



UNGEONOW 2024  
首届联合国地信周



# High resolution mapping of urban built environment: A perspective from construction materials

Zhou Huang & Yi Bao

Peking University

## What is urban built environment stocks?

Urban built environment material stocks refer to **the quality of materials (such as cement, steel, sand, and gravel) used in infrastructure** like buildings and roads that support human activities such as living, working, and transportation.

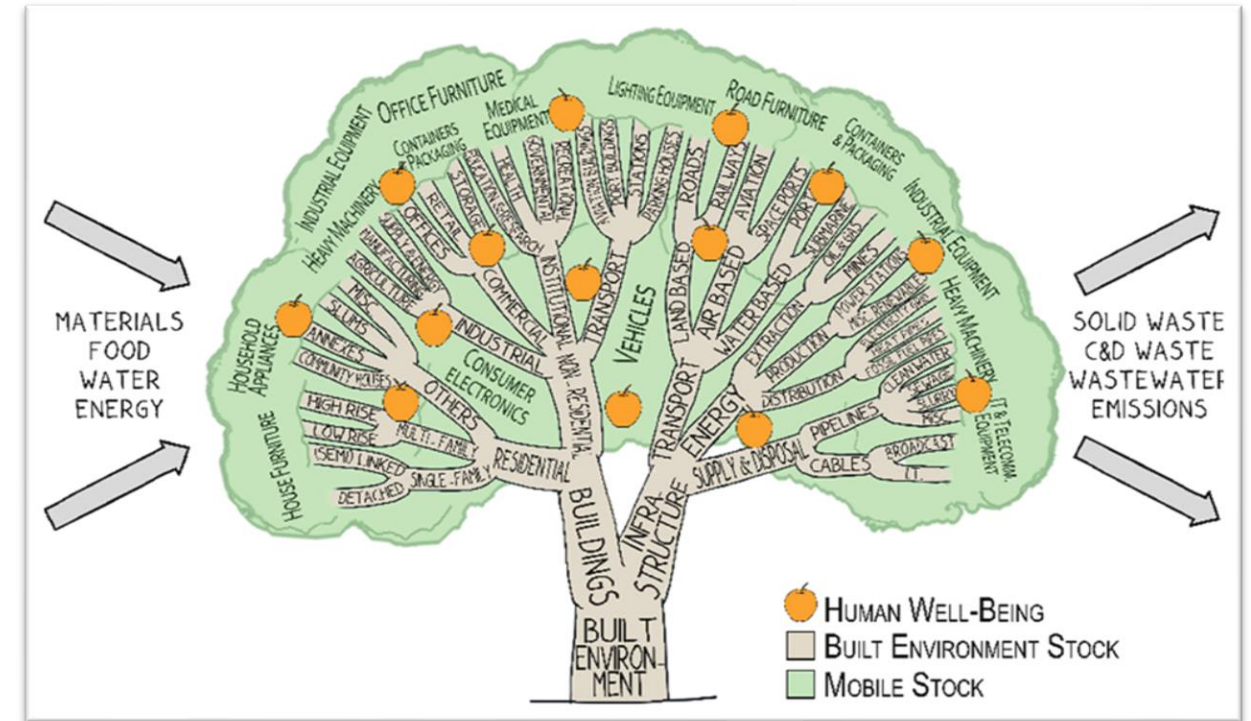


Figure 1: Schematic diagram of material stock in urban built environment<sup>[1]</sup>

[1] Lanau, M., Liu, G., Kral, U., Wiedenhofer, D., Keijzer, E., Yu, C., & Ehlert, C. (2019). Taking stock of built environment stock studies: Progress and prospects. Environmental science & technology, 53(15), 8499-8515.

# Introduction & Background



UNGEONOW 2024  
首届联合国地信周



Cities have promoted the development of human society

Urbanization has huge resource and environmental costs

Built environment is a major source of material accumulation

The mass of artificial materials doubles every 20 years, and the total global mass of buildings and infrastructure has exceeded **1 trillion tons**.

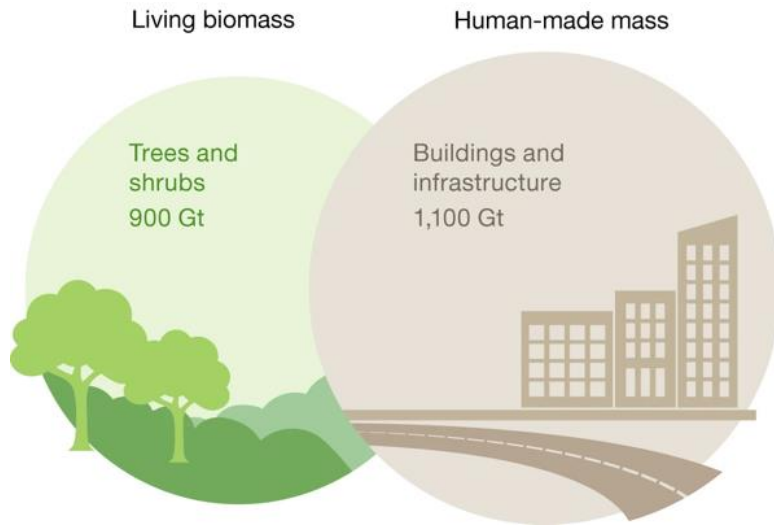


Figure 2: Comparison of artificial materials and biological materials<sup>[2]</sup>

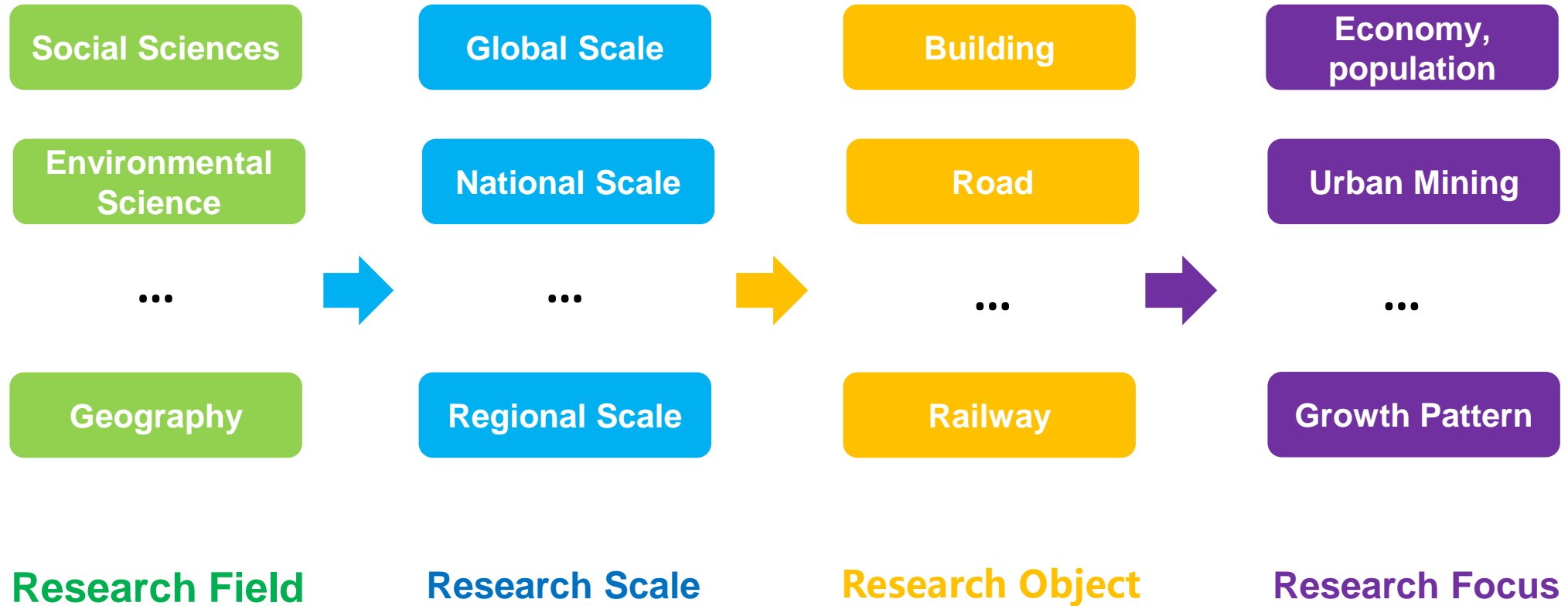
[2] Elhacham, E., Ben-Uri, L., Grozovski, J., Bar-On, Y. M., & Milo, R. (2020). Global human-made mass exceeds all living biomass. *Nature*, 588(7838), 442-444.

中国资源循环集团有限公司成立大会

中国·天津  
2024.10

中国资源循环集团有限公司  
China Resources Recycling Group Co., Ltd.

