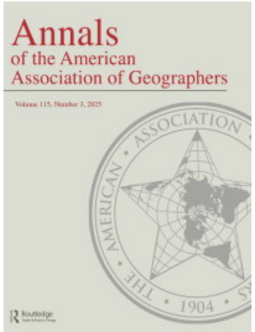

Annals of the American Association of Geographers

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/raag21

Measuring Temporal Evolution of Nationwide Urban Physical Disorder: An Approach Combining Time-Series Street View Imagery with Deep Learning

Yue Ma, Yan Li & Ying Long

ANNALS OF THE AMERICAN ASSOCIATION OF GEOGRAPHERS
https://doi.org/10.1080/24694452.2025.2467330

Check for updates

Measuring Temporal Evolution of Nationwide Urban Physical Disorder: An Approach Combining Time-Series Street View Imagery with Deep Learning

Yue Ma,[a] Yan Li,[a,b] and Ying Long[c]

[a]School of Architecture, Tsinghua University, China; [b]School of Land Science and Technology, China University of Geosciences, China; [c]School of Architecture and Hang Lung Center for Real Estate, Key Laboratory of Ecological Planning & Green Building, Ministry of Education, Tsinghua University, China

Urban physical disorder (UPD) is used to describe urban landscapes that are characterized by significant decay and deterioration. The phenomenon of UPD is also undergoing a process of evolution in conjunction with the developments that are taking place in urban areas. Measuring the evolution of UPD remains a challenge, however. This study innovatively employed time-series street view images and deep learning to analyze the temporal evolution of UPD on a nationwide scale, encompassing both overall levels and diverse manifestations. A total of 20 million street view images were collected in China from 2013 to 2022. The YOLOv8 object detection model was trained to accurately identify fourteen UPD elements. Subsequently, each element was assigned a weight to reflect the overall level of UPD. A clustering analysis based on graph neural networks identified four distinct manifestations, which were found to vary considerably across cities: good quality, vacancy and decay, under construction, and poor maintenance. The findings indicate a decrease in the overall level of UPD in China, with the primary issue shifting from poor maintenance to vacancy and decay. Economic growth correlates with overall improvements in UPD, whereas cities experiencing population decline tend to have more vacancies. The approach to measuring the evolution of UPD allows for a more nuanced understanding of the phenomenon and facilitates the prediction of urban space quality challenges, hence assisting urban planners in devising specific strategies for improvement.
Key Words: graph neural networks, neighborhood disorder, spatiotemporal changes, street view image, urban space quality.

Urban physical disorder (UPD) refers to highly decayed and deteriorated urban landscapes. This includes damaged and poorly maintained facades, abandoned buildings, street litter, graffiti, and broken roads in public spaces (Skogan 1990; Seo 2018). Such conditions not only have a detrimental impact on the quality of life of residents but are also associated with adverse public health and social stability outcomes. The challenge of UPD confronts cities worldwide. Consequently, the swift and precise identification of UPD represents a pivotal step (Sampson and Raudenbush 1999; Hu et al. 2023).

It is crucial to recognize that the urban environment is susceptible to change over time (Kropf 2001; Batty 2022). In addition to the typical wear and tear associated with the use of public spaces by residents, the issue of UPD is perpetually evolving due to a multitude of factors, including economic growth, policy implementation, ecological conditions, and population migration. Initiatives such as the East New York Neighborhood Plan in the United States (East New York Neighborhood Plan 2013), and China's Urban Renewal Actions (Urban Renewal Actions 2021) are actively addressing UPD and revitalizing public spaces. Meanwhile, the industrial decline and economic recession have left a considerable number of residential properties unoccupied or abandoned in the cities of the Rust Belt in the United States (Hackworth 2018; Pottie-Sherman 2020). Several European countries are experiencing

ARTICLE HISTORY
Initial submission, August 2024; revised submission, November 2024; final acceptance, January 2025
CORRESPONDING AUTHOR Ying Long ylong@tsinghua.edu.cn

refugee crises. The establishment and subsequent mismanagement of refugee camps has resulted in the deterioration of sanitary conditions and the accumulation of waste (Crawley and Skleparis 2018; Valvis et al. 2021). Given the constant complex transformations cities undergo, it is plausible that preexisting UPD concerns have either resolved, exacerbated, or given rise to new challenges. Just as urban life cycle theory delineates the stages of a city's development from inception to decline (Hall 2014), it is plausible that the UPD issues that cities face can evolve through these stages.

The majority of studies have concentrated on the evaluation of UPD at a specific point in time, with minimal consideration given to its temporal evolution (Dassopoulos et al. 2012; Milam et al. 2012). Quantifying the evolution of UPD can assist policymakers and researchers in identifying effective strategies to predict and mitigate UPD, which is essential for developing safe, healthy, and sustainable urban environments. This study examined the evolution of UPD on a large scale, prompting the formulation of two research questions:

1. How can the evolution of UPD over time be quantified?
2. What are the dynamic features and patterns of the evolution of UPD in a vast and diverse geographic area?

To address these questions, this study proposes a novel approach that combines time-series street view images and deep learning to reveal the temporal evolution of UPD on a large scale, both at the overall level and in different manifestations. China is a vast country with a diverse range of urban areas, exhibiting considerable variation in terms of development and socioeconomic background (Deng et al. 2020), as well as the significant changes in the urban environment during the previous rapid urbanization process, providing a suitable environment for the application of the approach. Simultaneously, the majority of previous UPD studies were based in developed countries in Europe and the United States, providing only a limited understanding of China's circumstances. Therefore, the empirical study was undertaken in China with the objective of confirming the usability of the methodology while portraying the dynamic features and patterns of UPD evolution.

Specifically, the study collected more than 20 million street view images (SVIs) in China from 2013 to 2022. Deep learning models were then trained to automate the identification of fourteen UPD elements applicable to Chinese cities. Subsequently, each UPD element was assigned a weight in accordance with its reflection of the extent to which public space quality was undermined. This was done to ascertain the overall level of UPD and its changes. Meanwhile, cluster analysis was employed to discern disparate UPD manifestations and to examine their interconversion and spatial patterns. Finally, the relationship between the economy, population, urban development, and the UPD evolution was investigated to ascertain the trends in UPD in China.

Literature Review

Measuring UPD

The concept of UPD encompasses the phenomenon of neighborhood neglect and blight, which pertain to the disruption of residents' lives and public spaces through the presence of noticeable or visible signs (Skogan 1990). Previous research has employed a variety of methods to assess UPD, including questionnaires, interviews, and qualitative field work (Dassopoulos et al. 2012; Benediktsson 2014; Hackworth 2018). These traditional methods are frequently costly, time-consuming, and even hazardous (Wallace and Schalliol 2015; D. Johnson et al. 2016). The advent of SVIs and deep learning techniques has facilitated the development of automated methods (N. Yang et al. 2024; F. Zhang et al. 2024). The utilization of SVIs for virtual audits has been demonstrated to reduce the time costs associated with UPD measurement without compromising accuracy (Mooney et al. 2017; L. Yang et al. 2024). Novack et al. (2020) applied a VGG16 CNN model to identify instances of graffiti on building facades, and Y. Li and Long (2024) used a Faster R-CNN model to identify vacant stores. In addition to studies focusing on specific UPD elements, Hu et al. (2023) developed a transformer-based framework for the comprehensive detection of UPD. Chen et al. (2023) assessed the prevalence of UPD in China, confirming its pervasiveness and offering valuable insights.

Regardless of whether traditional methods or approaches enabled by artificial intelligence (AI) are used, most studies employ checklists to identify UPD elements (Wei et al. 2005; Marco et al. 2017; Mayne et al. 2018). UPD is a complex and multifaceted phenomenon, however, and existing studies often provide a composite score to represent its level, which is insufficient for a comprehensive understanding of it. First, existing studies that employ indicator lists to measure UPD often assume that the contributions of the various elements are equal (Milam et al. 2012; Ndjila et al. 2019). The impact of different UPD elements on people's perception of space quality varies, however (W. Li et al. 2022). For instance, despite both being indicative of low-quality space, compared to the stores with poor signboards, damaged buildings could be perceived as a more significant space quality issue that is more challenging to accept. Therefore, the objective is to assign weights to the elements when measuring UPD to more accurately assess the overall level of UPD. Furthermore, there are cluttered and disorganized spaces due to misuse by many people and abandoned and vacant spaces due to lack of use. Both of these are regarded as forms of UPD and elicit negative emotional responses; however, their underlying causes are distinct. Therefore, an understanding of UPD that is limited to a numerical score is insufficient; it could manifest in various forms that need to be identified.

Observing the Evolution of Urban Appearance with SVIs

Urban environments are not static; rather, they evolve over time due to a multitude of factors, including urbanization, public policy, urban renewal, and economic development. Such alterations have the potential to markedly influence the well-being of residents, necessitating monitoring and evaluation (M. T. J. Johnson and Munshi-South 2017; Sarkar and Webster 2017). Time-series SVIs offer a valuable means of tracking and monitoring changes in the built environment over time. Wang, Ito, and Biljecki (2024) examined the temporal evolution of visual perception in New York and Singapore, assessing changes in perceptions of safety, vibrancy, boredom, wealth, and prosperity. Y. Li, Ma, and Long (2024) employed a multiyear approach, combining both self-collected and commercial SVIs to examine changes in UPD in Xining, China, over the period from 2014 through 2020. In another noteworthy study, Liang, Zhao, and Biljecki (2023) proposed a clustering method based on the convolutional neural network that considers both visual features and spatial dependency, thereby highlighting the manner in which these features evolved over time. These studies collectively confirm the utility of multiyear SVI with time stamps in detecting the evolution of urban appearance. There is a dearth of studies, however, that scrutinize the transformation of urban space from the perspective of negative space issues at the national level, highlighting their unique characteristics and trends.

Methods

Study Area and Data

This study employs China as the case study to elucidate the dynamic features and patterns of the evolution of UPD. In the case of Chinese cities, there is frequently a discrepancy between the administrative boundaries and the actual urban areas. The concept of a natural city posits that the spatial clustering of geographic features, including points of interest (POIs), road intersections, and artificial impervious areas, offers a more precise representation of urbanized regions than traditional administrative or statistical boundaries (Wang and Long 2023; Tu, Wang, and Long 2024).

To gain a comprehensive understanding of UPD changes in China, we sought to collate all SVIs of all natural cities across the country for all available years. The SVIs used in this study were obtained from Baidu Maps (see https://map.baidu.com/). Baidu Maps is currently the largest and only company in China providing updated multiyear commercial SVIs (Tencent Maps previously offered Chinese street views but has since ceased updating them). Specifically, sampling points were generated at 50-m intervals along all roads within the natural cities, and the Baidu Maps application programming interface (API) was used to query and download SVIs in four directions (front, back, left, and right) at each sampling point. Further details on the collection of SVIs and their code can be found in the protocol (Y. Li, Ma, and Long 2024). In conclusion, a total of 55.4 million images were collected from 2013 to 2022, encompassing 2,665 natural cities.

Not all locations in Baidu Maps have multiyear SVIs, necessitating the processing of vast data to further refine the study area. In this study, the ten-year period was divided into two intervals. The initial period, designated as Period 1, was followed by a subsequent period, Period 2. The fundamental data for these two time frames are derived from the years 2015 and 2020, respectively. In the event that a sampling point was devoid of data for the years 2015 or 2020, the data were supplemented with information from the two preceding or two subsequent years. A total of 2.93 million sampling points exhibited SVIs for both Period 1 and Period 2 and thus were defined as valid points. Ultimately, to explore the evolution of UPD at the urban scale, it is essential to ensure that each city has an adequate number of valid points to represent the city's condition. A 500-m buffer zone was created around all valid points, with the distance measured as half the spacing between adjacent main roads in Chinese cities. The proportion of the buffer area covered by valid points was then calculated in relation to the total area of the natural city. Cities were included in the study if the proportion of valid points within the buffer zone exceeded 50 percent and if the city possessed a minimum of forty valid points. In conclusion, our study encompassed 698 natural cities in China, comprising 2.64 million valid points and 21.11 million SVIs (Figure 1).

