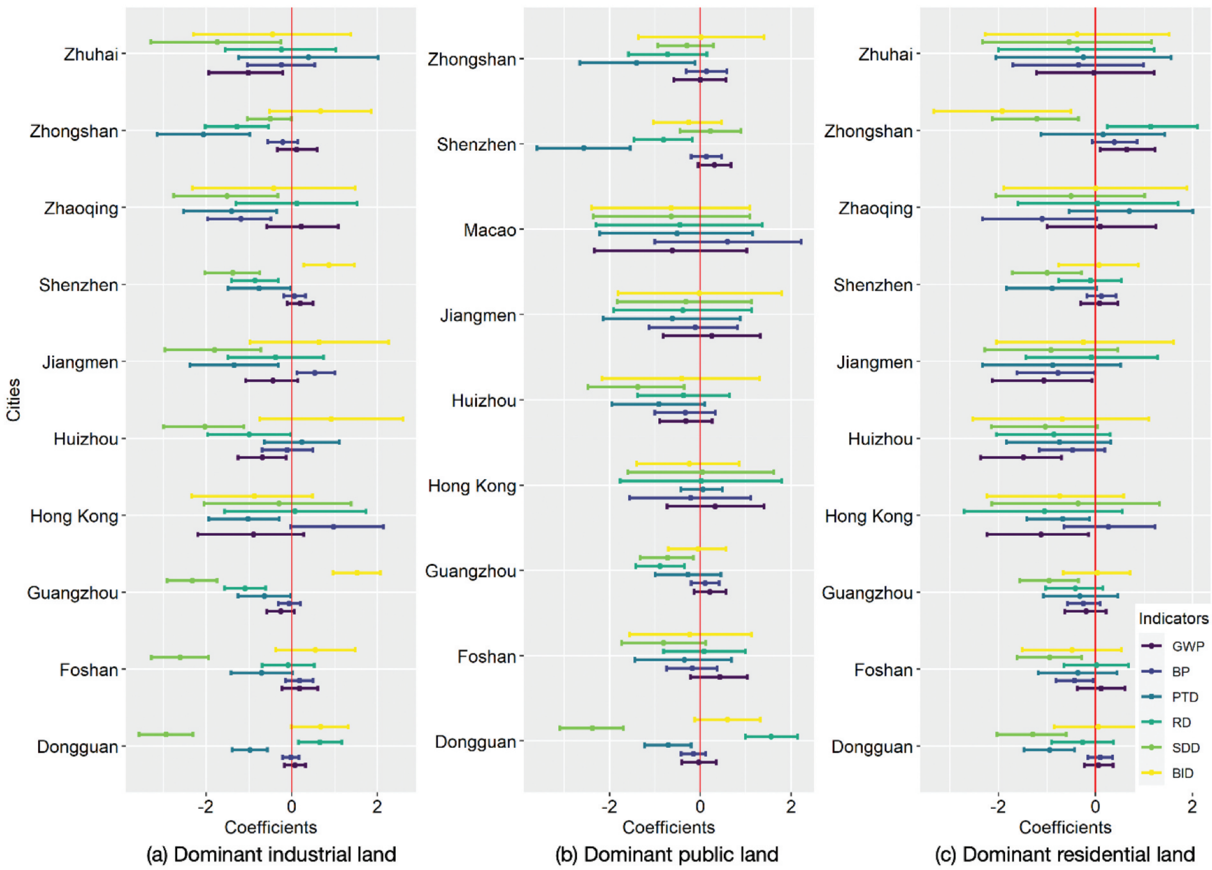


Figure 6. The fixed effects (with 95% intervals) of grid-level urban functional characteristics on dominant land uses in individual cities in the GBA.

since the year 1987. The findings in Hong Kong that less impact discrepancies of urbanization characteristics on the changes of urban built-up land support such stabilization of urban development.

4. Discussion

4.1. The mechanism behind the multi-spatial urbanization factors

This study revealed that dominant industrial land represented the largest area (percentage: 59.96%) among the newly formed urban built-up land in GBA. It could be explained by the rapid incremental urban expansion reshaping and strengthening for economic development in the Pearl River Delta Metropolitan Region and the incorporation of Hong Kong and Macao. For example, urban development strategies have been proposed by governments on Nansha District in Guangzhou, Nanshan District in Shenzhen, Cuiheng New District in Zhongshan, and Binhai Bay in Dongguan, implemented with public infrastructures to support industrial development.