## Research of Urban Built Environment Material Stocks



## 1. Top-down method

### Material Flow Analysis

MFA is a systematic approach used to track and quantify the flow and transformation of materials within a specific region or system.

$$\sum Input = \sum Output + \Delta Stock$$



### Dynamic Material Flow Analysis

Dynamic Material Flow Analysis (DMFA) **extends traditional MFA** by incorporating temporal dynamics, enabling the quantification and analysis of long-term, large-scale material stocks and flows, particularly suited for studying **global or national metal accumulation patterns** in iron, aluminum, copper, and other metals over decades.

$$dS(t) = (inflow(t) - outflow(t)) \cdot dt = net\ flow(t) \cdot dt$$

## 2. Bottom-up method

### Bottom-up method

The Bottom-up approach, also known as the coefficient-based method, is a labor-intensive computational method for estimating material stocks

$$MS_{m,i,j} = \sum_{m,i,j} (PS_{i,j} \times MCI_{m,i,j})$$

$MS_{m,i,j}$  represents Material stock,  $MCI_{m,i,j}$  is Material composition indicator,  $PS_{i,j}$  refer to physical size of the built environment



## 3. Nighttime Light based Regression method

### NTL based Regression

This method leverages the association between human activities, as reflected by NTL, and the accumulation of material stocks in built environments

$$Y = \alpha X$$

Advanced fitting techniques, such as power function fitting, enhance the accuracy of stock estimations

$$\log(\text{stock}) = k + \beta \cdot \log(\text{light})$$

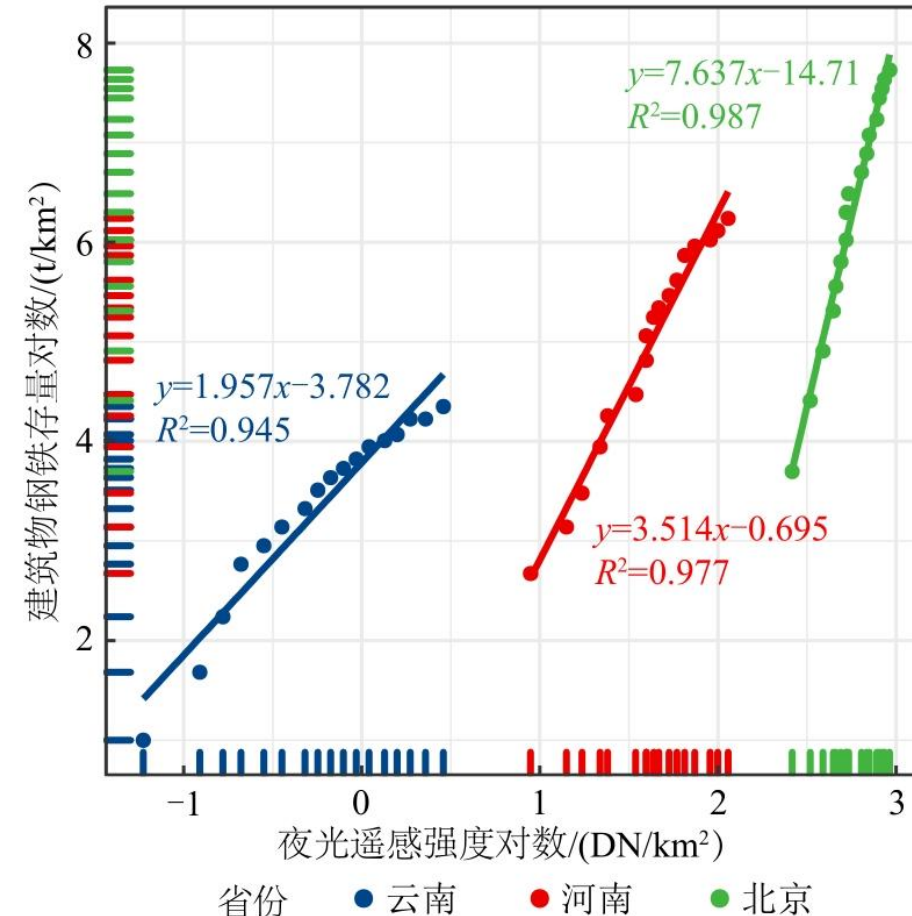


Figure 3: Relationship between NTL and steel stocks

## Problems and solutions

### Limitations of traditional methods

- 1. Data Limits:** Too much reliance on statistics makes these methods hard to use in areas with little data.
- 2. Spatio-temporal Constraints:** Most methods only work for certain time periods and areas, and are not good for long-term, large-area, high-resolution studies.
- 3. Model Incompatibility:**  
Poor comparability between models and  
Restricted scalability and generalizability

### Opportunities in the Era of Big Data

- 1. New Data:** Remote sensing images offer rich information at low cost and with wide coverage. Spatial-temporal data, such as POIs and trajectory data, can support more accurate estimations.
- 2. New Methods:** Machine learning methods, successful in fields like population and poverty studies, could greatly improve the accuracy and scope of material stock estimations.



## High-Resolution Mapping of the Urban Built Environment Stocks in Beijing

### Background and method

#### 1. Traditional bottom-up approaches:

- Labor-intensive, low efficiency
- Limited scalability at urban level

#### 2. Geo big data approaches:

- Infers building information (age, type) in urban areas.
- Expands applicability of bottom-up methods
- Enables large scale, high resolution material stock estimation

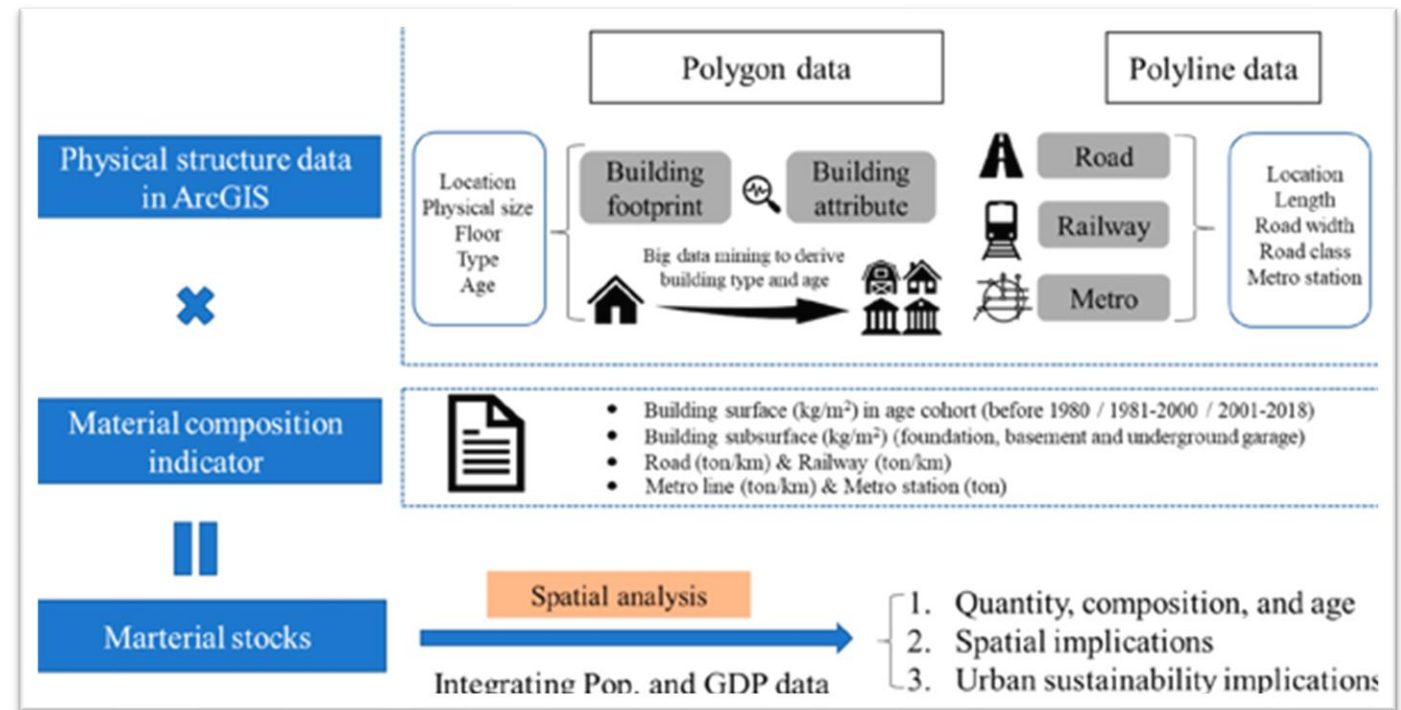


Figure 4: Work flow for high-resolution mapping of the built environment stocks in Beijing<sup>[4]</sup>