Furthermore, the subsequent analysis employed data pertaining to the economy and population. Urban area, average gross domestic product (GDP) per square kilometer (the Resources and Environmental Science Data Platform), population density (see https://hub.worldpop.org/), investment in municipal utilities construction, and investment in municipal sanitation (China Statistical Yearbook of Urban Construction) were obtained for each natural city in 2015 and 2020. Urban vitality was obtained by calculating the density of Dianping in 2014 and 2023 (see https://www.dianping.com/). The amount of change in these above indicators over the two time periods and the cumulative amount of investment in municipal utilities construction and investment in municipal sanitation from 2015 to 2020 were also calculated.

Detection of UPD Elements

The UPD indicator system, which has been adapted for use in Chinese cities (Chen et al. 2023), was employed in this study. This system, which underwent an audit process comprising both field surveys and virtual audits, includes fifteen elements distributed across five dimensions: architecture, commerce, road, greenery, and infrastructure. Given the considerable climatic variations across China's diverse regions, however, and the fact that SVIs were captured during different seasons, the assessment of greenery in the images was significantly influenced. Consequently, the element of greenery disorder was excluded, and the remaining fourteen elements were retained (Figure 2).

To accurately and expeditiously identify UPD elements, we developed a deep learning model. The initial step involved the generation of a training set. Following training using the virtual audit manual (Figures A.1–A.4 in the Appendix), auditors conducted virtual audits of randomly selected SVIs on the Roboflow platform (see https://roboflow.com/). All UPD elements present in the indicator system and observed in each SVI were annotated using rectangular boxes. This means that each image can be annotated with zero, one, or more instances of UPD elements. A total of 132,877 SVIs were annotated, and the data set was automatically divided into training, validation, and test sets, comprising 80 percent, 10 percent, and 10 percent, respectively. To enhance the model's capacity to detect objects from disparate angles, the images were subjected to augmentation through techniques such as horizontal flipping, 20 percent cropping, and fifteen-degree vertical and horizontal shearing.

Considering the huge amount of data and future generalizability of this study, a deep learning algorithm that is lightweight, efficient, and adaptable to hardware is needed for UPD target detection. As one of the latest iterations of the You Only Look Once (YOLO) model series, YOLOv8, implemented in Ultralytics, stands out due to its exceptional speed and accuracy, coupled with a streamlined architecture suitable for deployment on both high-end and low-end hardware (Sohan, Sai Ram, and Rami Reddy 2024). It has been widely used in remote sensing, transportation, and other fields (Shen, Lang, and Song 2023; Talaat and ZainEldin 2023; Bakirci 2024). Consequently, this study involved training the YOLOv8 model to identify fourteen UPD elements based on the training data set (Y. Li, Ma, and Long 2024). The learning rate, batch size, and number of epochs were set to 0.001, 4, and 200, respectively. As illustrated in Figure 3, the training results exhibited an average precision of 86.2 percent (the mean average precision [mAP] when the predicted bounding box overlaps with the true bounding box by at least 50 percent).

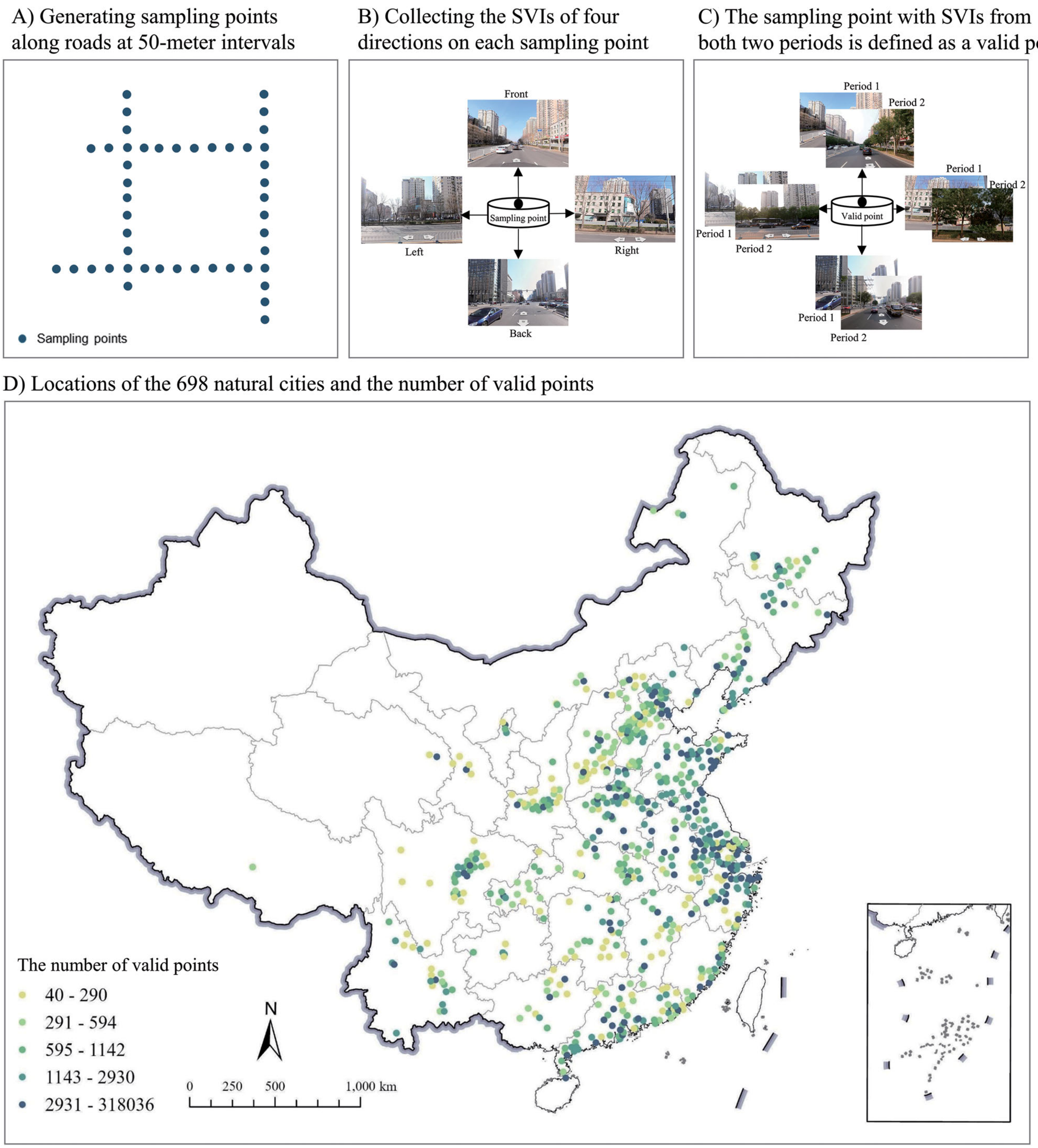

Figure 1. The process of collecting street view images (SVIs) within the study area.

Assigning Weights to UPD Elements

The Delphi method was employed to assign weights to the aforementioned elements, due to its simplicity, reliability, and ease of generalization (Steurer 2011). In particular, twenty-one experts from the fields of architecture and urban planning were invited to participate. The participants were presented with a list of fourteen UPD elements and the corresponding diagrams. Subsequently, the participants were requested to assign a score on a scale of 0 to 10 to each element, indicating the extent to which they believed it undermined the quality of urban public space. Following the initial scoring phase, the results were presented to the experts for

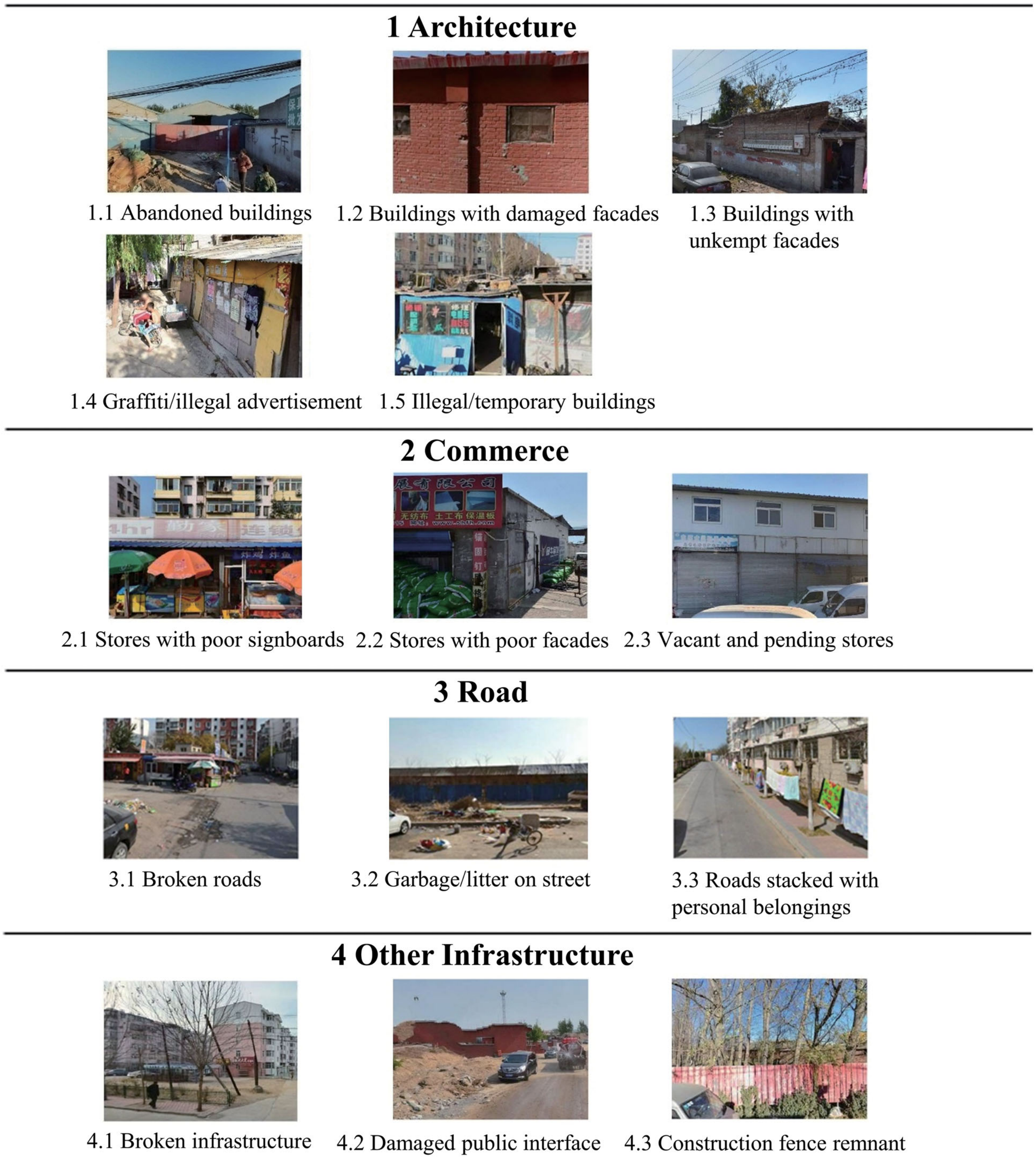

Figure 2. The indicator system of urban physical disorder in China.

discussion, after which a second round of scoring was conducted. The aforementioned process yielded a highly consistent outcome (Cronbach's alpha coefficient of 0.81), which was subsequently standardized and averaged to form a weighted UPD indicator system that is suitable for China.