The region-level socioeconomic factors showed significant unbalances of urban expansion, growing population, and the increasing GDP among 51 districts/counties/cities in GBA. This study supports the findings in previous research that increasing population can contribute to the urban land expansion (Liu et al. 2016; Yang et al. 2019). On the other hand, regions such as Liwan District in Guangzhou and Longhua District in Shenzhen represented the largest proportions of urban built-up land expansion, showing relatively low-level total population and GDP per capita in 2018 compared with other regions. Another unbalanced socioeconomic pattern was revealed in Bao'an District in Shenzhen. It has reached a total population of over 3 million accompanied by the newly formed urban built-up land occupied almost 30% of the total area, which were more intensive than the development of GDP per capita (Figure 7). The increasing urban built-up land and the population in these districts were closely correlated with the rural migrants moving into the cities for job opportunities and social resources. However, findings indicated that the GDP per capita was much lower in these districts compared with the rapid urban expansion or population growth. Since these districts are far away from the financial center of Guangzhou and Shenzhen, they received less economic supports and had less well-developed economies than the central districts (Cao et al. 2014).

The analysis of ecological clusters distinguished various impacts on different land uses of newly

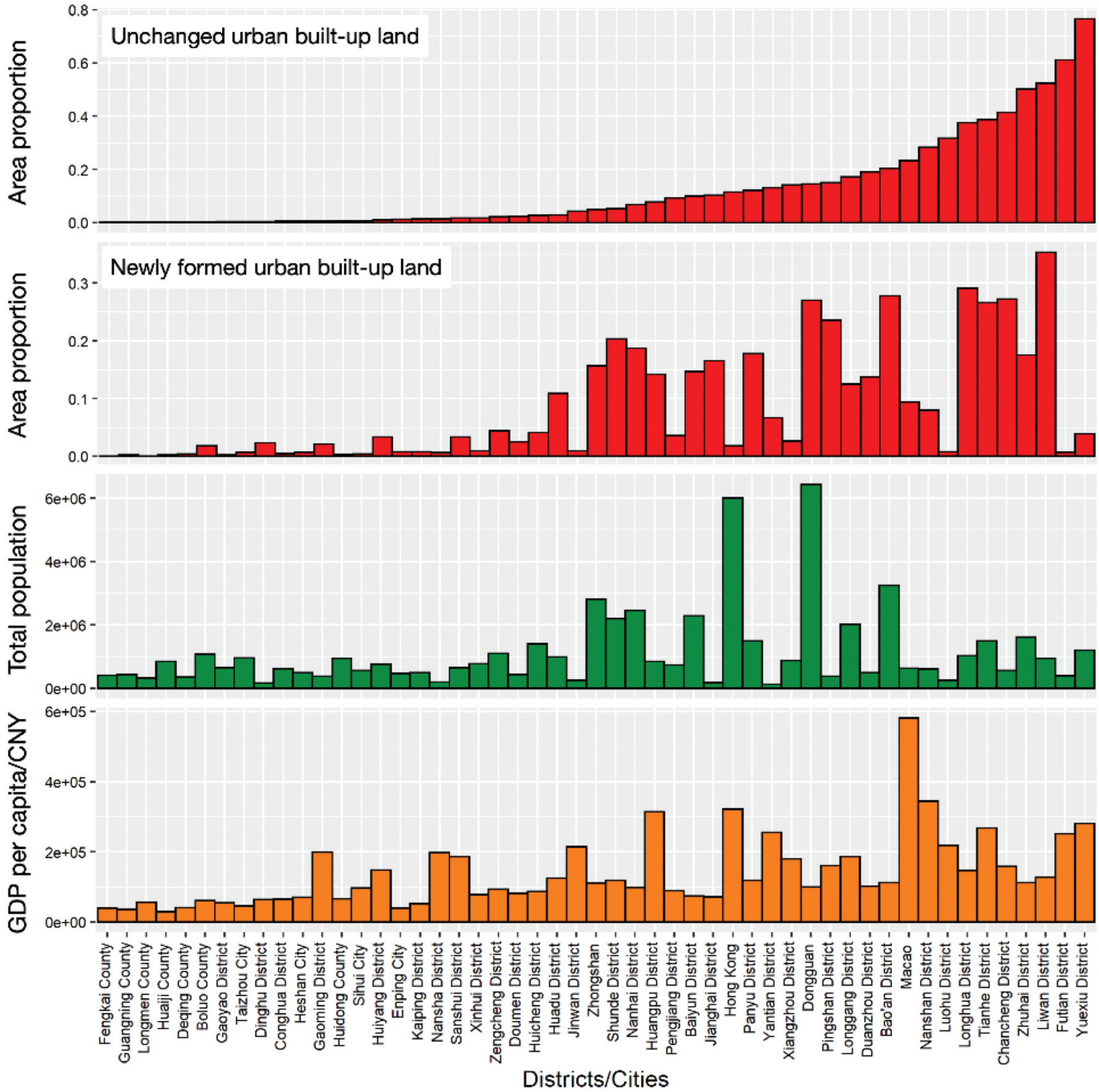


Figure 7. Proportion of newly formed urban built-up land, well-developed urban built-up land, total population, and GDP per capita in 2018 in districts/counties/cities in the GBA.