## High-Resolution Mapping of the Urban Built Environment Stocks in Beijing

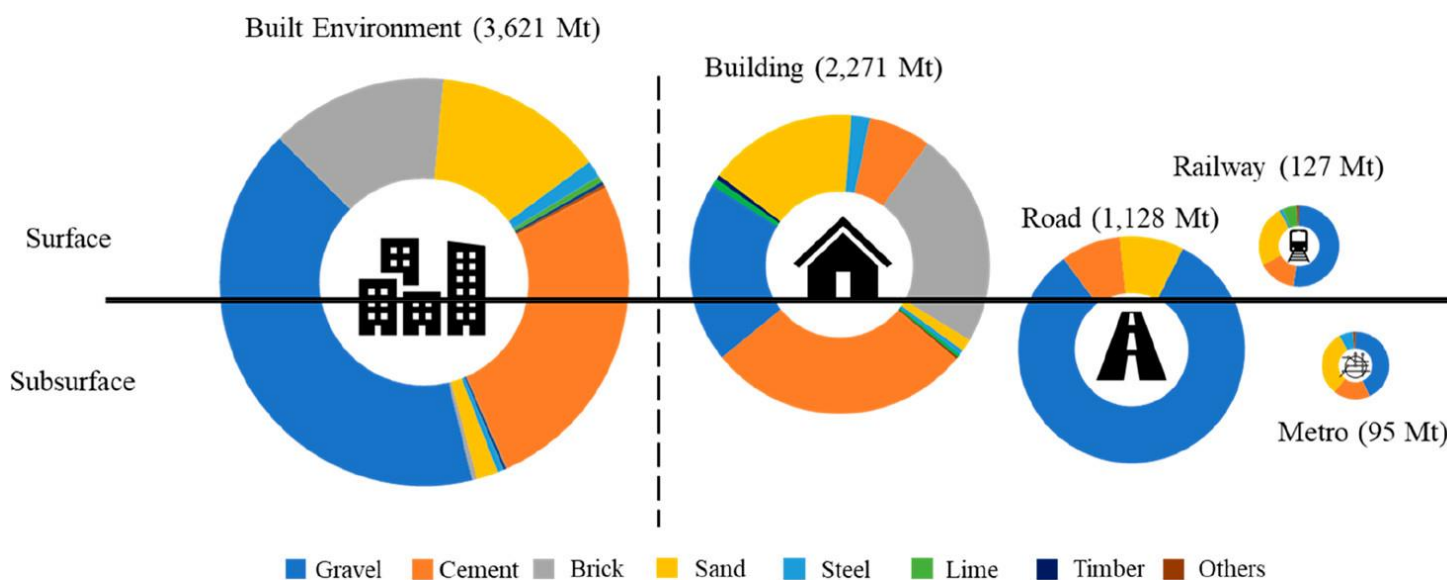


Figure 5: Quantity and composition of urban built environment stocks in 2018 in Beijing by typology and by material<sup>[4]</sup>

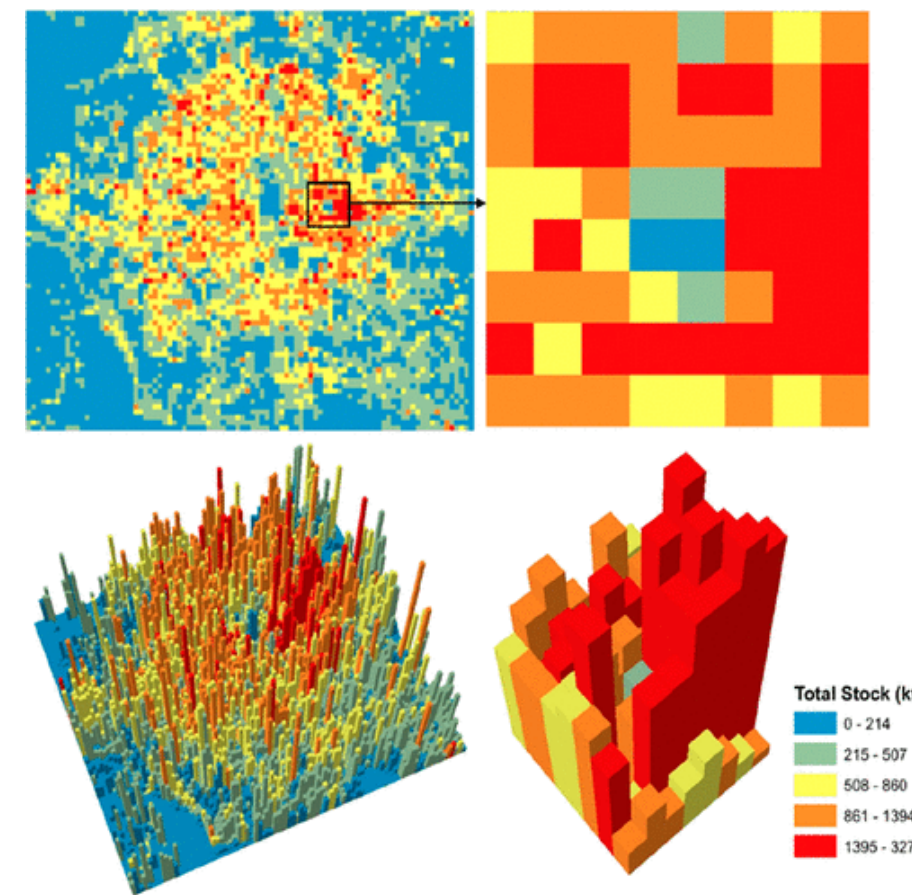
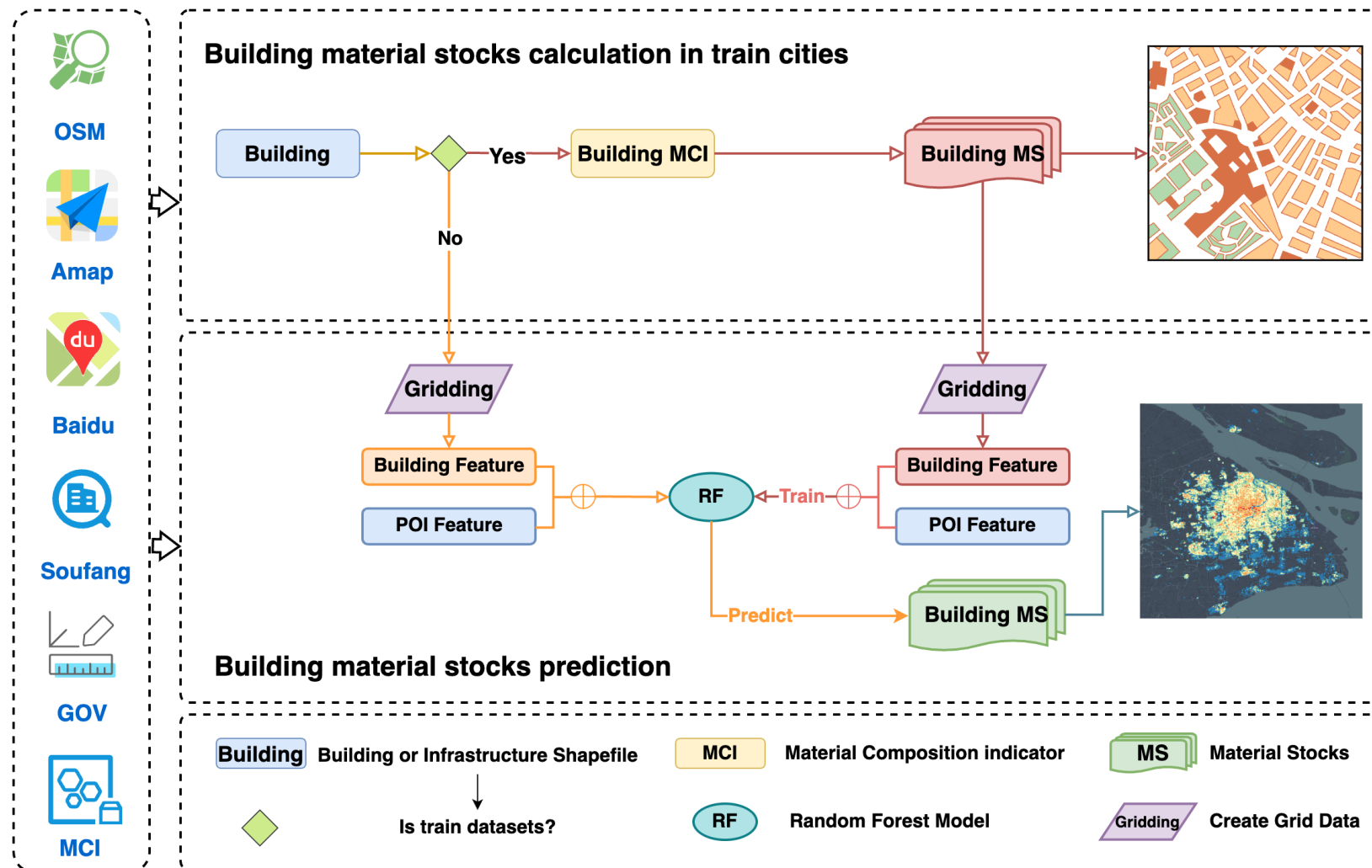
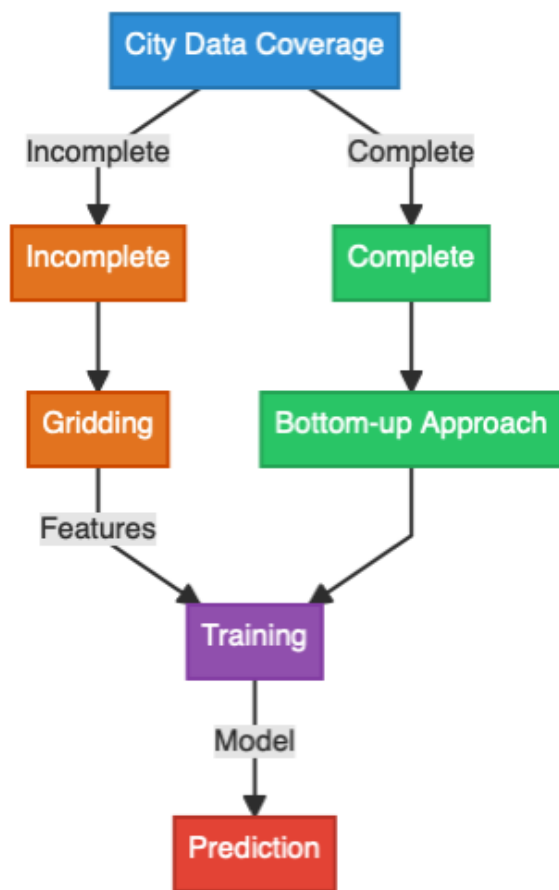


Figure 6: 500m grid distribution of environmental stock built in Beijing<sup>[4]</sup>

[4] Mao R, Bao Y, Huang Z, Liu Q, Liu G. High-resolution mapping of the urban built environment stocks in Beijing. Environmental science & technology. 2020 Apr 10;54(9):5345-55.