UPD Features Clustering

This study employs the theoretical tenets of Tobler's first law of geography, the broken windows theory, and a synthesis of urban studies (Tobler 1970; Yao et al. 2021) to posit that areas situated in close spatial proximity within a city tend to exhibit

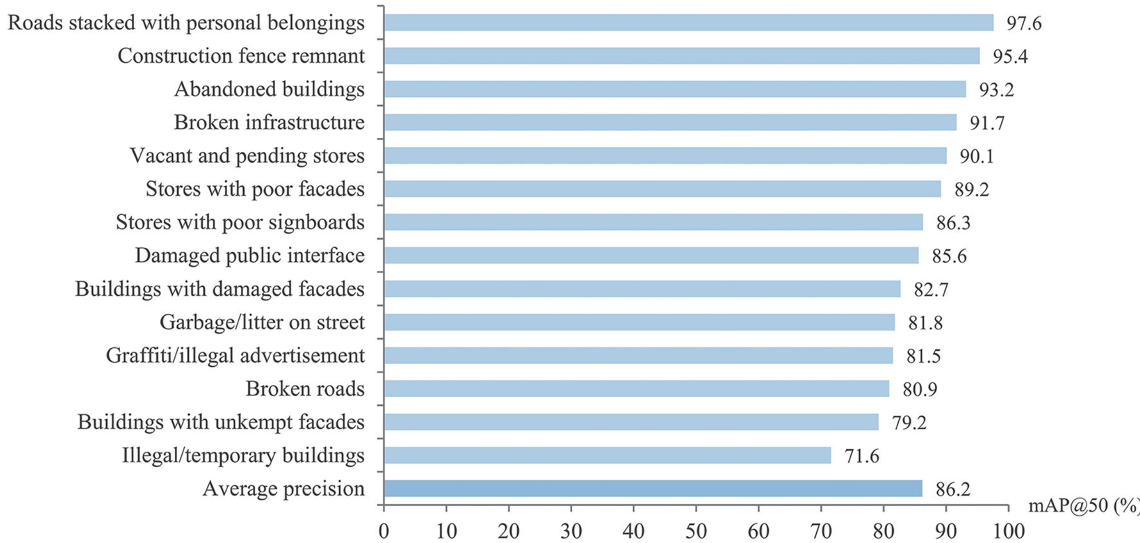

Figure 3. Accuracy of urban physical disorder target detection model represented by mAP@50.

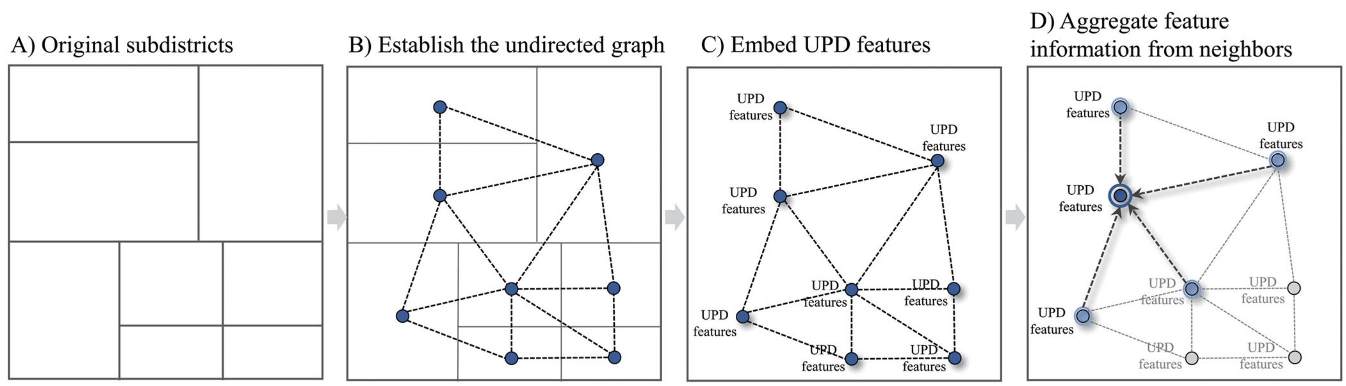

Figure 4. Generating graphs and feature matrices based on subdistricts. *Note:* UPD = urban physical disorder.

analogous characteristics. This is based on the premise that UPD in one area is often influenced by that in adjacent areas. To account for this spatial similarity, we employed network analysis to harmonize UPD features in accordance with geographical relationships. This approach improves the accuracy of clustering and reveals different manifestations of UPD.

To account for spatial correlation, an undirected graph was established, comprising nodes and edges. In this context, the smallest administrative unit in China, the subdistrict (*jiedao*), was selected as the study unit (Figure 4A). Each subdistrict was treated as a node in the graph network. In the event that two subdistricts are situated in close proximity to one another, an undirected edge is established to signify the spatial interaction between them (Figure 4B). Furthermore, the fourteen UPD elements within each study unit's SVI were aggregated to represent the UPD features. Each of the fourteen UPD features of the SVIs was subjected to a process of normalization, with values ranging from 0 to 1, using a min-max normalization technique. Subsequently, a feature matrix was constructed based on the features of all nodes. To achieve an effective integration of the undirected graph with the feature matrix, it is essential to employ a suitable feature embedding model for information extraction (Figure 4C). In this study, a spatial-based graph neural network (GNN) was employed to capture spatial correlations and to aggregate node information via graph convolution operations. The spatial-based GNN, specifically GraphSAGE (Hamilton, Ying, and Leskovec 2017), serves as an inductive framework for generating node embeddings. The method incorporates network structure while sampling and aggregating features from nodes' neighborhoods to derive low-dimensional vector representations of the nodes (Figure 4D). The aforementioned embeddings can be employed for subsequent tasks, such as classification and clustering. Their efficacy in urban studies has been demonstrated (Liang, Zhao, and Biljecki 2023).

Following the separate encoding of all features and spatial structures of the study units in Period 1 and Period 2 using neural network embeddings, the vector representations were clustered by K-means and hierarchical clustering to illustrate the division of UPD manifestations. K-means has been widely used in urban studies, successfully capturing essential spatial patterns for its simplicity, efficiency, and interpretability (Jain 2010; Spielman and Singleton 2015; Cai et al. 2019). To address the sensitivity of K-means to initial cluster assignments, we employed the K-means++ initialization method and ran multiple iterations, ensuring robust convergence to stable cluster centers. Hierarchical cluster analysis using the Ward method was also employed. Instead of specifying the number of clusters in advance, the method represents the hierarchical structure of the data by building a dendrogram (Murtagh and Heck 2012). We compared these two clustering results to decide the most appropriate method. To ensure the comparability of identified clusters over time, data from both time periods were incorporated into the clustering process. Ultimately, the mean values of the diverse UPD components were determined for each cluster, thereby elucidating the distinctive attributes of these clusters.

Quantifying the Evolution of UPD

The evolution of UPD was investigated from both the weighted overall level and the manifestations. For each SVI, a value of 1 was assigned if a specific UPD element was present and 0 if it was absent. The standardized weights were then applied to each element to calculate the overall level of UPD, with the overall UPD score for each image ranging from 0 to 100. The mean value of all SVIs in a natural city was calculated to represent the overall UPD level. The changes in this overall level were quantified using Equation 1.

$$\Delta N = N_2 - N_1 \tag{1}$$

where ΔN stands for the changes in the overall levels of UPD, N_1 represents the overall levels of UPD of a city in Period 1, and N_2 represents the overall levels of UPD of a city in Period 2.

To identify UPD manifestations, we first embedded the average identification results of the fourteen elements from all images within each subdistrict and performed clustering to ascertain the UPD manifestations of each subdistrict. Subsequently, the spatial distribution characteristics of each manifestation were observed at the city scale. In examining the relationship between economic and population shifts and the progression of UPD, we employed Equation 2 to quantify the evolution of UPD manifestations.

$$\Delta M_i = \frac{s_{i2}}{s_{\mathrm{all}}} - \frac{s_{i1}}{s_{\mathrm{all}}} \tag{2}$$

where i stands for UPD manifestation types, including vacancy and decay, under construction, and poorly maintained; ΔM_i represents the change of a city in the manifestation type i; s_{i1} represents the number of subdistricts in the city with manifestation type i in Period 1; s_{i2} represents the number in Period 2; and s_{all} represents the total number of subdistricts in the city.

Results

Overall UPD Levels

To more accurately reflect the overall UPD level, the weights of the various indicators were determined through expert scoring. The most detrimental factors to the quality of public space were identified as damaged building facades and construction fence remnant. Conversely, stores with poor signboards were found to have the least impact on the quality of space (Table 1). Based on these weights, the overall UPD level was calculated, revealing a decline from an average of 2.16 in Period 1 to 1.73 in Period 2 across all valid points. At the city scale, 563 natural cities (80.7 percent) exhibited a decline in overall UPD levels, whereas 135 natural cities (19.3 percent) demonstrated an increase (Figure 5). Cities with improved quality were predominantly located in proximity to the Yangtze River Delta, whereas those with deteriorating conditions were situated primarily in the central and northeastern regions.

Identification of UPD Manifestations

Following the encoding of all UPD features and spatial structures of the study units for Period 1 and Period 2, validation measures representing connectedness (connectivity), compactness (Dunn index), and cluster separation (silhouette width) were calculated to decide on the most appropriate method and the most appropriate number of clusters. Figure 6 illustrates the internal validity measures for K-means and hierarchical clustering. K-means had lower connectivity values (Figure 6A) and produced higher Dunn index values (Figure 6B). In addition, in both methods, the mean silhouette width of four clusters is only surpassed by that of the two clusters (Figure 6C). These values indicate that K-means significantly outperforms hierarchical clustering, and therefore K-means was chosen as the preferred clustering algorithm in this study, and the number of clusters was determined to be four.

Table 1. Weights of urban physical disorder (UPD) elements

UPD elements	Weights
Buildings with damaged facades	9.70
Construction fence remnant	9.35
Illegal/temporary buildings	8.81
Garbage/litter on street	8.44
Roads stacked with personal belongings	8.09
Damaged public interface	8.00
Broken infrastructure	7.72
Broken roads	7.64
Buildings with unkempt facades	6.65
Graffiti/illegal advertisement	6.20
Vacant and pending stores	5.75
Stores with poor facades	5.18
Abandoned buildings	4.58
Stores with poor signboards	3.90
Total	100

To facilitate the interpretation of our findings, the mean values of each UPD element within each cluster were calculated (the results of hierarchical clustering are shown in the Appendix, Figure A.5. In accordance with their defining characteristics, the four clusters represent four distinct types of UPD manifestations (Figure 7):

- Type 1: Good quality. These areas are distinguished by a pristine and well-ordered environment, devoid of any notable UPD concerns. The streets are kept in a clean state, and the buildings and infrastructure are well maintained.
- Type 2: Vacancy and decay. These areas are characterized by a paucity of pedestrian traffic and diminished commercial activity. The primary issue is the prevalence of vacant stores and buildings.

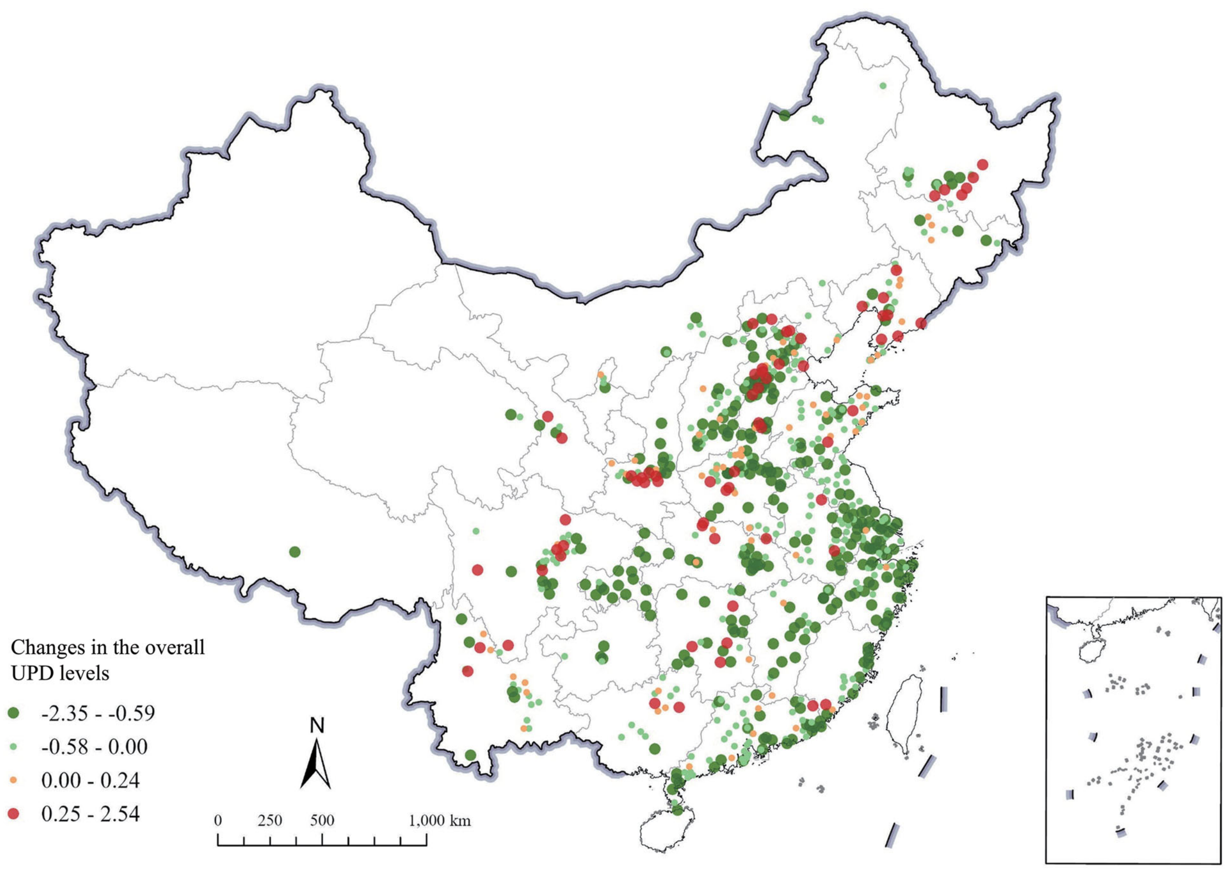

Figure 5. Changes in the overall urban physical disorder (UPD) levels at the city scale.