formed urbanized areas from well-developed ones in GBA. Results indicated that lower edge densities of urban built-up land and less land cover complexities exhibit higher impacts on dominant industrial and public land. It explained the dramatic increase in continuous urban built-up land driven by the economic development, indicating that such urban expansion pattern was specifically focused on the industrial land. And the public land was heavily invested including the public facilities and infrastructures to support the industrial evolution (Wei and Ye 2014). Moreover, the lower complexity of urban built-up land indicated the fast development of real estate for residential needs accompanied by the dramatic growth of population in urban areas (Lin et al. 2015; Wen et al. 2020).

While previous studies have revealed the important role of urban functional morphologies across the overall urbanization area (Xing and Meng 2020a, 2020b), this study found no significant impacts of building and road density on the newly formed urban built-up land compared with the well-developed area between 2000 and 2018. It suggests that strategic planning by the government on real estate, road network, and natural resources, despite the various land uses, was consistent during megacity evolution to provide social support and serve basic functions for the residents.

Moreover, the distribution patterns of business and industrial places showed increasing probabilities to identify both dominant industrial land and public land than those classifying well-developed land use, while decreasing probabilities were resulted in identifying dominant residential land. Such land use heterogeneity was consistent with the policies implemented in GBA to promote industrialization (Yang 2012), especially the transformation from agriculture to manufacturing land uses that led to the tendency of edge-center patterns of the megalopolis. However, the decreasing probability based on densities of public transportation and shopping/dining distribution indicated that although urban sprawl has brought tremendous opportunities to develop industrial infrastructures, there were shortages of public amenities and commercial facilities in the newly formed urban built-up land that intensified the unbalanced development between central and sprawling urban areas.

4.2. Limitations

Despite there are significant findings of this study, some limitations still exist. The first challenge is the availability and the quality of the spatial data. High-resolution land cover and land use data cannot be obtained in many places, which could lead to biases in assessing urbanization changes in the continuous regions. Moreover, the data quality may vary among regions. For instance, since OSM is a geographical database based on crowdsourcing volunteered data, the completeness and accuracies of the OSM data in some countries and regions are below standard. As a result, inaccurate results could be obtained in assessing the urbanization process in megacities. To reduce the biases caused by data quality, the required data should be carefully validated in terms of the spatial locations and the land use attribution using sampling strategies in future studies.

Second, the identification of dominant urban land uses should be improved. In this study, specific dominant land use types were not included in several cities. For example, newly formed dominant industrial land and residential land were not extracted in Macao, and dominant public land was not included in Zhuhai and Zhaoqing. This could be explained by (1) the selection of 1 km grids that could not capture finer patterns of newly formed urban built-up land and (2) the identification of dominant classes (based on the highest proportion and edge density of land use class) that ignores scattered small areas of land uses and mixed land uses. To fill this gap, grids with smaller sizes (such as $500\,\text{m} \times 500\,\text{m}$ grids) or blocks delineated by streets, as well as mixed land uses should be considered to capture finer-resolution multi-function urban built-up patterns in future studies.

Third, the proposed multi-spatial urbanization factors in this study, which have been depicted from urban functional, ecological, and socioeconomic perspectives, might not comprehensively represent the environmental and social changes in other megacity evolution. There are other geographical factors that could mediate the urbanization process, such as the air quality and the proximity to other cities (Taubenböck et al. 2014; Zhang et al. 2022). In addition, such urbanization framework should be assessed in other megacities, such as the Beijing–Tianjin–Hebei (BTH) and Yangtze River Delta (YRD) in China. The investigation on different megacities provides evidence to assess the changing urbanization characteristics regarding the varieties of environmental and socio-economic development.

4.3. Policy recommendation

The varying effects of urbanization factors on newly formed and well-developed urban areas provide evidence for urban planning policies to better understand urbanization trends, which in turn could effectively guide the sustainable development of urban morphologies and socioeconomics. Thus, it is important to find up-to-date suggestions about urban function optimization, ecological allocation, and socioeconomic sustainability in megacities, not limited to the GBA, for the urban policymakers. Particularly, the increasing region-level population exhibited higher possibilities of forming dominant industrial, public, and residential land in this study. Such population burdens have generated severe challenges to social resources and environmental sustainability (Song et al. 2021). Meanwhile, the phenomenon of city shrinkage has been found in many places nowadays that exhibited population decline and economic downturn (Liu and Liu 2022). It revealed the necessity of balancing the urban population growth and the urban carrying capacity in different urbanization stages.