## End-to-end material stock estimation based on architectural vector features

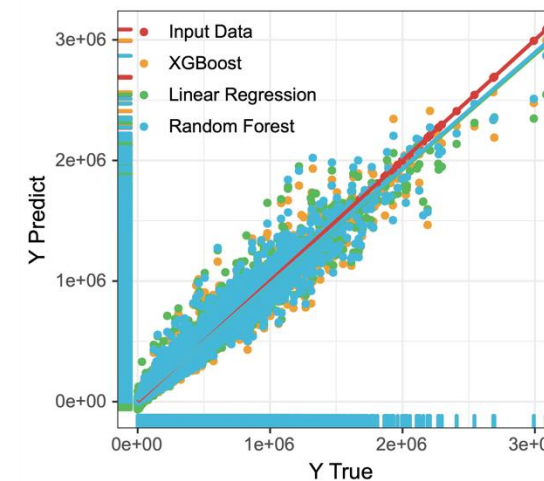
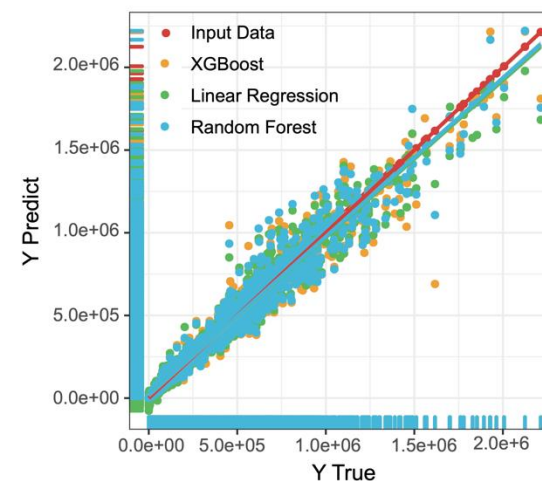
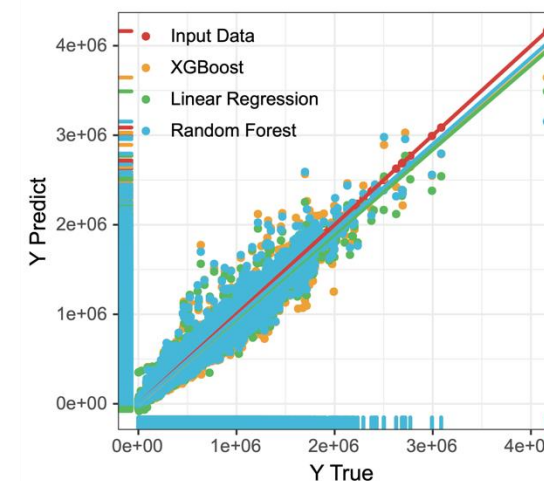
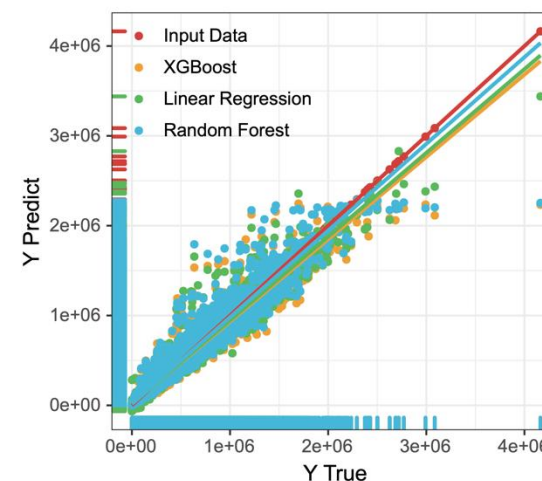


## End-to-end material stock estimation based on architectural vector features

- ① One city for training, another for validation.
- ② Two cities for training, the third for validation.
- ③ 80% of grids within a city for training, 20% for validation.
- ④ 80% of mixed grids from all cities for training, 20% for validation.

		RMSE	MAE	MAPE
	<b>Linear</b>	99444	58111	71.5891
(1)	<b>XGBoost</b>	106513	58309	0.3318
	<b>Random Forest</b>	98869	50531	0.3027
		RMSE	MAE	MAPE
	<b>Linear</b>	78679	50340	8.5788
(3)	<b>XGBoost</b>	84170	48990	0.1514
	<b>Random Forest</b>	79213	47595	0.1524

		RMSE	MAE	MAPE
	<b>Linear</b>	97653	60597	26.8986
(2)	<b>XGBoost</b>	107919	62693	0.2538
	<b>Random Forest</b>	98900	55811	0.2251
		RMSE	MAE	MAPE
	<b>Linear</b>	91230	53440	3006.78
(4)	<b>XGBoost</b>	88685	49804	4.6270
	<b>Random Forest</b>	88408	49047	0.4682



## Building material stock estimation based on multi-source remote sensing

Can an end-to-end model leverage readily available remote sensing data to compensate for lack of vector data coverage?

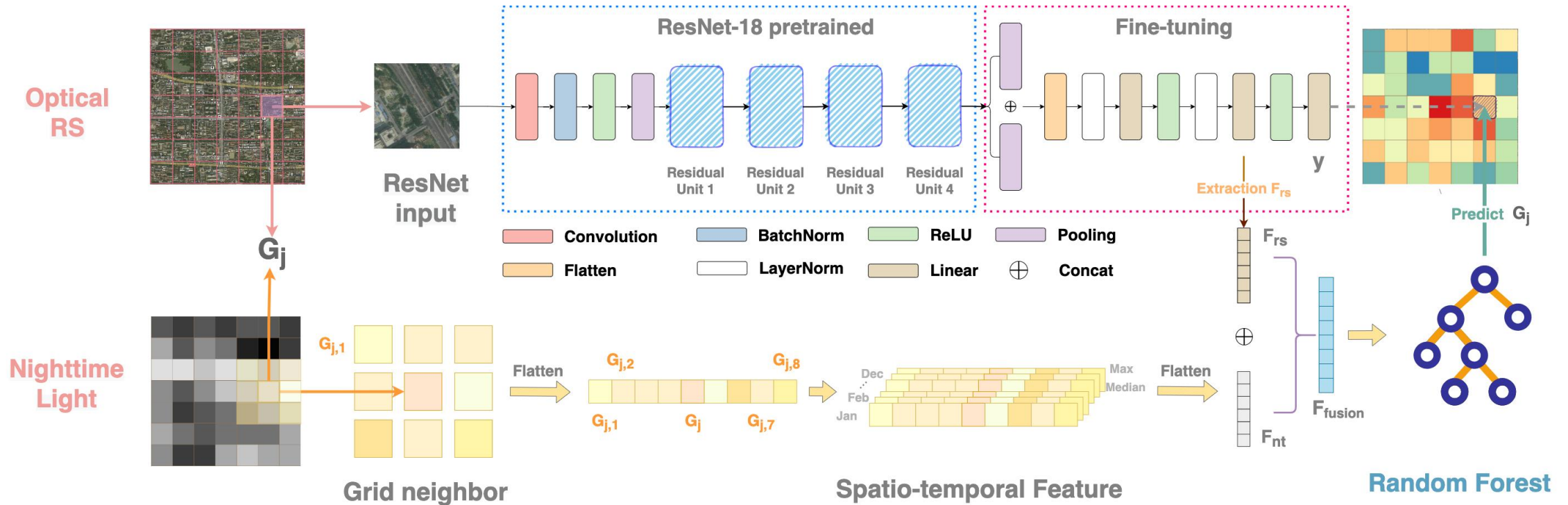


Figure 7: The framework of building-stock estimation through multi-source remote sensing and machine learning<sup>[6]</sup>

[5] Bao, Y., Huang, Z., Mao, R., Liu, G., Wang, H., & Yin, G. (2023). High-resolution mapping of material stocks in the built environment across 50 Chinese cities. Resources, Conservation and Recycling, 199, 107232.