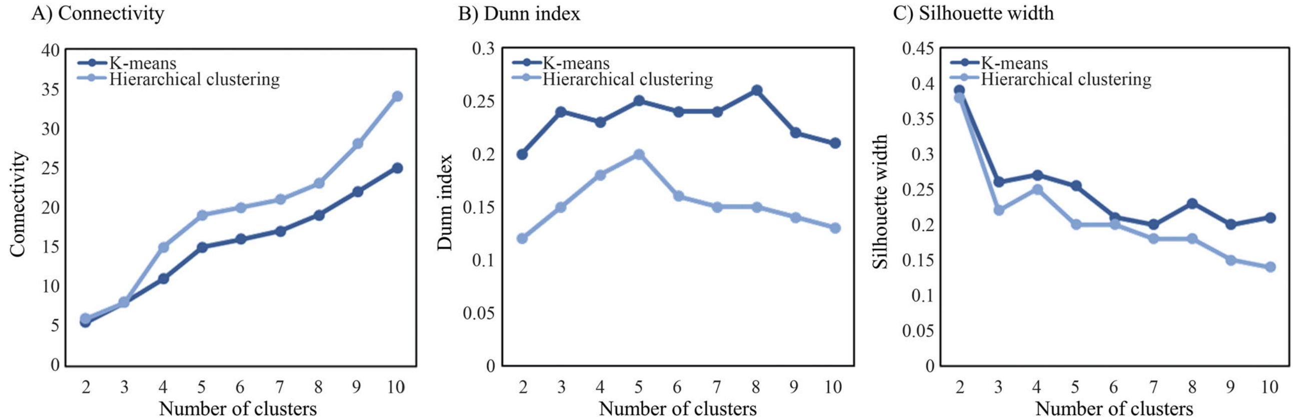

Figure 6. Internal validation measures for two clustering algorithms.

- Type 3: Under construction. These areas are typically undergoing construction. The primary issues pertain to the presence of construction fencing and damaged interfaces.
- Type 4: Poor maintenance. These areas frequently exhibit evident indications of residential activity, including concerns such as damaged infrastructure, garbage, and illegal advertisements.

Evolution of UPD Manifestations

The investigation of the evolution of UPD manifestations is divided into two aspects: quantity and spatial patterns. In terms of quantity, over half of the subdistricts were found to retain good quality. The most notable change was observed in 5.89 percent of subdistricts, which exhibited a shift from good quality to vacancy and decay. The most prevalent UPD issue shifted from poor maintenance to vacancy and decay (Figure 8A). Examples of the evolution between different UPD manifestations from Period 1 to Period 2 are shown in Figure 8B.

Regarding the spatial patterns of UPD, we first find the static UPD spatial distribution patterns. By synthesizing the distribution characteristics of three UPD manifestation clusters, which reflect spatial issues beyond those pertaining to good quality, we categorize them into four spatial distribution patterns: global, centralized, localized, and scattered (Figure 9A). Our findings indicate that subdistricts of vacancy and decay and under construction are predominantly distributed globally in cities, whereas subdistricts of poor maintenance exhibit more localized distributions (Figure 9B).

Second, the spatial patterns of the dynamic evolution of UPD can be classified into three categories: shrinkage, expansion, and transition (Figure 10). It is observed that at the national scale, 23.78 percent of cities experienced an expansion of the phenomena of vacancy and decay, which are distributed across the country in a relatively even manner. Cities with shrinking areas under construction are mainly located in south China (9.89 percent). Furthermore, cities with shrinking areas of poor maintenance (11.17 percent) are predominantly situated in central China (Figure 11).

Factors Associated with UPD Evolution

To gain further insight into the evolution of UPD, multiple regression models were constructed to explore the relationship between changes in UPD and economic, demographic, and urban development factors (Table 2). The expansion of the urban area has resulted in an increase in UPD of vacancy and decay and under construction. Furthermore, population loss and reduced vitality are also associated with increased vacancy and decay, but a growing population puts increased pressure on maintenance. From an economic standpoint, an uptick in GDP tends to diminish the overall UPD levels. Investments in municipal utilities construction and municipal sanitation have been shown to be effective in curbing UPD of poor maintenance, but they have not been observed to exert a notable influence on other forms of UPD.

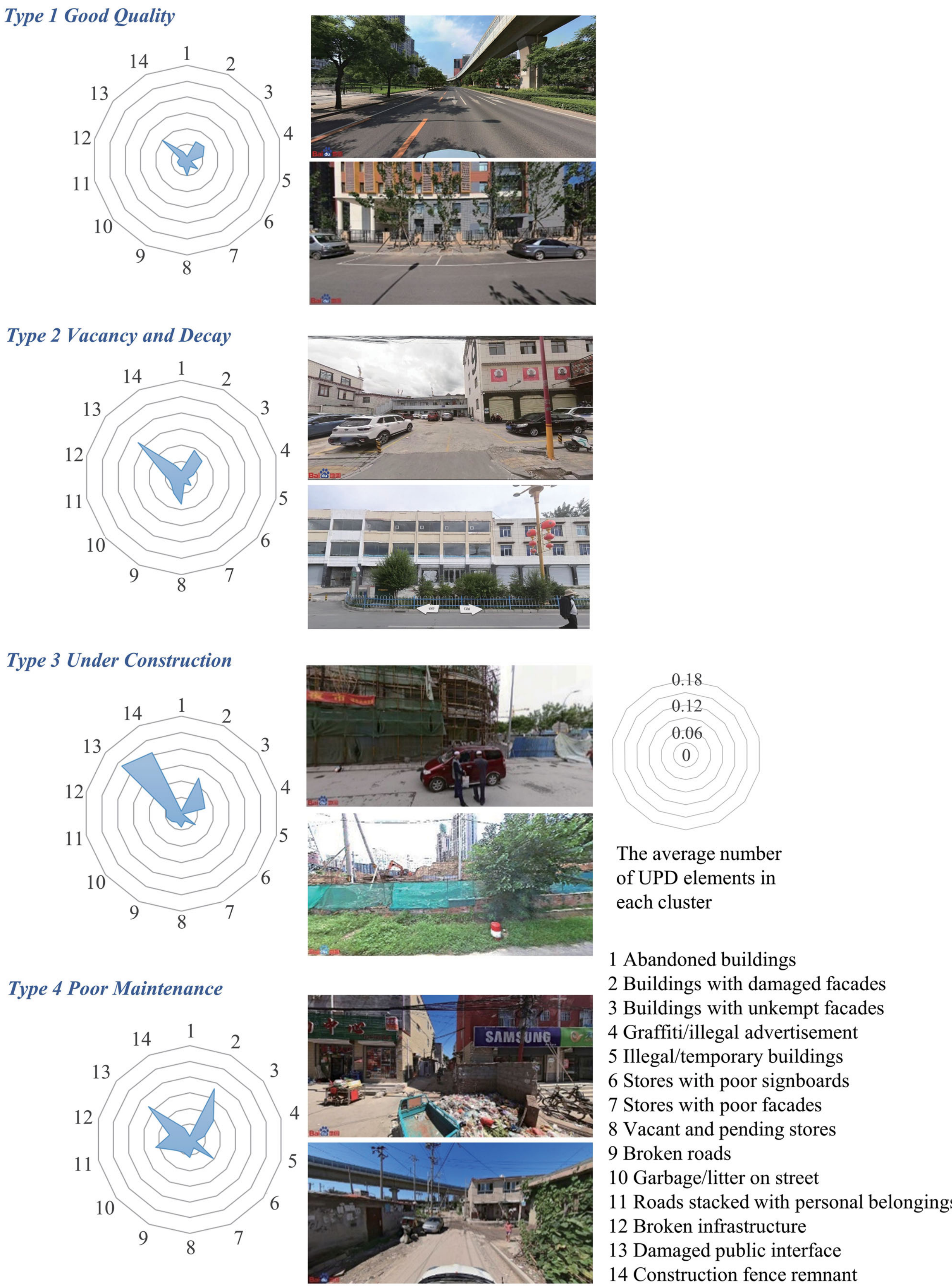

Figure 7. The average number of each urban physical disorder (UPD) elements and examples of the street view for the four manifestations.

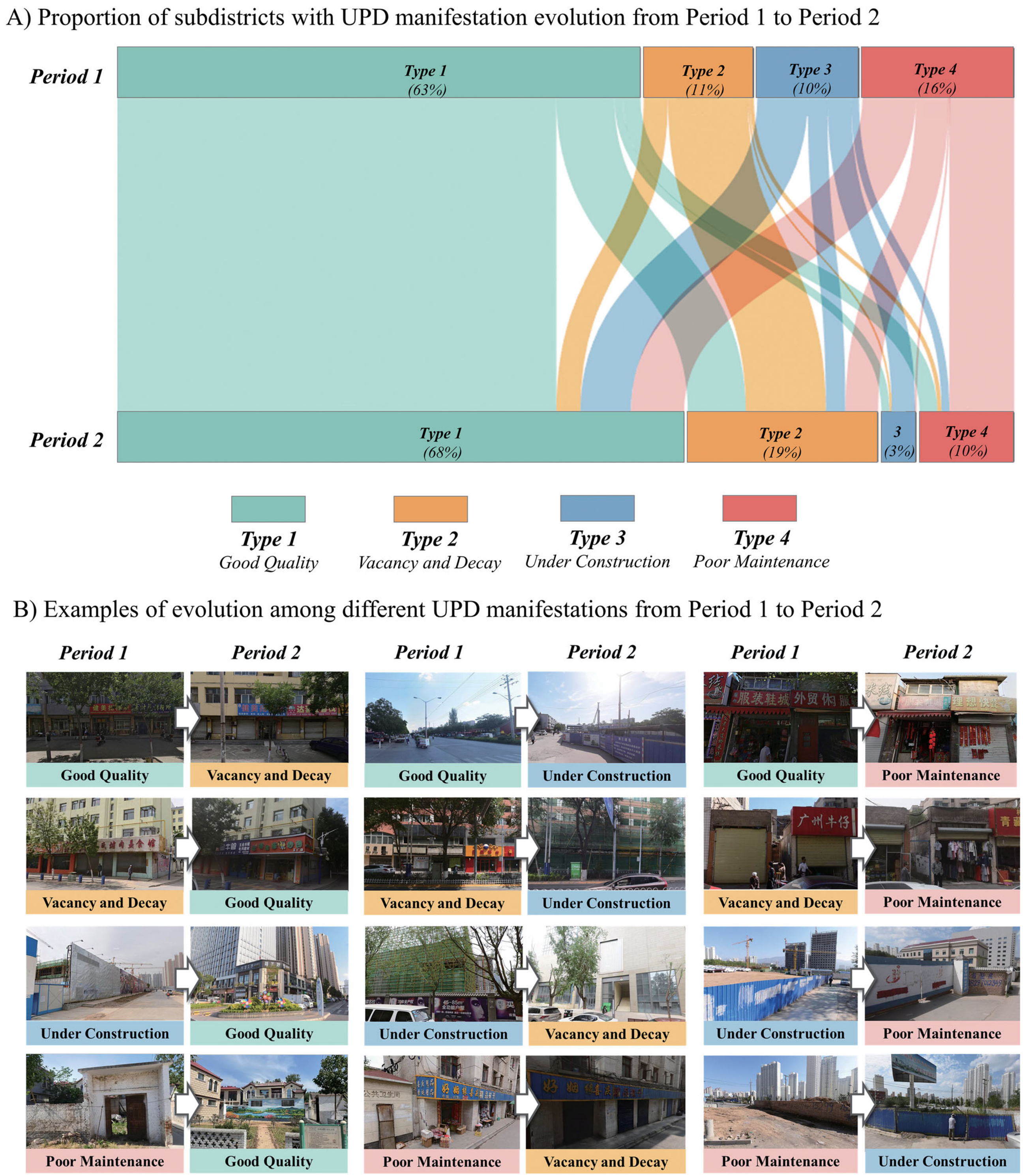

Figure 8. Proportion and the examples of evolution among urban physical disorder (UPD) manifestations from Period 1 to Period 2.