In terms of the ecological environment, findings have revealed the close linkage between high-level occupation, low-level complexity urban built-up land, and the newly formed dominant land uses. It suggested the importance of proposing scientific allocation strategies for developing land cover diversities. For instance, water body is one of the major natural sources to support residents' basic needs and cities' sustainable development (Rashid, Manzoor, and Mukhtar 2018). Moreover, the rapid shift from rural to urban land and the increasing human demands have been subject to large-scale forest loss (Liu et al. 2016); thus, the governments need to pay attention to maintaining the coordination of megacity evolution and forest protection.

Moreover, the megacities showed the significant development of the urban functions. The improvements of transportation and commercial, industrial facilities have contributed to the industrialization process. Besides, the enhancement of transportation system is necessary, especially with increasing urban expansion and population, which has also been shown by the findings that high-density public transportation contributes to the development of industrial and public land in this study. In addition, for the sustainability in megacity evolution, the urban function allocation could be managed and planned beyond city administrative boundaries.

5. Conclusion

This study has presented a multi-spatial framework to compare the changing impacts of urban morphologies and socioeconomics on newly formed urban land uses with well-developed areas in megacities. A three-level Bayesian hierarchical model was designed to distinguish the changing impacts of region-level socioeconomics, cluster-level ecological morphologies, and grid-level urban functional morphologies in GBA. Findings indicated that the constructed Bayesian hierarchical model could ffectively assess the changing influences of urban morphologies and socioeconomics on newly formed urban land uses. With the well-developed urbanized area in 2000 as the reference point, region-level socioeconomics exhibited an increasing impact of total population on forming dominant residential land in most regions. Cluster-level ecological morphologies with higher proportion, lower edge density of urban built-up land, and lower-degree land cover complexity contributed to forming dominant industrial land and public lands. Regarding grid-level urban functional morphologies, high-level public transportation, and shopping/dining densities indicated decreasing probabilities of forming urban land uses, while high-level densities of business and industry facilities exhibited increasing probabilities of forming dominant industrial/public land and decreasing probabilities of forming dominant residential land. In addition, urban function morphologies varied among cities, elucidating substantial discrepancies between GBA-scale and city-scale analyses. The proposed framework has provided new insights into understanding the impact of multi-level urbanization structures on land use transformation in megacities.

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References

Atasoy, M. 2018. "Monitoring the Urban Green Spaces and Landscape Fragmentation Using Remote Sensing: A Case Study in Osmaniye, Turkey." *Environmental Monitoring and Assessment* 190 (12): 713. https://doi.org/10.1007/s10661-018-7109-1.

Aznar-Sánchez, J. A., M. Piquer-Rodríguez, J. F. Velasco-Muñoz, and F. Manzano-Agugliaro. 2019. "Worldwide Research Trends on Sustainable Land Use in Agriculture." *Land Use Policy* 87:104069. https://doi.org/10.1016/j.landusepol.2019.104069.

Baio, G., and M. Blangiardo. 2010. "Bayesian Hierarchical Model for the Prediction of Football Results." *Journal of Applied Statistics* 37 (2): 253–264. https://doi.org/10.1080/02664760802684177.

Cao, S., Y. Lv, H. Zheng, and X. Wang. 2014. "Challenges Facing China's Unbalanced Urbanization Strategy." *Land Use Policy* 39:412–415. https://doi.org/10.1016/j.landusepol.2013.12.004.

Cao, X., S. Ouyang, W. Yang, Y. Luo, B. Li, and D. Liu. 2019. "Transport Accessibility and Spatial Connections of Cities in the Guangdong-Hong Kong-Macao Greater Bay Area." *Chinese Geographical Science* 29 (5): 820–833. https://doi.org/10.1007/s11769-019-1034-2.

Chakraborty, S., H. Dadashpoor, J. Novotný, I. Maity, A. Follmann, P. P. Patel, U. Roy, and S. Pramanik. 2022. "In Pursuit of Sustainability–Spatio-temporal Pathways of Urban Growth Patterns in the World's Largest Megacities." *Cities* 131:103919. https://doi.org/10.1016/j.cities.2022.103919.

Chang, S., J. Wang, F. Zhang, L. Niu, and Y. Wang. 2020. "A Study of the Impacts of Urban Expansion on Vegetation Primary Productivity Levels in the Jing-Jin-Ji Region, Based on Nighttime Light Data." *Journal of*

Cleaner Production 263:121490. https://doi.org/10.1016/j.jclepro.2020.121490.

Chen, M., J. Bai, S. Zhu, B. Yang, and F. Dai. 2021. "The Influence of Neighborhood-Level Urban Morphology on PM2. 5 Variation Based on Random Forest Regression." *Atmospheric Pollution Research* 12 (8): 101147. https://doi.org/10.1016/j.apr.2021.101147 .