## Building material stock estimation based on multi-source remotes sensing

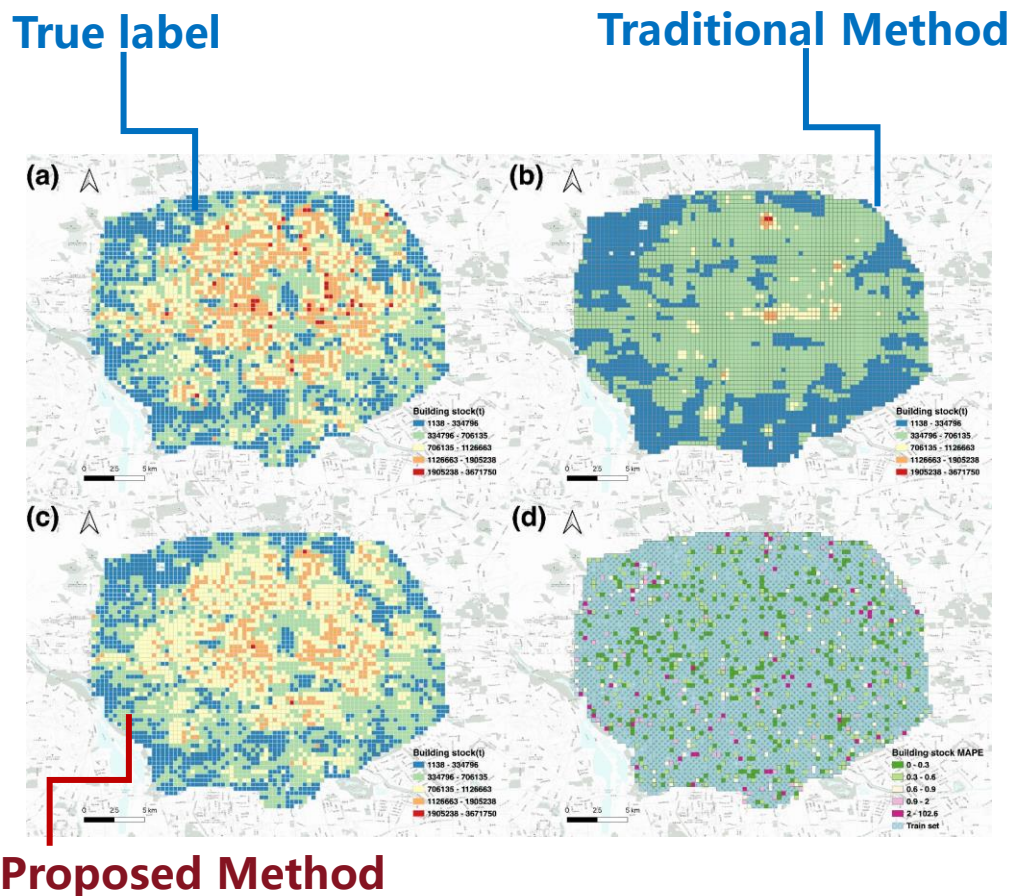


Figure 8: Prediction results at the grid scale

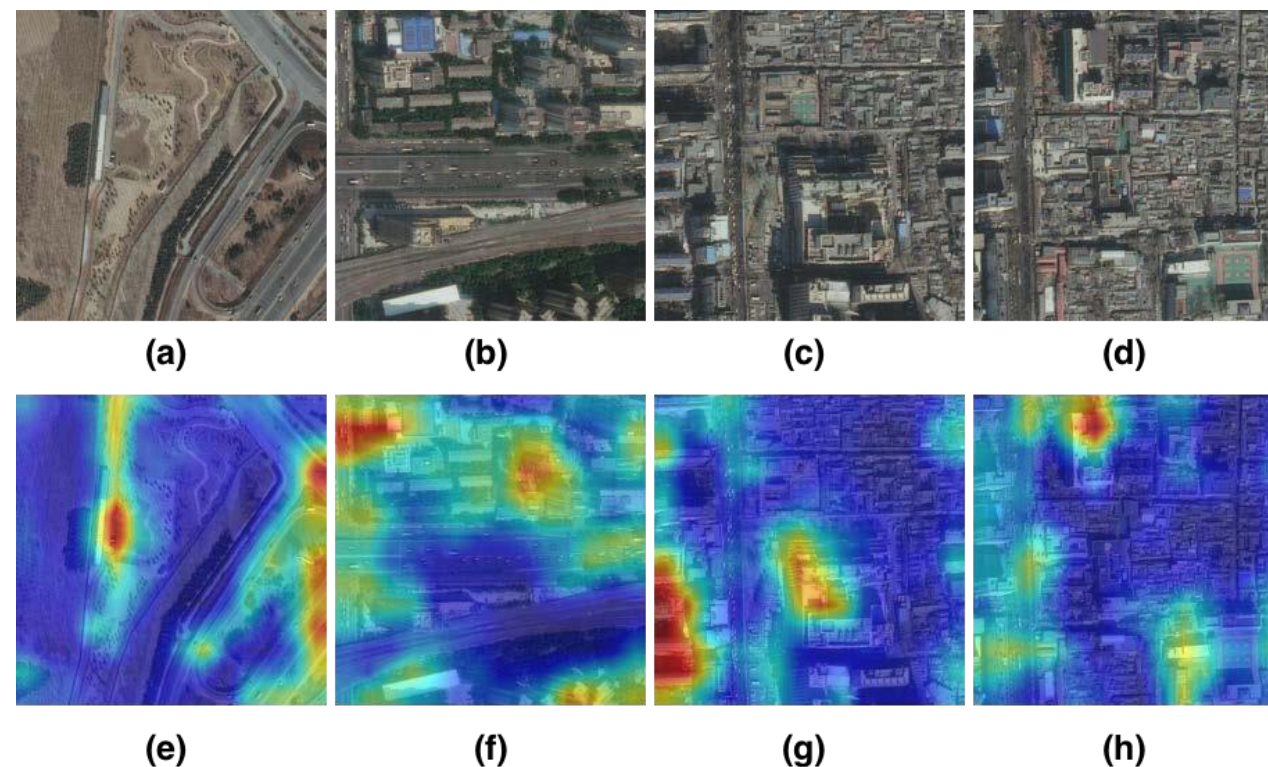


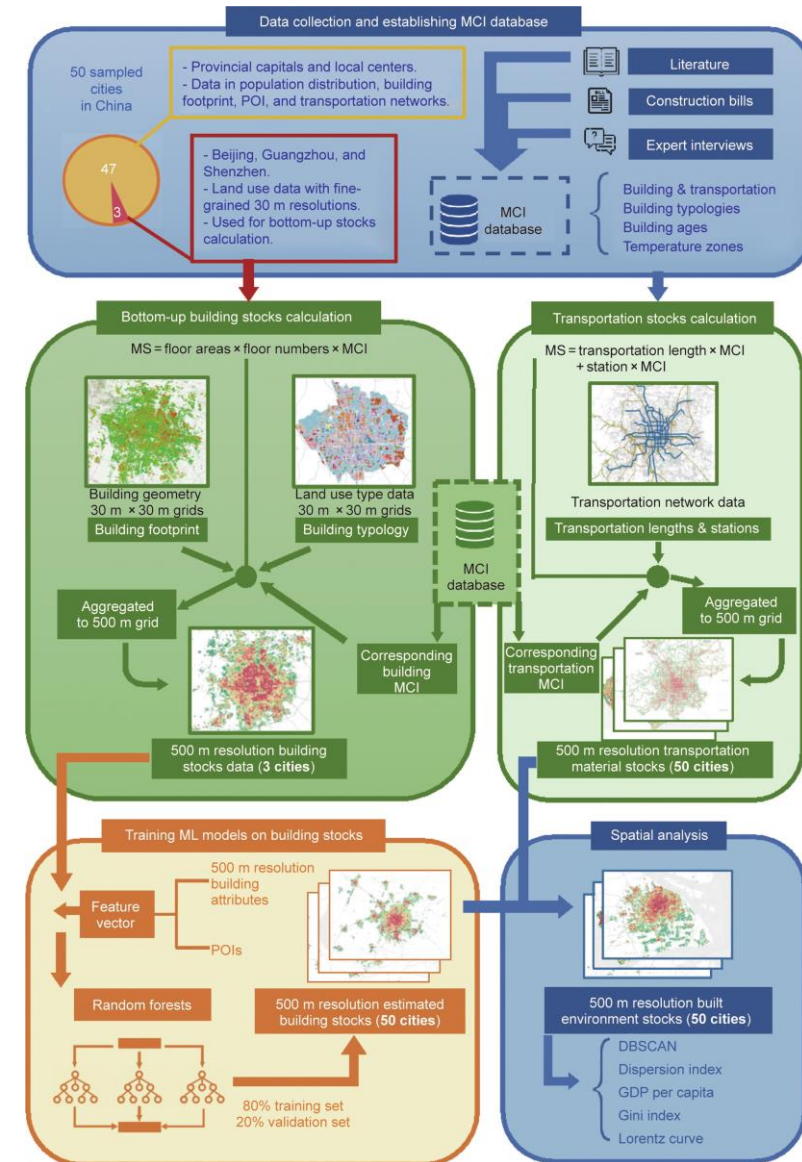
Figure 9: Feature Importance Visualization Based on Grad-CAM