Discussion

UPD has an adverse impact on the quality of public space in cities. Researchers have proposed various methods for assessing UPD. This study introduces a novel approach for elucidating the temporal evolution of UPD. The primary contributions of this study are twofold: First, a comprehensive measure of the temporal evolution of UPD is achieved based on time-series SVIs and deep learning; second, an

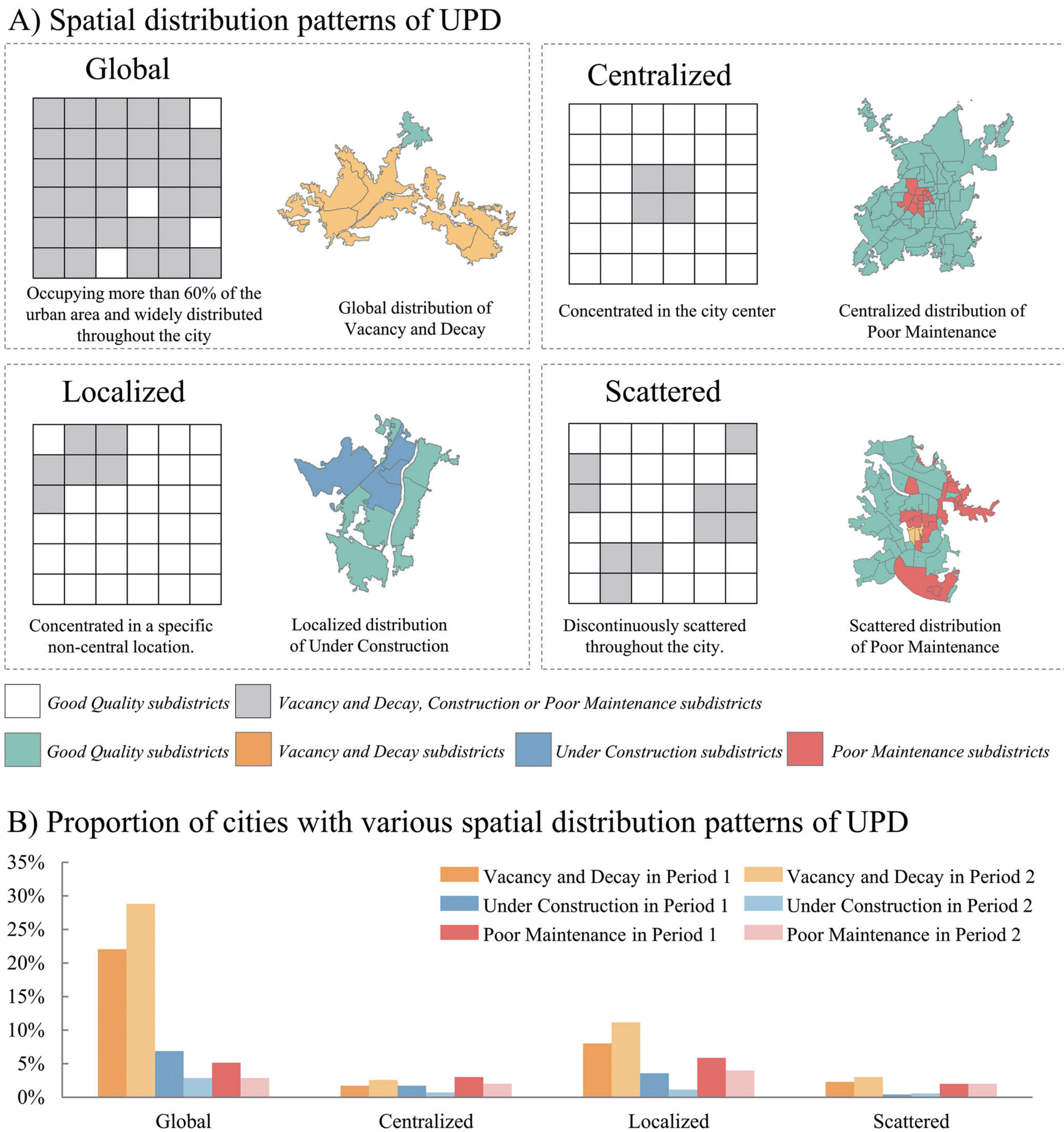

Figure 9. Spatial distribution patterns of urban physical disorder (UPD) manifestations and the proportion of each pattern in Period 1 and Period 2.

empirical investigation in China reveals the dynamic features and patterns of the evolution of UPD in the vast and diverse geographic area over the past decade.

Global Perspectives on UPD

This study focuses on the evolution of UPD in China. Indeed, UPD is a problem faced by cities across the globe. Mooney et al. (2017) conducted a study in

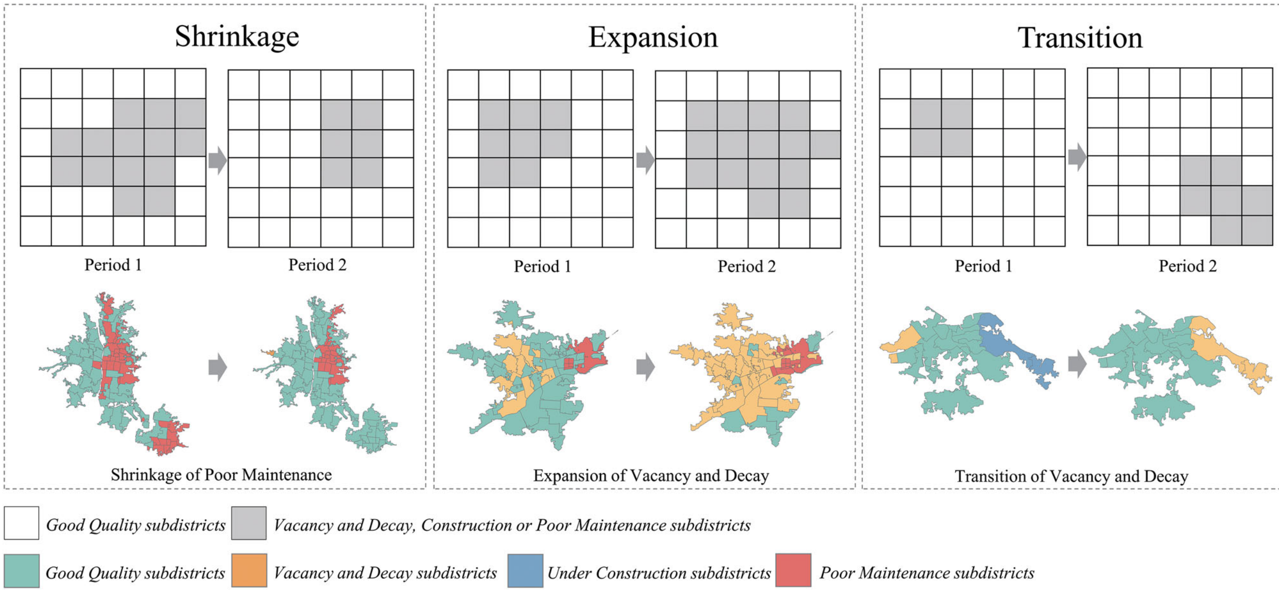

Figure 10. Spatial patterns of the urban physical disorder (UPD) manifestation evolution.

Detroit, Michigan, to assess UPD and validate the utilization of virtual audits via SVI. O'Brien and Sampson (2015) employed large-scale administrative data, comprising the nonemergency services records of Boston, Massachusetts, to quantify changes in UPD. Plascak et al. (2022) constructed spatiotemporal regressions to predict UPD in Essex County, New Jersey. The evolution of residents' perceptions of UPD in the Netherlands was tracked through the administration of questionnaires at different points in time. A review of studies on UPD in Latin America revealed that the elements of UPD that have received the most attention are public street features such as litter and vacancy (Magalhães et al. 2023). These studies confirm the widespread presence of UPD worldwide. The final assessment of the aforementioned methods, however, is limited to a judgment of an overall value and fails to provide an in-depth discussion of the forms and spatial patterns of UPD.

This study offers a dynamic assessment of the overall level of UPD, while also identifying the evolution of the different manifestations of UPD in China. The reasons for the formation of different UPD manifestations vary and confirm the need to refine the manifestations of UPD. Meanwhile, it makes us realize that different regions of the world are at disparate stages of urbanization, and they could experience different UPD problems. To illustrate, numerous cities in Europe and the United States that have reached the zenith of industrialization have subsequently undergone a period of decline, leading to socioeconomic and physical environment problems such as vacant housing and urban decay (Shetty and Reid 2014; Hartt 2019; Hou et al. 2025). Japan's street space is generally considered to be of high quality, with few features of UPD (Annear, Fristedt, and Laddawong 2024), but many cities are experiencing vacant housing as aging increases (Yui, Kubo, and Miyazawa 2017). India, on the other hand, is facing a demographic challenge with overpopulation, resulting in littering, poor air quality, and dilapidated streets becoming typical manifestations of UPD (Saroha 2016). Meanwhile, a significant proportion of the population in Latin American countries resides in informal settlements characterized by a lack of basic utilities and sanitation (Sandoval and Sarmiento 2020). The various manifestations have not been differentiated and portrayed in previous studies measuring UPD but rather described by a single numerical value, which prevents a more comprehensive understanding of UPD.