Chong, Z., and S. Pan. 2020. "Understanding the Structure and Determinants of City Network Through Intra-Firm Service Relationships: The Case of Guangdong-Hong Kong-Macao Greater Bay Area." *Cities* 103:102738. https://doi.org/10.1016/j.cities.2020.102738.

Deng, H., K. Zhang, F. Wang, and A. Dang. 2021. "Compact or Disperse? Evolution Patterns and Coupling of Urban Land Expansion and Population Distribution Evolution of Major Cities in China, 1998–2018." *Habitat International* 108:102324. https://doi.org/10.1016/j.habitatint.2021.102324.

Gong, P., B. Chen, X. Li, H. Liu, J. Wang, Y. Bai, J. Chen, X. Chen, L. Fang, and S. Feng. 2020. "Mapping Essential Urban Land Use Categories in China (EULUC-China): Preliminary Results for 2018." *Science Bulletin* 65 (3): 182–187. https://doi.org/10.1016/j.scib.2019.12.007.

Han, K.-S., J.-L. Champeaux, and J.-L. Roujean. 2004. "A Land Cover Classification Product Over France at 1 km Resolution Using SPOT4/VEGETATION Data." *Remote Sensing of Environment* 92 (1): 52–66. https://doi.org/10.1016/j.rse.2004.05.005.

Han, Y., K. Zhang, Q. Lin, S. Huang, and X. Yang. 2023. "Assessing Lake Ecosystem Health from Disturbed Anthropogenic Landscapes: Spatial Patterns and Driving Mechanisms." *Ecological Indicators* 147:110007. https://doi.org/10.1016/j.ecolind.2023.110007.

Huai, S., and T. Van de Voorde. 2022. "Which Environmental Features Contribute to Positive and Negative Perceptions of Urban Parks? A Cross-Cultural Comparison Using Online Reviews and Natural Language Processing Methods." *Landscape and Urban Planning* 218:104307. https://doi.org/10.1016/j.landurbplan.2021.104307 .

Hui, E. C., X. Li, T. Chen, and W. Lang. 2020. "Deciphering the Spatial Structure of China's Megacity Region: A New Bay Area—The Guangdong-Hong Kong-Macao Greater Bay Area in the Making." *Cities* 105:102168. https://doi.org/10.1016/j.cities.2018.10.011.

Kidokoro, T., M. Matsuyuki, and N. Shima. 2022. "Neoliberalization of Urban Planning and Spatial Inequalities in Asian Megacities: Focus on Tokyo, Bangkok, Jakarta, and Mumbai." *Cities* 130:103914. https://doi.org/10.1016/j.cities.2022.103914.

Li, H., Y. Liu, H. Zhang, B. Xue, and W. Li. 2021. "Urban Morphology in China: Dataset Development and Spatial Pattern Characterization." *Sustainable Cities and Society* 71:102981. https://doi.org/10.1016/j.scs.2021.102981.

Li, J., H. Zhang, and Z. Sun. 2020. "Spatiotemporal Variations of Land Urbanization and Socioeconomic Benefits in a Typical Sample Zone: A Case Study of the Beijing-Hangzhou Grand Canal." *Applied Geography* 117:102187. https://doi.org/10.1016/j.apgeog.2020.102187.

Li, Z., Z. Han, J. Xin, X. Luo, S. Su, and M. Weng. 2019. "Transit Oriented Development Among Metro Station Areas in Shanghai, China: Variations, Typology, Optimization and Implications for Land Use Planning." *Land Use Policy* 82:269–282. https://doi.org/10.1016/j.landusepol.2018.12.003.

Lin, X., Y. Wang, S. Wang, and D. Wang. 2015. "Spatial Differences and Driving Forces of Land Urbanization in China." *Journal of Geographical Sciences* 25 (5): 545–558. https://doi.org/10.1007/s11442-015-1186-7.

Lin, Y., R. Qiu, J. Yao, X. Hu, and J. Lin. 2019. "The Effects of Urbanization on China's Forest Loss from 2000 to 2012: Evidence from a Panel Analysis." *Journal of Cleaner Production* 214:270–278. https://doi.org/10.1016/j.jclepro.2018.12.317.

Liu, C., and D. Duan. 2020. "Spatial Inequality of Bus Transit Dependence on Urban Streets and Its Relationships with Socioeconomic Intensities: A Tale of Two Megacities in China." *Journal of Transport Geography* 86:102768. https://doi.org/10.1016/j.jtrangeo.2020.102768.