# Built environment stock spatial distribution



Data Type	Data Description	Application	Source
Buildings	Physical characteristics of buildings	Building material stock calculation	Baidu Maps
Infrastructure	Characteristics of roads, railways, and subways	Infrastructure material stock calculation	OpenStreetMap, AutoNavi Maps
POI	17 POI categories	Features for predicting building material stock	AutoNavi Maps
Building Characteristics	Building types and ages in Beijing, Guangzhou, and Shenzhen	Calculating building material stock using bottom-up approach	Urban Planning Departments, SouFun, AutoNavi Maps

## Training in Beijing, Guangzhou, and Shenzhen, with predictions for the other 47 cities.



# Built environment stock spatial distribution

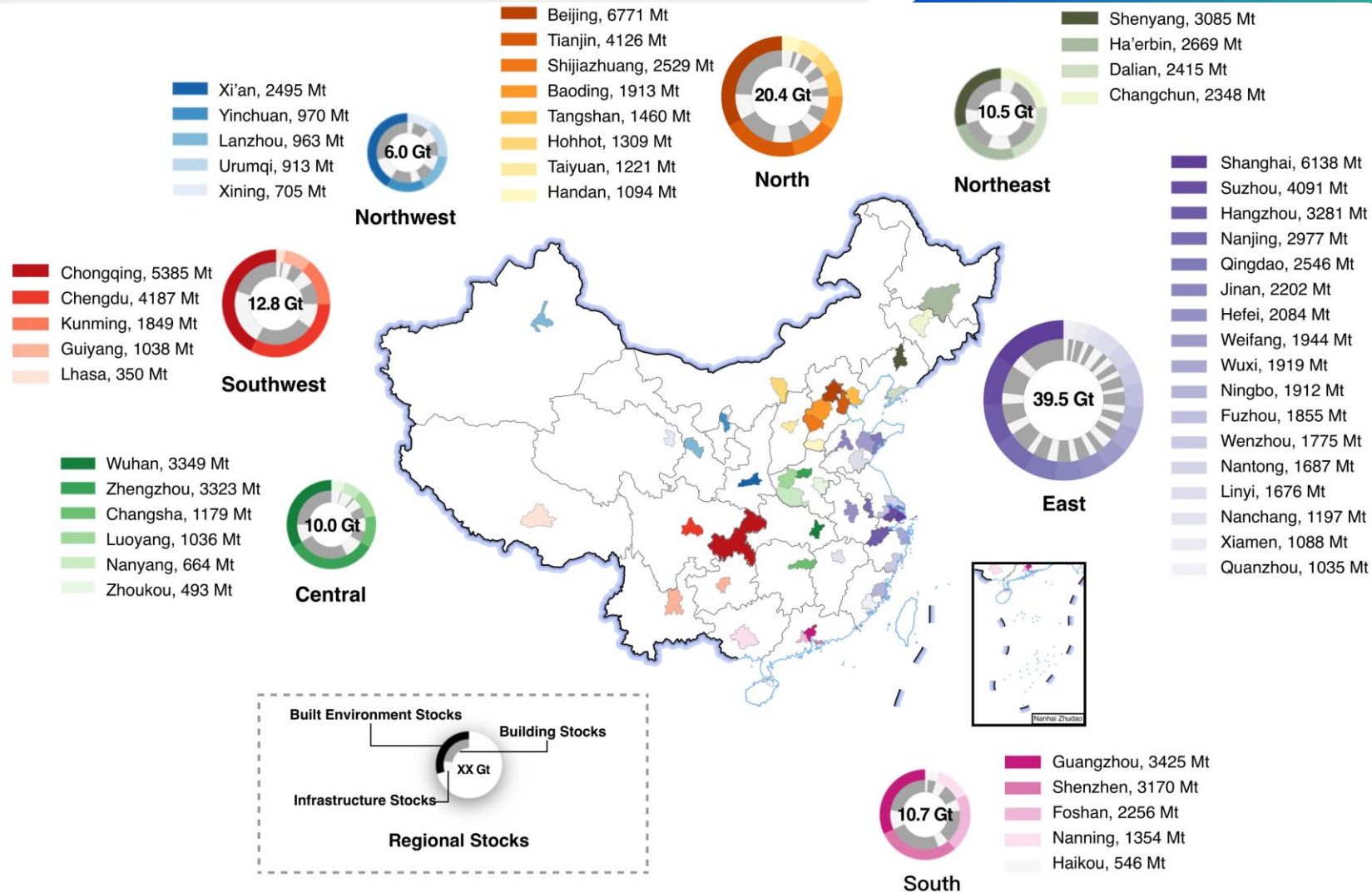


Figure 10: Urban built environment stocks of the 50 selected cities in China



# Built environment stock spatial distribution

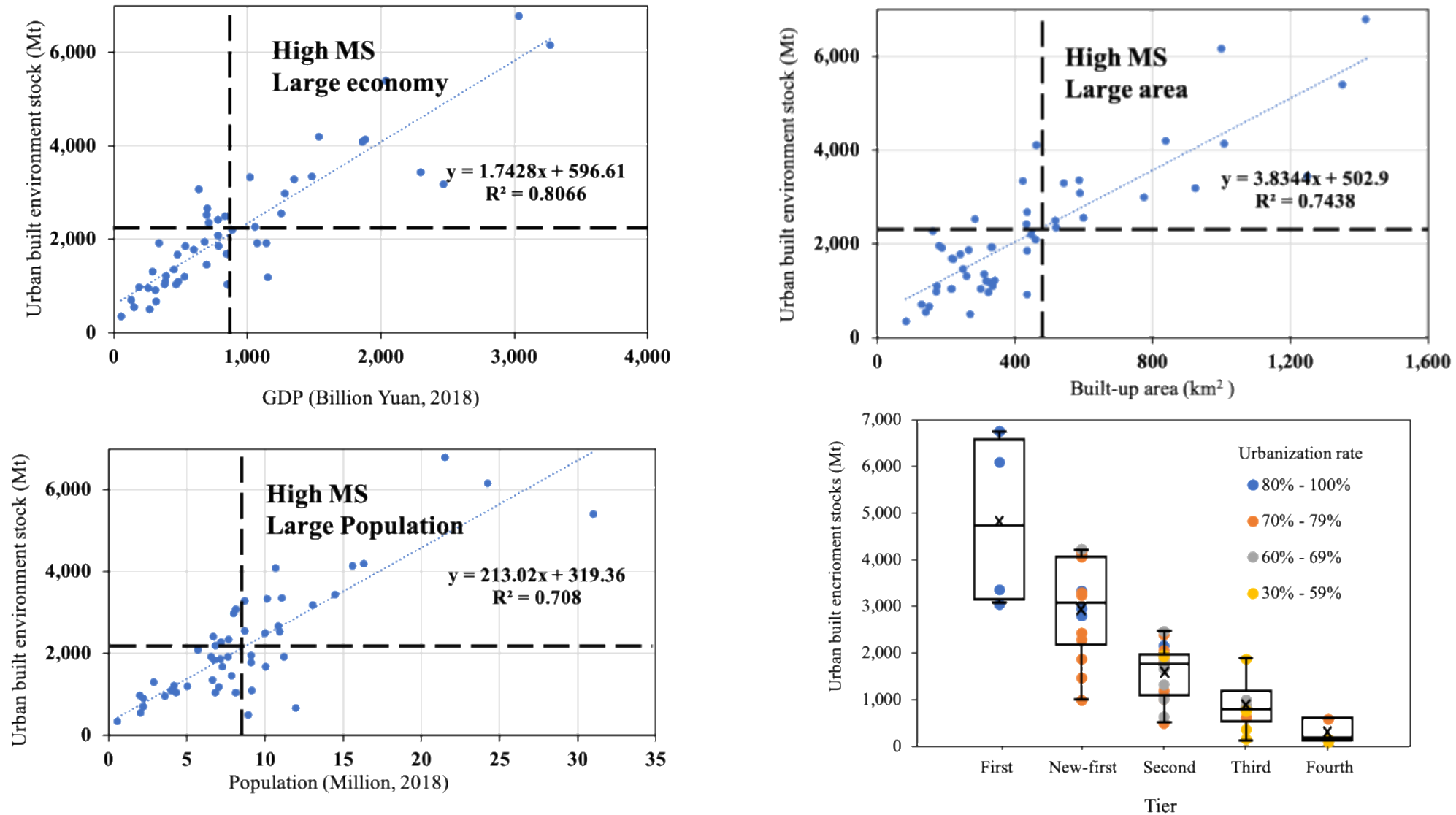


Figure 11: The relationship between the material stock of the built environment and indicators such as urban population, GDP, built-up area, and urban level.