The rapid identification of the evolution of UPD in China with high precision and on a large scale can be regarded as a beginning. The methodological framework can serve as a foundation for elucidating the evolution of UPD in terms of elemental weights, manifestations, and relationships with population and economy in a greater number of regions across the globe. It is important to note, however, that many studies measure UPD based on lists of indicators derived from U.S. cities, such as the Neighborhood Disorder Scale proposed by Sampson

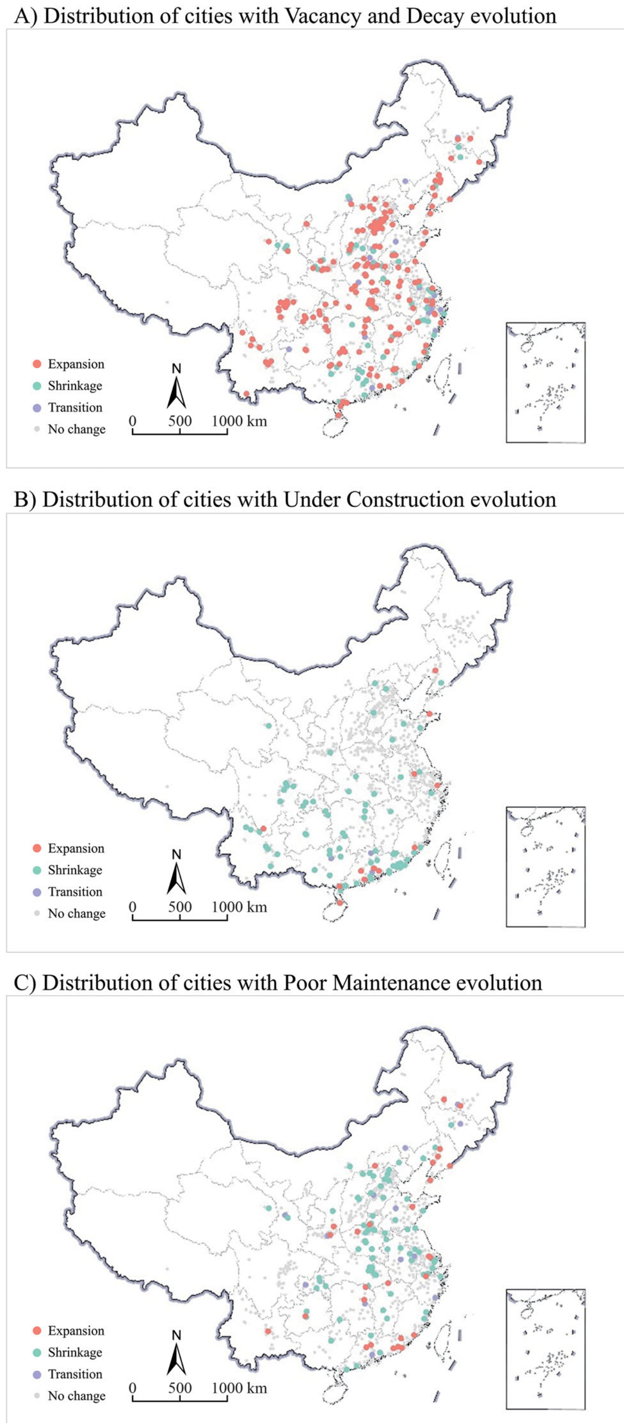

Figure 11. Distribution of cities with different spatial patterns of the urban physical disorder (UPD) manifestation evolution.

and Raudenbush (2004) and NIfETy (Furr-Holden et al. 2008). In this study, the UPD list applicable to China excludes elements such as needles on the street and graffiti, which are not common in Chinese cities, and adds elements such as illegal construction, which are common in China. To assess UPD in an area, it is necessary to construct more targeted indicator lists, which is what we are putting forth.

Economy, Population, Urban Development, and UPD

In a return to findings of this study, as previously indicated by urban economic theories of urban change, improvements in neighborhood environments are predicted by economic levels and population density (Bettencourt 2013; Bilal et al. 2020; Jamal and Ajmal 2020); our results indicate that economic development plays an important role in mitigating UPD. The level of economic development in a city is positively correlated with the funding allocated to infrastructure development and public services, as well as the efficiency with which the city is managed, both of which contribute to a reduction in UPD. IMUC (Investments in Municipal Utilities Construction) and IMS (Investments in Municipal Sanitation) play a positive role, further demonstrating the critical role of economic resources in urban governance. Cities experiencing rapid economic growth might tend to sprawl, however, leading to UPD of under construction that requires attention. Concurrently, whereas increased population density brings about the adverse consequence of poor maintenance, cities with declining populations are more prone to indications of vacancy and decay, which currently represent the most significant UPD problem in China.

Furthermore, urban development and morphological changes are also strongly associated with UPD. It can be observed that UPD of under construction is distributed globally and locally in noncentral areas of cities, and that there is a significant positive correlation between the growth of urban areas and under construction status. This might imply that UPD of under construction is closely associated with urban expansion. It is also noteworthy that the expansion of urban areas is accompanied by an increase in vacancy and decay. This, in conjunction with the large number of subdistricts that have shifted from good quality to vacancy and decay, suggests that a significant proportion of urban expansion might be excessive, or even a form of sprawl. Although efforts are made to renovate and redevelop old cities to improve the quality of poorly maintained areas, there is a simultaneous expansion of

Table 2. Regression analysis of urban physical disorder (UPD) evolution and related factors from Period 1 to Period 2

	Changes in overall UPD levels	Changes in vacancy and decay	Changes in under construction	Changes in poor maintenance
Changes in urban area	0.056	0.102**	0.098**	0.065
Changes in population density	−0.072	−0.113**	0.135	0.142*
Changes in urban vitality	−0.059	−0.121**	0.118	0.076*
Changes in GDP	−0.126**	0.079	0.101*	−0.167**
IMUC from 2015 to 2020	−0.221**	−0.071	0.011*	−0.128***
IMS from 2015 to 2020	−0.124*	−0.010	−0.009	−0.195**
N	698			
R^2	0.256	0.217	0.125	0.174

Note: GDP = gross domestic product; IMUC = investments in municipal utilities construction; IMS = investments in municipal sanitation. Changes in each indicator represent the difference between the values of that indicator in Period 1 and Period 2. The standardized coefficients (standardized beta) are listed in the table.
*10% significance level.
**5% significance level.
***1% significance level.

urban boundaries. This could lead to the emergence of numerous unoccupied and vacant buildings, potentially hollowing out inner cities or turning new areas into ghost towns. A number of studies of urban form and vitality have yielded comparable insights (Long and Wu 2016; Jin et al. 2017; Jiang et al. 2023; X. Zhang et al. 2023). Although the time span of this study is not sufficient to observe the development pattern of the city in depth, in the future, the evolution of UPD can be used as an entry point to gain insights into the preliminary trends of urban development from a micro perspective.

Policy Implications

By analyzing the UPD evolution in China, this study is expected to provide practical guidance to urban planners and policymakers. To understand the relevant policies that already exist in China, a collation was undertaken of the policies implemented in the study area between 2015 and 2020 that aim to improve urban spatial quality. For each policy, the UPD elements involved were identified (see Appendix, Figure A.6). The findings demonstrate that the majority of attention was directed toward addressing infrastructure issues, whereas the least attention was allocated to vacant buildings and commercial spaces. The study results suggest, however, that the most prevalent UPD issue has undergone a transition from poor maintenance to vacancy and decay. Therefore, in the face of a changing UPD, the previous policy has not kept pace and requires immediate revision and updating.

First, to enhance the efficacious management of diverse manifestations of UPD, the implementation of a zoning classification and management mechanism is recommended. The distribution of resources will be more rational, according to the extent and type of the problem, and targeted strategies will be implemented. The study revealed that the issue of vacancy and decay is particularly prevalent in Chinese cities, particularly in areas with declining populations. To address this issue, it is recommended that economic and business incentives be implemented in these areas and that more revitalization projects and policy incentives be introduced with the objective of attracting investment and enhancing regional vitality. It is also necessary to consider the limitation of urban sprawl and the alteration of the function of built-up but vacant areas to accommodate the impact of population loss. Such a process could include the conversion of commercial, office, and residential land into ecological green space or even farmland.

Poor maintenance often reflects a contradiction between the visible signs of space use and the lack of maintenance. Community management and the frequency of public services should be strengthened from the top, and community participation and public awareness should be encouraged from the bottom. It might therefore be advisable to recommend the establishment of community environmental management committees and to organize residents on a regular basis to participate in the maintenance of the space, with a view to enhancing their sense of belonging to the public space.

The under construction UPD can be attributed to the implementation of large-scale infrastructure development or urban renewal projects. In these areas, it is imperative that more sophisticated construction management plans be implemented, which will advocate for environmentally friendly construction techniques and facilitate enhanced communication with the surrounding residents to mitigate the impact on spatial quality. Finally, a dynamic monitoring mechanism can be implemented to track alterations in UPD on a consistent basis. The effectiveness of governance in pivotal domains can be reassessed as a foundation for policy modifications, thereby facilitating the rational distribution of resources and precise governance interventions to enhance the quality of urban space.

Limitation and Future Work

First, the overall performance of the YOLOv8-based UPD target detection model still has room for improvement. The model faces several challenges in processing SVIs, including strong lighting variations, shadows, and UPD elements that are partially or fully occluded by objects such as foliage and vehicles. Furthermore, the variable appearance of the UPD elements affected the model's performance, exhibiting relatively low accuracy in identifying diverse forms of illegal or temporary buildings, as well as small targets such as garbage on the street and advertisements on the walls. Future work will focus on expanding the training data set to enhance the representativeness of the data set and optimizing the model architecture and hyperparameters to better accommodate the specific features of each element type. Meanwhile, with the advent of visual AI, the utilization of multimodal large language models for zero-sample image recognition could become a revolutionary new approach in the future.

In terms of data, SVI is deficient in its coverage of inaccessible paths and alleys. Considering that these areas tend to be more unregulated and unsupervised, the results of the study might underestimate the actual UPD problem in urban public spaces. In addition, the coarse temporal granularity of the commercial SVI collection precludes the identification of seasonally sensitive UPD elements, such as greening, which are therefore excluded from the indicator system. Future research will integrate new data sources, such as unmanned aerial vehicles and satellite images, to provide aerial perspectives and more frequent temporal sampling for more comprehensive and realistic UPD identification.

Conclusions

This study introduces an approach for measuring the temporal evolution of UPD at a large scale, with a dual focus on both the overall level and the various manifestations of UPD. The methodology was applied in China to reveal the dynamic features and patterns of the evolution of UPD in a vast and diverse geographic area. The evolution of UPD was quantified in 698 natural cities in China. The findings revealed that from 2013 to 2022, the overall level of UPD in China exhibited a decline. The primary concern, however, has shifted from poor maintenance to vacancy and decay, particularly in cities experiencing population loss.

Overall, this study illustrates the efficacy of integrating time-series SVIs and deep learning to measure the temporal evolution of UPD at a national scale. It offers a rapid and effective approach for government agencies and urban planners to identify urban spatial quality concerns and ascertain areas requiring improvement in the future. The application in Chinese cities has revealed the dynamic features and patterns of the evolution of UPD, thereby broadening our understanding of this phenomenon. It is anticipated that this method will be extended to more regions and to other urban planning and geographic studies in the future.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China [No. 62394331, 62394335, 52178044].

ORCID

Yue Ma http://orcid.org/0009-0005-9022-380X

Yan Li http://orcid.org/0000-0001-6650-7726
Ying Long http://orcid.org/0000-0002-8657-6988

Data Availability

The data of this study is available at Mendeley Data (doi: 10.17632/b6b4sdxy95.1).

References

Annear, M., S. Fristedt, and T. Laddawong. 2024. Walkability in Japan's aging neighborhoods: A comparative audit analysis of pedestrian journeys in urban Tokyo. *Journal of Transport & Health* 35:101755. doi: 10.1016/j.jth.2024.101755.

Bakirci, M. 2024. Enhancing vehicle detection in intelligent transportation systems via autonomous UAV platform and YOLOv8 integration. *Applied Soft Computing* 164:112015. doi: 10.1016/j.asoc.2024.112015.

Batty, M. 2022. The shape of future cities: Three speculations. *Transactions in Urban Data, Science, and Technology* 1 (1–2):7–12. doi: 10.1177/27541231221113945.

Benediktsson, M. O. 2014. Territories of concern: Vacant housing and perceived disorder on three suburban blocks. *City & Community* 13 (3):191–213. doi: 10.1111/cico.12069.

Bettencourt, L. M. A. 2013. The origins of scaling in cities. *Science* 340 (6139):1438–41. doi: 10.1126/science.1235823.

Bilal, U., M. Franco, B. Lau, D. Celentano, and T. Glass. 2020. Measuring neighbourhood social and economic change for urban health studies. *Urban Studies* 57 (6):1301–19. doi: 10.1177/0042098019880754.

Cai, L., J. Xu, J. Liu, T. Ma, T. Pei, and C. Zhou. 2019. Sensing multiple semantics of urban space from crowdsourcing positioning data. *Cities* 93:31–42. doi: 10.1016/j.cities.2019.04.011.

Chen, J., L. Chen, Y. Li, W. Zhang, and Y. Long. 2023. Measuring physical disorder in urban street spaces: A large-scale analysis using street view images and deep learning. *Annals of the American Association of Geographers* 113 (2):469–87. doi: 10.1080/24694452.2022.2114417.