Liu, D., Z. Feng, Y. Yang, and Z. You. 2011. "Spatial Patterns of Ecological Carrying Capacity Supply-Demand Balance in China at County Level." *Journal of Geographical Sciences* 21 (5): 833–844. https://doi.org/10.1007/s11442-011-0883-0.

Liu, J., Z. Zhang, X. Xu, W. Kuang, W. Zhou, S. Zhang, R. Li, C. Yan, D. Yu, and S. Wu. 2010. "Spatial Patterns and Driving Forces of Land Use Change in China During the Early 21st Century." *Journal of Geographical Sciences* 20 (4): 483–494. https://doi.org/10.1007/s11442-010-0483-4.

Liu, T.-Y., and C.-W. Su. 2021. "Is Transportation Improving Urbanization in China?" *Socio-Economic Planning Sciences* 77:101034. https://doi.org/10.1016/j.seps.2021.101034.

Liu, Y., Y. Feng, Z. Zhao, Q. Zhang, and S. Su. 2016. "Socioeconomic Drivers of Forest Loss and Fragmentation: A Comparison Between Different Land Use Planning Schemes and Policy Implications." *Land Use Policy* 54:58–68. https://doi.org/10.1016/j.landusepol.2016.01.016.

Liu, Y., and Y. Li. 2017. "Revitalize the World's Countryside." *Nature News* 548 (7667): 275. https://doi.org/10.1038/548275a.

Liu, Y., K. Wu, and H. Cao. 2022. "Land-Use Change and Its Driving Factors in Henan Province from 1995 to 2015." *Arabian Journal of Geosciences* 15 (3): 247. https://doi.org/10.1007/s12517-022-09509-1.

Liu, Z., H. Huang, S. E. Werners, and D. Yan. 2016. "Construction Area Expansion in Relation to Economic-Demographic Development and Land Resource in the Pearl River Delta of China." *Journal of Geographical Sciences* 26 (2): 188–202. https://doi.org/10.1007/s11442-016-1262-7.

Liu, Z., and S. Liu. 2022. "Urban Shrinkage in a Developing Context: Rethinking China's Present and Future Trends." *Sustainable Cities and Society* 80:103779. https://doi.org/10.1016/j.scs.2022.103779.

Long, H., and Y. Qu. 2018. "Land Use Transitions and Land Management: A Mutual Feedback Perspective." *Land Use Policy* 74:111–120. https://doi.org/10.1016/j.landusepol.2017.03.021.

Luo, M., G. Hu, G. Chen, X. Liu, H. Hou, and X. Li. 2022. "1 Km Land Use/Land Cover Change of China Under Comprehensive Socioeconomic and Climate Scenarios for 2020–2100." *Scientific Data* 9 (1): 1–13. https://doi.org/10.1038/s41597-022-01204-w.

Ma, J., Y. Sun, D. Meng, S. Huang, N. Li, and H. Zhu. 2021. "Accuracy Assessment of Two Global Gridded Population Dataset: A Case Study in China." In *2021 The 4th International Conference on Information Science and Systems*; Edinburgh.

Masoumi, H. E., F. Terzi, and Y. M. Serag. 2019. "Neighborhood-Scale Urban Form Typologies of Large Metropolitan Areas: Observations on Istanbul, Cairo, and Tehran." *Cities* 85:170–186. https://doi.org/10.1016/j.cities.2018.09.005.

Miao, J. T., and N. A. Phelps. 2021. "Urban Sprawl as Policy Sprawl: Distinguishing Chinese Capitalism's Suburban Spatial Fix." *Annals of the American Association of Geographers* 112 (4): 1–16. https://doi.org/10.1080/24694452.2021.1959294.

Naikoo, M. W., M. Rihan, A. H. Peer, S. Talukdar, J. Mallick, M. Ishtiaq, and A. Rahman. 2022. "Analysis of Peri-Urban Land Use/Land Cover Change and Its Drivers Using Geospatial Techniques and Geographically Weighted Regression." *Environmental Science and Pollution Research* 1–19. https://doi.org/10.1007/s11356-022-18853-4.

Ning, J., J. Liu, W. Kuang, X. Xu, S. Zhang, C. Yan, R. Li, S. Wu, Y. Hu, and G. Du. 2018. "Spatiotemporal Patterns and Characteristics of Land-Use Change in China During 2010–2015." *Journal of Geographical Sciences* 28 (5): 547–562. https://doi.org/10.1007/s11442-018-1490-0 .

Overman, H. G., D. Puga, and M. A. Turner. 2008. "Decomposing the Growth in Residential Land in the United States." *Regional Science and Urban Economics* 38 (5): 487–497. https://doi.org/10.1016/j.regsciurbeco.2008.05.006.