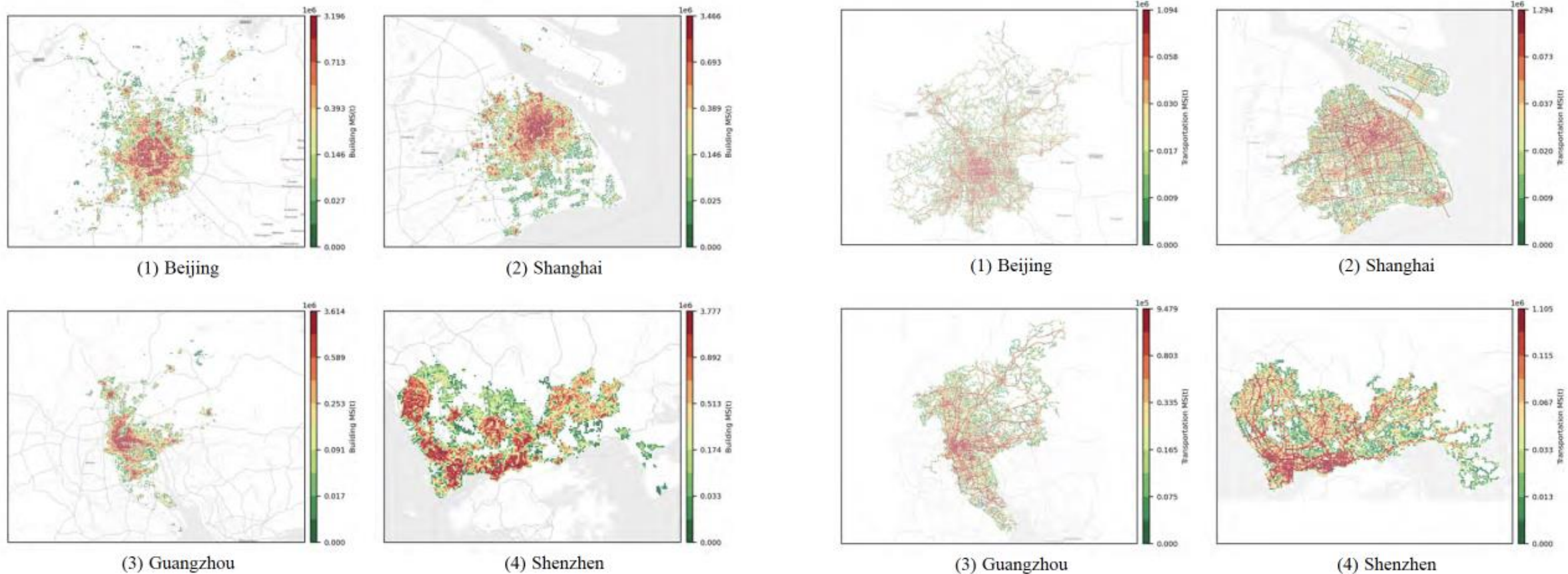


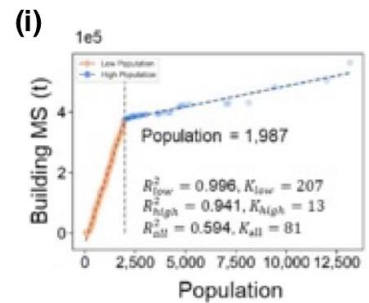
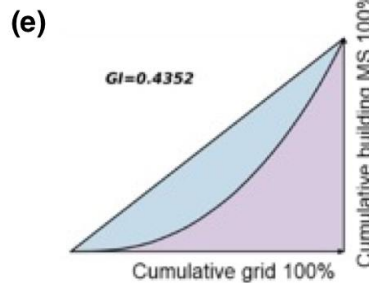
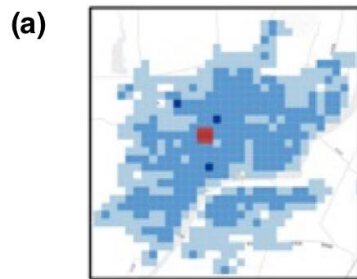
Figure 12: The spatial distribution of built environment stock in a 500m grid in the four cities of Beijing, Shanghai, Guangzhou, and Shenzhen.

# Built environment stock spatial distribution



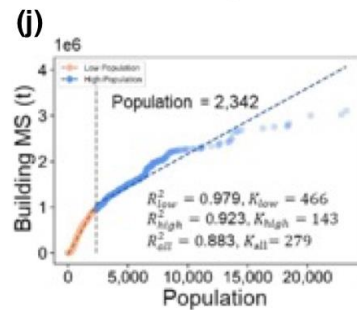
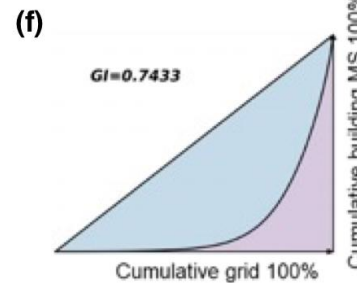
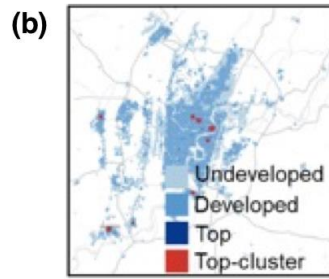
## Monocentric-concentration

Nanyang  
Building MS = 92 (Mt)  
GDP/cap = 26.5 (1,000 Yuan)



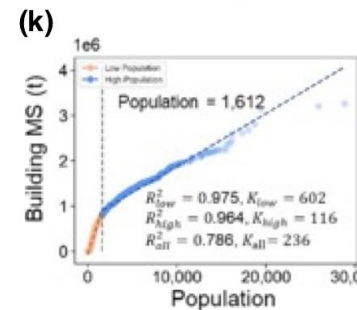
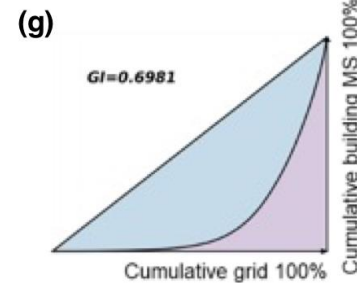
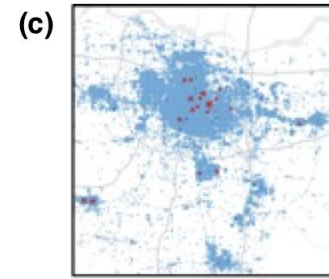
## Multicentric-dispersion

Chongqing  
Building MS = 2,594 (Mt)  
GDP/cap = 65.6 (1,000 Yuan)



## Multicentric-dispersion

Zhengzhou  
Building MS = 2,426 (Mt)  
GDP/cap = 100.6 (1,000 Yuan)



## Multicentric-concentration

Beijing  
Building MS = 4,939 (Mt)  
GDP/cap = 140.9 (1,000 Yuan)

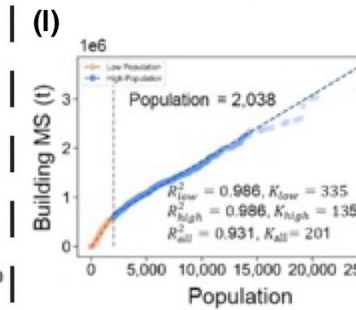
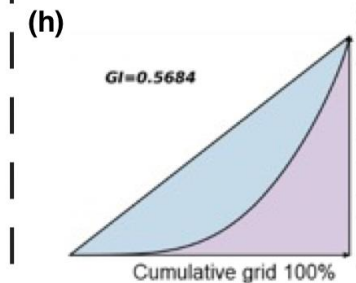
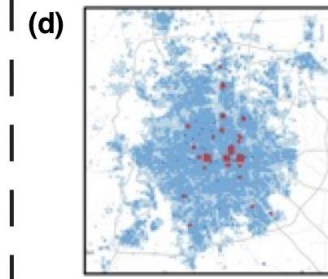