Crawley, H., and D. Skleparis. 2018. Refugees, migrants, neither, both: Categorical fetishism and the politics of bounding in Europe's "migration crisis." *Journal of Ethnic and Migration Studies* 44 (1):48–64. doi: 10.1080/1369183X.2017.1348224.

Dassopoulos, A., C. D. Batson, R. Futrell, and B. G. Brents. 2012. Neighborhood connections, physical disorder, and neighborhood satisfaction in Las Vegas. *Urban Affairs Review* 48 (4):571–600. doi: 10.1177/1078087411434904.

Deng, Y., W. Qi, B. Fu, and K. Wang. 2020. Geographical transformations of urban sprawl: Exploring the spatial heterogeneity across cities in China 1992–2015. *Cities* 105:102415. doi: 10.1016/j.cities.2019.102415.

Furr-Holden, C. D. M., M. J. Smart, J. L. Pokorni, N. S. Ialongo, P. J. Leaf, H. D. Holder, and J. C. Anthony. 2008. The NIfETy method for environmental assessment of neighborhood-level indicators of violence, alcohol, and other drug exposure. *Prevention Science* 9 (4):245–55. doi: 10.1007/s11121-008-0107-8.

Hackworth, J. 2018. Race and the production of extreme land abandonment in the American Rust Belt. *International Journal of Urban and Regional Research* 42 (1):51–73. doi: 10.1111/1468-2427.12588.

Hall, P. 2014. *Cities of tomorrow: An intellectual history of urban planning and design since 1880*. Hoboken, NJ: Wiley. https://books.google.com/books?hl=zh-CN&lr=&id=79EsAwAAQBAJ&oi=fnd&pg=PR12&dq=Cities+of+Tomorrow:+An+Intellectual+History+of+Urban+Planning+and+Design+Since+1880.+John+Wiley+%26+Sons.&ots=hM4X2fn8rL&sig=f7Kk_5prN276J3QnSu4IC2Zd1c.

Hartt, M. 2019. The prevalence of prosperous shrinking cities. *Annals of the American Association of Geographers* 109 (5):1651–70. doi: 10.1080/24694452.2019.1580132.

Hou, C., F. Zhang, Y. Kang, S. Gao, Y. Li, F. Duarte, and S. Li. 2025. Transferred bias uncovers the balance between the development of physical and socioeconomic environments of cities. *Annals of the American Association of Geographers* 115 (1):148–66. doi: 10.1080/24694452.2024.2412173.

Hu, C., S. Jia, F. Zhang, C. Xiao, M. Ruan, J. Thrasher, and X. Li. 2023. UPDExplainer: An interpretable transformer-based framework for urban physical disorder detection using street view imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 204:209–22. doi: 10.1016/j.isprsjprs.2023.08.017.

Jain, A. K. 2010. Data clustering: 50 years beyond K-means. *Pattern Recognition Letters* 31 (8):651–66. doi: 10.1016/j.patrec.2009.09.011.

Jamal, S., and U. Ajmal. 2020. Assessing the relationship between neighbourhood socio-economic status and environmental quality. In *Urban health risk and resilience in Asian cities*, ed. R. B. Singh, B. Srinagesh, and S. Anand, 445–59. Singapore: Springer Singapore. doi: 10.1007/978-981-15-1205-6_25.

Jiang, Y., Y. Zhang, Y. Liu, and Z. Huang. 2023. A review of urban vitality research in the Chinese world. *Transactions in Urban Data, Science, and Technology* 2 (2–3):81–99. doi: 10.1177/27541231231154705.

Jin, X., Y. Long, W. Sun, Y. Lu, X. Yang, and J. Tang. 2017. Evaluating cities' vitality and identifying ghost cities in China with emerging geographical data. *Cities* 63:98–109. doi: 10.1016/j.cities.2017.01.002.

Johnson, D., E. R. Maguire, S. A. Maass, and J. Hibdon. 2016. Systematic observation of disorder and other neighborhood conditions in a distressed Caribbean community. *Journal of Community Psychology* 44 (6):729–46. doi: 10.1002/jcop.21798.

Johnson, M. T. J., and J. Munshi-South. 2017. Evolution of life in urban environments. *Science* 358 (6363):eaam8327. doi: 10.1126/science.aam8327.

Kropf, K. S. 2001. Conceptions of change in the built environment. *Urban Morphology* 5 (1):29–42. doi: 10.51347/jum.v5i1.3891.

Li, W., Y. Long, M.-P. Kwan, N. Liu, Y. Li, and Y. Zhang. 2022. Measuring individuals' mobility-based exposure to neighborhood physical disorder with wearable cameras. *Applied Geography* 145:102728. doi: 10.1016/j.apgeog.2022.102728.

Li, Y., and Y. Long. 2024. Inferring storefront vacancy using mobile sensing images and computer vision approaches. *Computers, Environment and Urban Systems* 108:102071. doi: 10.1016/j.compenvurbsys.2023.102071.

Li, Y., Y. Ma, and Y. Long. 2024. Protocol for assessing neighborhood physical disorder using the YOLOv8 Deep Learning Model. *STAR Protocols* 5 (1):102778. doi: 10.1016/j.xpro.2023.102778.

Liang, X., T. Zhao, and F. Biljecki. 2023. Revealing spatio-temporal evolution of urban visual environments with street view imagery. *Landscape and Urban Planning* 237:104802. doi: 10.1016/j.landurbplan.2023.104802.

Long, Y., and K. Wu. 2016. Shrinking cities in a rapidly urbanizing China. *Environment and Planning A: Economy and Space* 48 (2):220–22. doi: 10.1177/0308518X15621631.

Magalhães, A. S., A. C. de Souza Andrade, B. D. S. Moreira, A. A. D. S. Lopes, and W. T. Caiaffa. 2023. Physical and social neighborhood disorder in Latin American cities: A scoping review. *Cadernos de saude publica* 39 (9):e00038423. Brasildoi: 10.1590/0102-311xen038423.

Marco, M., E. Gracia, M. Martín-Fernández, and A. López-Quílez. 2017. Validation of a Google Street View-based neighborhood disorder observational scale. *Journal of Urban Health* 94 (2):190–98. doi: 10.1007/s11524-017-0134-5.

Mayne, S. L., A. Jose, A. Mo, L. Vo, S. Rachapalli, H. Ali, J. Davis, and K. N. Kershaw. 2018. Neighborhood disorder and obesity-related outcomes among women in Chicago. *International Journal of Environmental Research and Public Health* 15 (7):1395. doi: 10.3390/ijerph15071395.

Milam, A. J., C. Debra, M. Furr-Holden, P. T. Harrell, D. E. Whitaker, and P. J. Leaf. 2012. Neighborhood disorder and juvenile drug arrests: A preliminary investigation using the NIfETy instrument. *The American Journal of Drug and Alcohol Abuse* 38 (6):598–602. doi: 10.3109/00952990.2012.701357.

Mooney, S. J., M. D. M. Bader, G. S. Lovasi, J. O. Teitler, K. C. Koenen, A. E. Aiello, S. Galea, E. Goldmann, D. M. Sheehan, and A. G. Rundle. 2017. Street audits to measure neighborhood disorder: Virtual or in-person? *American Journal of Epidemiology* 186 (3):265–73. doi: 10.1093/aje/kwx004.

Murtagh, F., and A. Heck. 2012. *Multivariate data analysis*. Berlin: Springer Science & Business Media. https://www.google.com/books?hl=zh-CN&lr=&id=LZfuCAAAQBAJ &oi=fnd&pg=PR11&dq=Multivariate+Data+Analy- sis,&ots=KduTQ2HORs&sig=-GfoxE3uzIc25AM-si4HOEtfn1o.

Ndjila, S., G. S. Lovasi, D. Fry, and A. A. Friche. 2019. Measuring neighborhood order and disorder: A rapid literature review. *Current Environmental Health Reports* 6 (4):316–26. doi: 10.1007/s40572-019-00259-z.

Novack, T., L. Vorbeck, H. Lorei, and A. Zipf. 2020. Towards detecting building facades with graffiti artwork based on street view images. *ISPRS International Journal of Geo-Information* 9 (2):98. doi: 10.3390/ijgi9020098.

O'Brien, D. T., and R. J. Sampson. 2015. Public and private spheres of neighborhood disorder: Assessing pathways to violence using large-scale digital records. *Journal of Research in Crime and Delinquency* 52 (4):486–510. doi: 10.1177/0022427815577835.

Plascak, J. J., S. J. Mooney, M. Schootman, A. G. Rundle, A. A. M. Llanos, B. Qin, C.-C. Hong, K. Demissie, E. V. Bandera, and X. Xu. 2022. Validating a spatio-temporal model of observed neighborhood physical disorder. *Spatial and Spatio-Temporal Epidemiology* 41:100506. doi: 10.1016/j.sste.2022.100506.

Pottie-Sherman, Y. 2020. Rust and reinvention: Im/migration and urban change in the American Rust Belt. *Geography Compass* 14 (3):e12482. doi: 10.1111/gec3.12482.

Sampson, R. J., and S. W. Raudenbush. 1999. Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology* 105 (3):603–51. doi: 10.1086/210356.

Sampson, R. J., and S. W. Raudenbush. 2004. Seeing disorder: Neighborhood stigma and the social construction of "broken windows." *Social Psychology Quarterly* 67 (4):319–42. doi: 10.1177/019027250406700401.

Sandoval, V., and J. P. Sarmiento. 2020. A neglected issue: Informal settlements, urban development, and disaster risk reduction in Latin America and the Caribbean. *Disaster Prevention and Management: An International Journal* 29 (5):731–45. doi: 10.1108/DPM-04-2020-0115.

Sarkar, C., and C. Webster. 2017. Urban environments and human health: Current trends and future directions. *Current Opinion in Environmental Sustainability* 25:33–44. doi: 10.1016/j.cosust.2017.06.001.

Saroha, J. 2016. Sustainable urbanization in India: Experiences and challenges. In *Spatial diversity and dynamics in resources and urban development*, ed. A. K. Dutt, A. G. Noble, F. J. Costa, R. R. Thakur, and S. K. Thakur, 81–98. Dordrecht, The Netherlands: Springer. doi: 10.1007/978-94-017-9786-3_5.

Seo, W. 2018. Does neighborhood condition create a discount effect on house list prices? Evidence from physical disorder. *Journal of Real Estate Research* 40 (1):69–88. doi: 10.1080/10835547.2018.12091492.

Shen, L., B. Lang, and Z. Song. 2023. DS-YOLOv8-based object detection method for remote sensing images. *IEEE Access* 11:125122–37. doi: 10.1109/ACCESS.2023.3330844.

Shetty, S., and N. Reid. 2014. Dealing with decline in old industrial cities in Europe and the United States: Problems and policies. *Built Environment* 40 (4):458–74. doi: 10.2148/benv.40.4.458.

Skogan, W. G. 1990. *Disorder and decline: Crime and the spiral of decay in American cities*. New York: The Free Press. https://www.scholars.northwestern.edu/en/publications/disorder-and-decline-crime-and-the-spiral-of-decay-in-american-ci.

Sohan, M., T. Sai Ram, and C. V. Rami Reddy. 2024. A review on YOLOv8 and its advancements. In *Data intelligence and cognitive informatics*, ed. I. J. Jacob, S. Piramuthu, and P. Falkowski-Gilski, 529–45. Singapore: Springer Nature Singapore. doi: 10.1007/978-981-99-7962-2_39.

Spielman, S. E., and A. Singleton. 2015. Studying neighborhoods using uncertain data from the American Community Survey: A contextual approach. *Annals of the Association of American Geographers* 105 (5):1003–25. doi: 10.1080/00045608.2015.1052335.

Steurer, J. 2011. The Delphi method: An efficient procedure to generate knowledge. *Skeletal Radiology* 40 (8):959–61. doi: 10.1007/s00256-011-1145-z.

Talaat, F. M., and H. ZainEldin. 2023. An improved fire detection approach based on YOLO-v8 for smart cities. *Neural Computing and Applications* 35 (28):20939–54. doi: 10.1007/s00521-023-08809-1.