Pandey, B., C. Brelsford, and K. C. Seto. 2022. "Infrastructure Inequality is a Characteristic of Urbanization." *Proceedings of the National Academy of Sciences* 119 (15): e2119890119. https://doi.org/10.1073/pnas.2119890119.

Post, J. R., H. G. Ward, K. L. Wilson, G. L. Sterling, A. Cantin, and E. B. Taylor. 2022. "Assessing Conservation Status with Extensive but Low-Resolution Data: Application of Frequentist and Bayesian Models to Endangered Athabasca River Rainbow Trout." *Conservation Biology* 36 (3): e13783. https://doi.org/10.1111/cobi.13783.

Rashid, H., M. M. Manzoor, and S. Mukhtar. 2018. "Urbanization and Its Effects on Water Resources: An Exploratory Analysis." *Asian Journal of Water, Environment & Pollution* 15 (1): 67–74. https://doi.org/10.3233/AJW-180007.

Sadeghirad, B., F. Foroutan, M. J. Zoratti, J. W. Busse, R. Brignardello-Petersen, G. Guyatt, and L. Thabane. 2022. "Theory and Practice of Bayesian and Frequentist Frameworks for Network Meta-Analysis." *BMJ Evidence-Based Medicine* 28 (3): 204–209. https://doi.org/10.1136/bmjebm-2022-111928.

Schmitt, A., P. Uth, I. Standfuß, B. Heider, S. Siedentop, and H. Taubenböck. 2023. "Quantitative Assessment and Comparison of Urban Patterns in Germany and the United States." *Computers, Environment and Urban Systems* 100:101920. https://doi.org/10.1016/j.compenvurbsys.2022.101920.

Song, X., Q. Feng, F. Xia, X. Li, and J. Scheffran. 2021. "Impacts of Changing Urban Land-Use Structure on Sustainable City Growth in China: A Population-Density Dynamics Perspective." *Habitat International* 107:102296. https://doi.org/10.1016/j.habitatint.2020.102296.

Song, Y., B. Chen, H. C. Ho, M.-P. Kwan, D. Liu, F. Wang, J. Wang, J. Cai, X. Li, and Y. Xu. 2021. "Observed Inequality in Urban Greenspace Exposure in China." *Environment International* 156:106778. https://doi.org/10.1016/j.envint.2021.106778 .

Tang, R., and S. Ellison. 2019. "Greater Bay Area: A 2030 Outlook – Opportunities and Challenges Over the Next Decade." Colliers International. https://www.colliers.com/en-hk/research/colliers-radar-greater-bay-area-a-2030-outlook.

Taubenböck, H., M. Wiesner, A. Felbier, M. Marconcini, T. Esch, and S. Dech. 2014. "New Dimensions of Urban Landscapes: The Spatio-Temporal Evolution from a Polynuclei Area to a Mega-Region Based on Remote Sensing Data." *Applied Geography* 47:137–153. https://doi.org/10.1016/j.apgeog.2013.12.002.

Taylor, P., and B. Derudder. 2015. *World City Network: A Global Urban Analysis*. Routledge.

Wang, C., Y. Li, S. W. Myint, Q. Zhao, and E. A. Wentz. 2019. "Impacts of Spatial Clustering of Urban Land Cover on Land Surface Temperature Across Köppen Climate Zones in the Contiguous United States." *Landscape and Urban Planning* 192:103668. https://doi.org/10.1016/j.landurbplan.2019.103668.

Wang, J., and X. Zhang. 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., Q. Zhou, and Y. Tian. 2020. "Understanding Completeness and Diversity Patterns of OSM-Based Land-Use and Land-Cover Dataset in China." *ISPRS International Journal of Geo-Information* 9 (9): 531. https://doi.org/10.3390/ijgi9090531.

Wang, X. 2013. *The Role of Economic Development Zones in National Development Strategies: The Case of China*. Santa Monica, CA: The Pardee RAND Graduate School.

Wang, Z., Y. Yue, B. He, K. Nie, W. Tu, Q. Du, and Q. Li. 2021. "A Bayesian Spatio-Temporal Model to Analyzing the Stability of Patterns of Population Distribution in an Urban Space Using Mobile Phone Data." *International Journal of Geographical Information Science* 35 (1): 116–134. https://doi.org/10.1080/13658816.2020.1798967.

Wei, Y. D., and X. Ye. 2014. "Urbanization, Urban Land Expansion and Environmental Change in China." *Stochastic Environmental Research and Risk Assessment* 28 (4): 757–765. https://doi.org/10.1007/s00477-013-0840-9.

Wen, Y., Z. Zhang, D. Liang, and Z. Xu. 2020. "Rural Residential Land Transition in the Beijing-Tianjin-Hebei Region: Spatial-Temporal Patterns and Policy Implications." *Land Use Policy* 96:104700. https://doi.org/10.1016/j.landusepol.2020.104700.