Figure 13: Urban built environment stocks of the 50 selected cities in China

# Built environment stock spatial distribution



$$pdf(x; \mu, \theta) = \frac{1}{\theta} e^{-\frac{x-\mu}{\theta}}$$

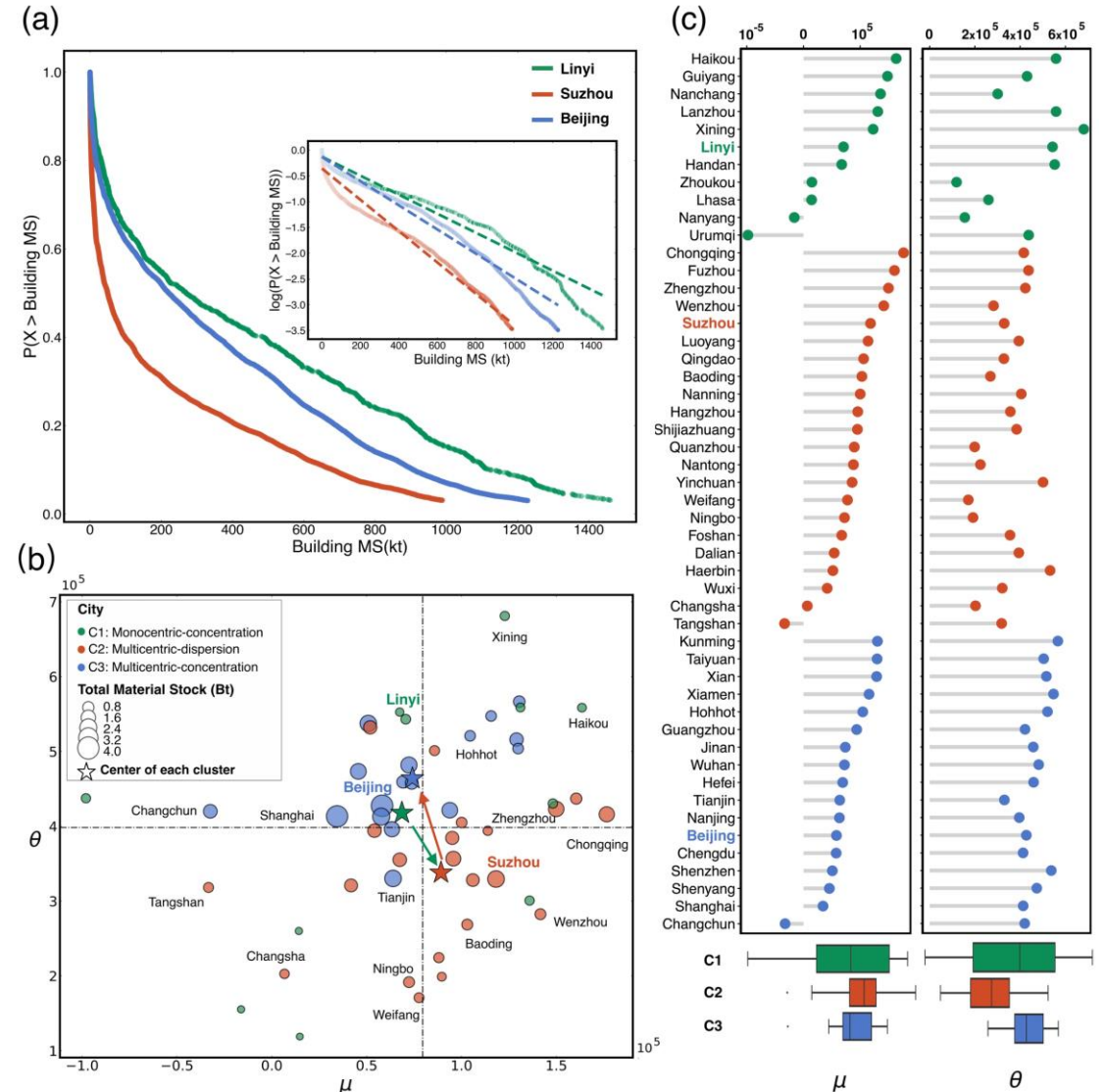
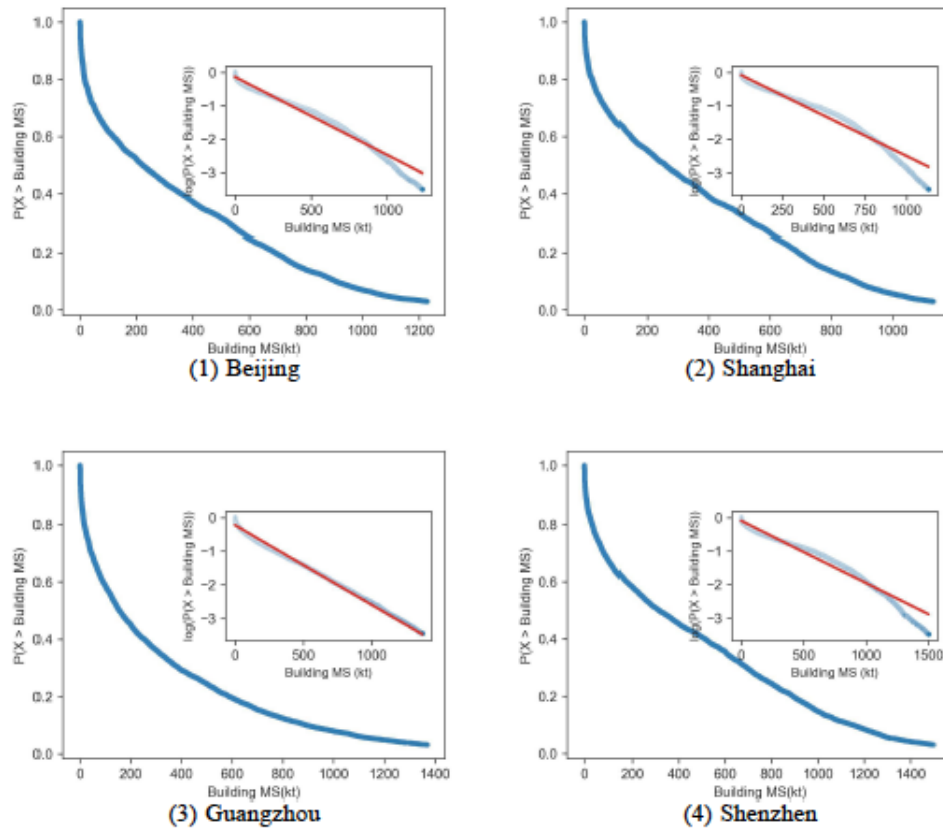
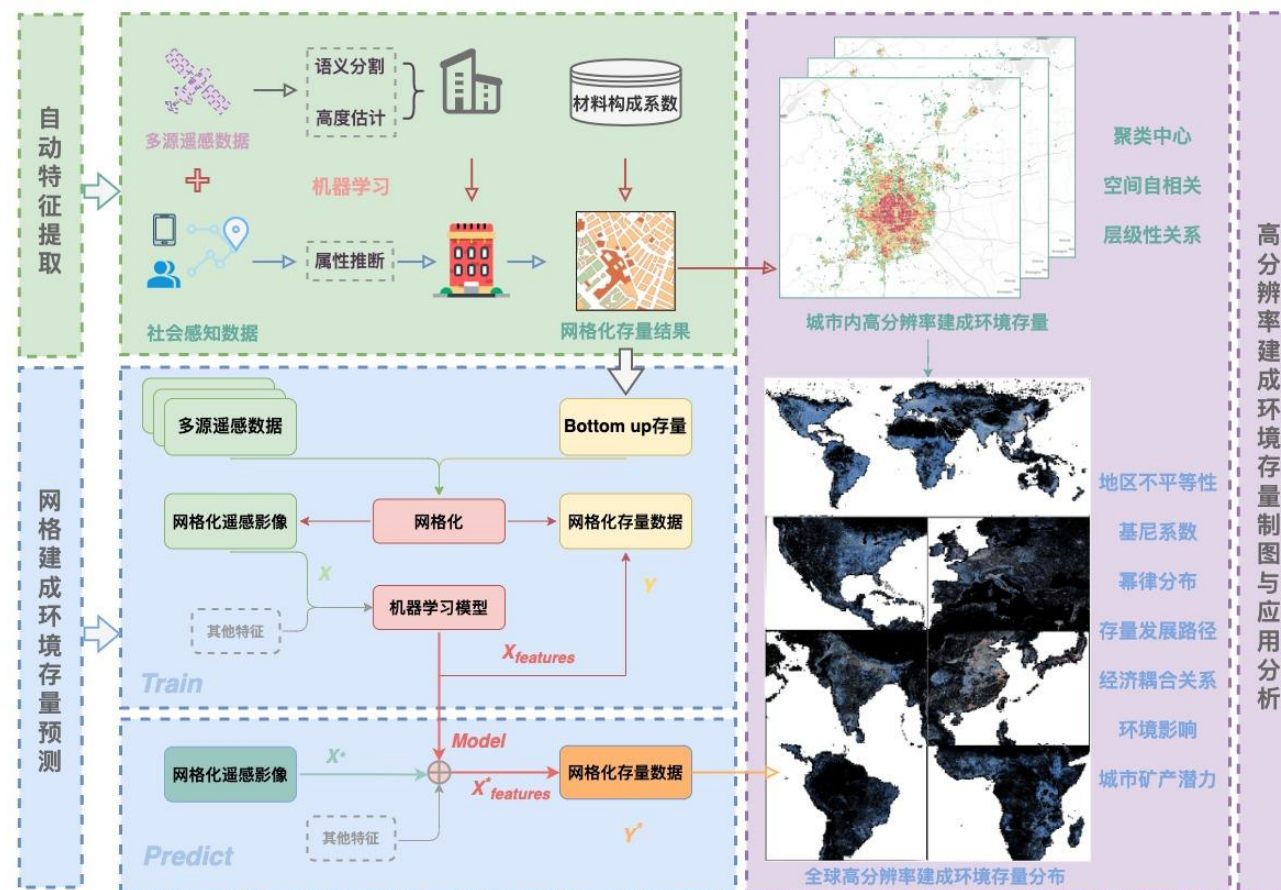


Figure 15: The dual-parameter exponential distribution model of material stock in urban buildings in China and urban development paths

## A Computational and Analytical Framework for Built Environment Material Stock Based on Multi-source Geospatial Big Data

- ① Developed high-resolution model for predicting building material stock.
- ② Mapped material stock distribution in major Chinese cities





UNGEONOW 2024  
首届联合国地信周



**THANK YOU**