Tobler, W. R. 1970. A computer movie simulating urban growth in the Detroit region. *Economic Geography* 46 (sup1):234–40.

Tu, T., X. Wang, and Y. Long. 2024. Spatiotemporal changes of urban vacant land and its distribution patterns in shrinking cities on the globe. *The Science of the Total Environment* 947:174424. doi: 10.1016/j.scitotenv.2024.174424.

Valvis, A., S. Petropoulos, K. Kaisari, and A. Huliaras. 2021. Blessing or curse? The impact of the refugee crisis on organized civil society in Greece. *Southeastern Europe* 45 (1):93–122. doi: 10.30965/18763332-45010006.

Wallace, D., and D. Schalliol. 2015. Testing the temporal nature of social disorder through abandoned buildings and interstitial spaces. *Social Science Research* 145:104704. doi: 10.1016/j.cities.2023.104704.

Wang, Z., K. Ito, and F. Biljecki. 2024. Assessing the equity and evolution of urban visual perceptual quality with time series street view imagery. *Cities* 54:177–94. doi: 10.1016/j.ssresearch.2015.06.013.

Wang, X., and Y. Long. 2023. Future shrinking cities on the globe: A projection map for 2020–2100 based on global gridded population dataset. *Environment and Planning B: Urban Analytics and City Science* 50 (7):1994–97. doi: 10.1177/23998083231186153.

Wei, E., A. Hipwell, D. Pardini, J. M. Beyers, and R. Loeber. 2005. Block observations of neighbourhood physical disorder are associated with neighbourhood crime, firearm injuries and deaths, and teen births. *Journal of Epidemiology and Community Health* 59 (10):904–08. doi: 10.1136/jech.2004.027060.

Yang, L., H. Yang, J. Cui, Y. Zhao, and F. Gao. 2024. Non-linear and synergistic effects of built environment factors on older adults' walking behavior: An analysis integrating LightGBM and SHAP. *Transactions in Urban Data, Science, and Technology* 3 (1–2):46–60. doi: 10.1177/27541231241249866.

Yang, N., Z. Deng, F. Hu, Q. Guan, Y. Chao, and L. Wan. 2024. Urban perception assessment from street view images based on a multifeature integration encompassing human visual attention. *Annals of the American Association of Geographers* 114 (7):1424–42. doi: 10.1080/24694452.2024.2363783.

Yao, Y., J. Wang, Y. Hong, C. Qian, Q. Guan, X. Liang, L. Dai, and J. Zhang. 2021. Discovering the homogeneous geographic domain of human perceptions from street view images. *Landscape and Urban Planning* 212:104125.

Yui, Y., T. Kubo, and H. Miyazawa. 2017. Shrinking and super-aging suburbs in Japanese metropolis. *Sociology Study* 7 (4):195–204.

Zhang, F., A. Salazar-Miranda, F. Duarte, L. Vale, G. Hack, M. Chen, Y. Liu, M. Batty, and C. Ratti. 2024. Urban visual intelligence: Studying cities with artificial intelligence and street-level imagery. *Annals of the American Association of Geographers* 114 (5):876–97. doi: 10.1080/24694452.2024.2313515.

Zhang, X., Q. Zhang, X. Zhang, and R. Gu. 2023. Spatial-temporal evolution pattern of multidimensional urban shrinkage in China and its impact on urban form. *Applied Geography* 159:103062. doi: 10.1016/j.apgeog.2023.103062.

YUE MA is a PhD Student in the School of Architecture, Tsinghua University, Beijing, China 100084. E-mail: mayue22@mails.tsinghua.edu.cn. Her research focuses on quantifying urban public space quality.

YAN LI was a Postdoctoral Fellow in the School of Architecture, Tsinghua University, Beijing, China 100084. E-mail: yanli427@hotmail.com. Her research interests include the quantification of urban public space quality and GIScience.

YING LONG is a Tenured Professor in the School of Architecture, Tsinghua University, Beijing, China 100084. E-mail: ylong@tsinghua.edu.cn. His research focuses on urban science, including applied urban modeling, urban big data analytics and visualization, data-augmented design, and future cities.

Appendix

Figure A.1. The virtual audit manual of urban physical disorder in architecture.

Figure A.2. The virtual audit manual of urban physical disorder in commerce.

Figure A.3. The virtual audit manual of urban physical disorder in road.

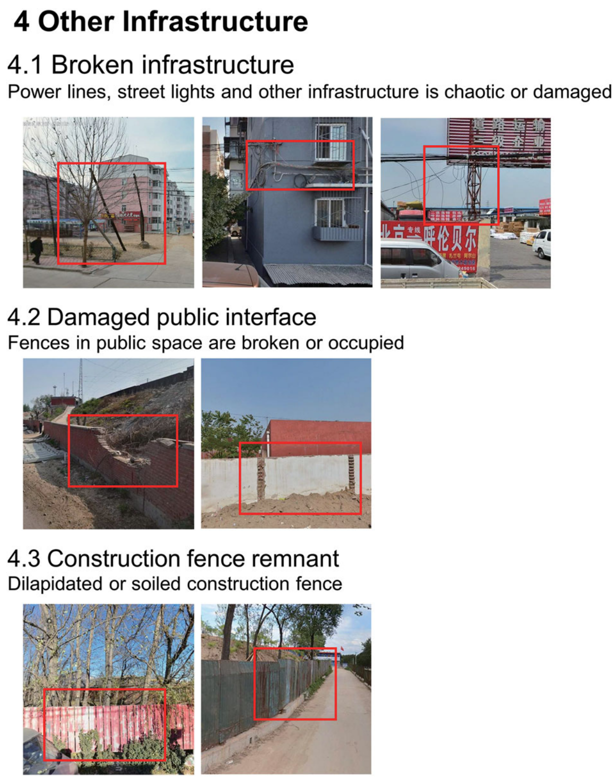

Figure A.4. The virtual audit manual of urban physical disorder in other infrastructure.

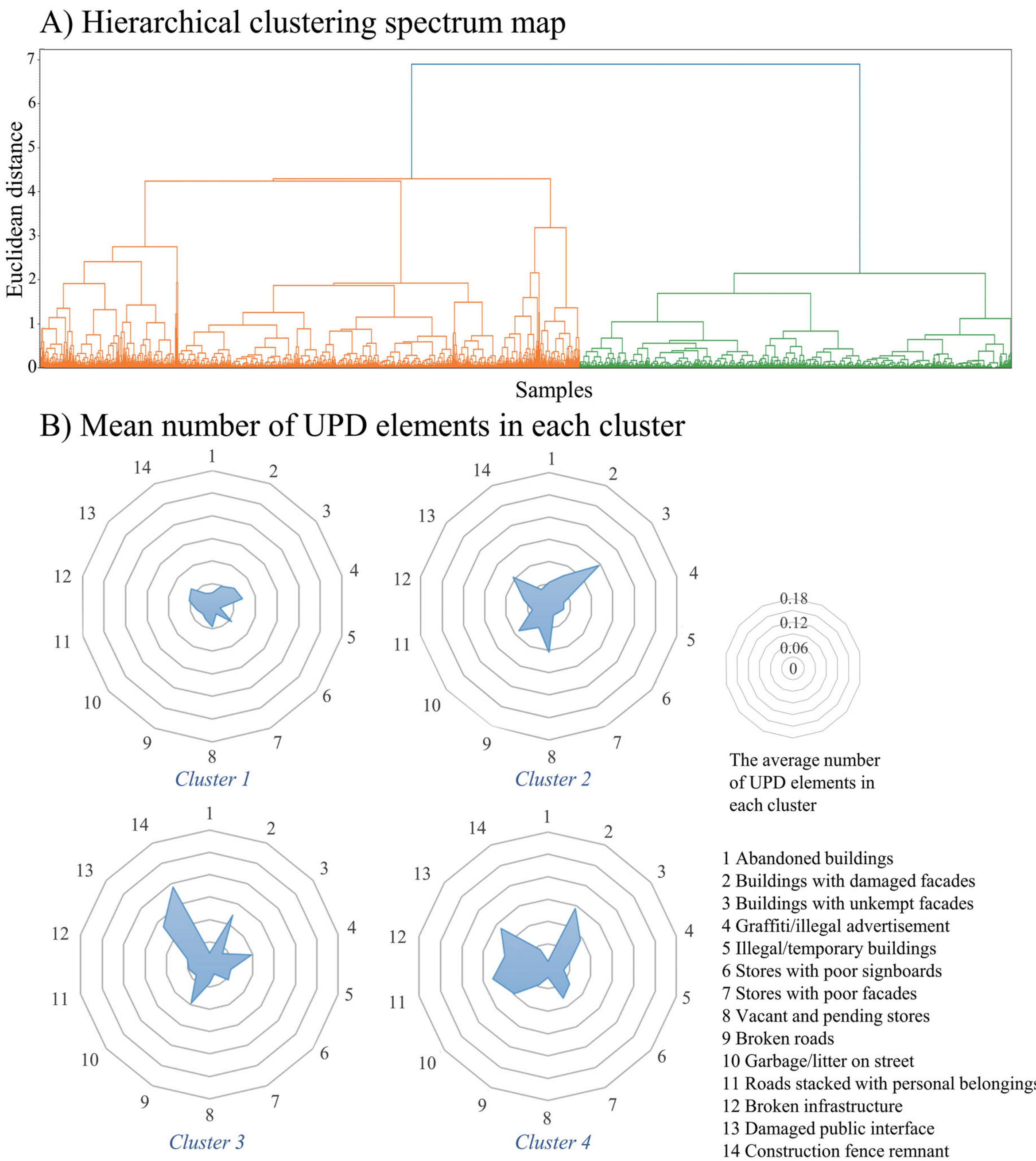

Figure A.5. Results of hierarchical clustering. *Note:* UPD = urban physical disorder.

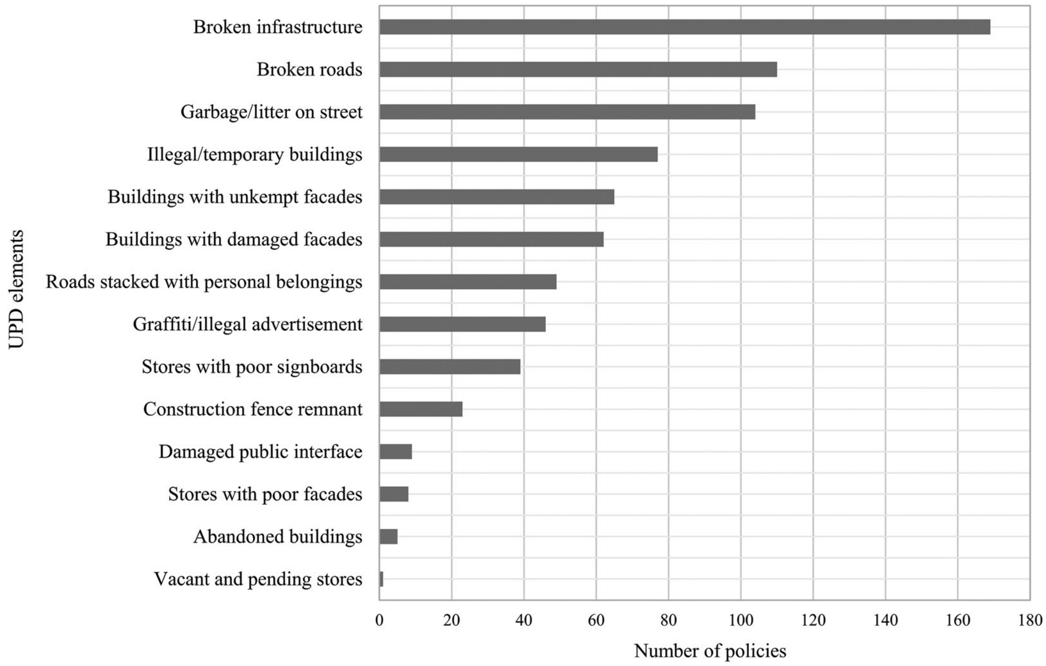

Figure A.6. Number of policies related to urban space quality improvement. *Note:* UPD = urban physical disorder.