Wu, H., A. Lin, X. Xing, D. Song, and Y. Li. 2021. "Identifying Core Driving Factors of Urban Land Use Change from Global Land Cover Products and POI Data Using the Random Forest Method." *International Journal of Applied Earth Observation and Geoinformation* 103:102475. https://doi.org/10.1016/j.jag.2021.102475.

Wuttke, C. 2011. "From Industrial Enclaves to Prototypes of the Modern Chinese City: Development Zones in Guangdong." *Local Economy: The Journal of the Local Economy Policy Unit* 26 (5): 363–372. https://doi.org/10.1177/0269094211409137.

Xia, C., A. G. O. Yeh, and A. Zhang. 2020. "Analyzing Spatial Relationships Between Urban Land Use Intensity and Urban Vitality at Street Block Level: A Case Study of Five Chinese Megacities." *Landscape and Urban Planning* 193:103669. https://doi.org/10.1016/j.landurbplan.2019.103669.

Xing, H., and Y. Meng. 2020a. "Measuring Urban Landscapes for Urban Function Classification Using Spatial Metrics." *Ecological Indicators* 108:105722. https://doi.org/10.1016/j.ecolind.2019.105722.

Xing, H., and Y. Meng. 2020b. "Revealing Deep Semantic Commercial Patterns: Insights from Urban Landscape Depiction." *Computers, Environment and Urban Systems* 79:101404. https://doi.org/10.1016/j.compenvurbsys.2019.101404.

Yang, C. 2012. "Restructuring the Export-Oriented Industrialization in the Pearl River Delta, China: Institutional Evolution and Emerging Tension." *Applied Geography* 32 (1): 143–157. https://doi.org/10.1016/j.apgeog.2010.10.013.

Yang, D. 2019. "Between the Past and Future: The Transformation of the Pearl River Delta."

Yang, C., Q. Li, T. Zhao, H. Liu, W. Gao, T. Shi, M. Guan, and G. Wu. 2019. "Detecting Spatiotemporal Features and Rationalities of Urban Expansions within the Guangdong–Hong Kong–Macau Greater Bay Area of China from 1987 to 2017 Using Time-Series Landsat Images and Socioeconomic Data." *Remote Sensing* 11 (19): 2215. https://doi.org/10.3390/rs11192215.

Yang, R., F. Ren, W. Xu, X. Ma, H. Zhang, and W. He. 2022. "China's Ecosystem Service Value in 1992–2018: Pattern and Anthropogenic Driving Factors Detection Using Bayesian Spatiotemporal Hierarchy Model." *Journal of Environmental Management* 302:114089. https://doi.org/10.1016/j.jenvman.2021.114089.

Yeh, A. G.-O., and Z. Chen. 2020. "From Cities to Super Mega City Regions in China in a New Wave of Urbanisation and Economic Transition: Issues and Challenges." *Urban Studies* 57 (3): 636–654. https://doi.org/10.1177/0042098019879566.

You, H., and X. Yang. 2017. "Urban Expansion in 30 Megacities of China: Categorizing the Driving Force Profiles to Inform the Urbanization Policy." *Land Use Policy* 68:531–551. https://doi.org/10.1016/j.landusepol.2017.06.020.

Yu, J., K. Zhou, and S. Yang. 2019. "Land Use Efficiency and Influencing Factors of Urban Agglomerations in China." *Land Use Policy* 88:104143. https://doi.org/10.1016/j.landusepol.2019.104143.

Yu, L., W. Zheng, T. Yu, and Y. Wu. 2021. "How to Identify Urban Centers/Subcenters in Metropolises? An Analytical Review." *Habitat International* 115:102397. https://doi.org/10.1016/j.habitatint.2021.102397.

Zhang, X., L. Han, H. Wei, X. Tan, W. Zhou, W. Li, and Y. Qian. 2022. "Linking Urbanization and Air Quality Together: A Review and a Perspective on the Future Sustainable Urban Development." *Journal of Cleaner Production* 346:130988. https://doi.org/10.1016/j.jclepro.2022.130988.

Zhao, S., D. Qi, R. Li, W. Cheng, and C. Zhou. 2021. "Performance Comparison Among Typical Open Global DEM Datasets in the Fenhe River Basin of China." *European Journal of Remote Sensing* 54 (1): 145–157. https://doi.org/10.1080/22797254.2021.1891577.

Zheng, Y., Y. He, Q. Zhou, and H. Wang. 2022. "Quantitative Evaluation of Urban Expansion Using NPP-VIIRS Nighttime Light and Landsat Spectral Data." *Sustainable Cities and Society* 76:103338. https://doi.org/10.1016/j.scs.2021.103338.