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High-Resolution Mapping of Urban Residential Building Stock Using Multisource Geographic Data

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Abstract: The rapid pace of urbanization and the increasing concentration of populations in urban areas have generated a substantial demand for architectural structures, resulting in a significant increase in building stock and continuous material flows that interact with the environment. This study emphasizes the importance of high-spatial-resolution mapping of residential building stock for effective urban-construction resource management, planning, and waste management. Focusing on Xi'an as a case study, the research develops a comprehensive framework for mapping urban residential building stock by integrating diverse data dimensions, including temporal, spatial, network, and multi-attribute aspects. The findings indicate that between 1990 and 2020, approximately 4758 residential communities were established in central Xi'an. The analysis of seven key residential construction materials revealed that the building stock escalated from 1.53 million tons to 731.12 million tons, with a steady spatial expansion of material distribution. The study attributes this growth to factors such as population increase, economic advancement, and policy initiatives, which, in turn, have driven the demand for residential building materials and reinforced the interdependence between urban expansion and residential construction development. Remarkably, from 1990 to 2020, the population surged by 2.1-fold, the economy by 66-fold, and the stock of residential building materials by 477-fold, indicating that the growth rate of material stock consistently outpaced that of both population and economic growth. Over the past three decades, the rapid expansion of residential buildings has led to the encroachment of urban ecological spaces by concrete structures. The methodology proposed in this study for quantifying building material offers valuable insights for policymakers and urban and environmental planners to foster responsible resource consumption and supports component-level circularity in the built environment.

Keywords: material stock; multisource integration; sustainability; spatialization method

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1. Introduction

Over the past 40 years, China has experienced unprecedented rapid urbanization, with the urban population proportion increasing from 17.92% in 1978 to 63.89% in 2020 and the urban built-up area increasing by more than 8-fold (China Statistical Yearbook, 2020). In addition to the rapid concentration of populations, urbanization has also driven an increased demand for urban housing and prompted a broad spectrum of urban renewal activities [1–4].

By around 2012, China's stockpile of materials had already surpassed that of all other countries and was growing at an annual rate of approximately 8%. The consumption of construction materials in China accounted for half of the global stockpile by 2015 [5]. Since building stocks consume several materials and generate a large volume of construction and demolition (C&D) waste during their life cycles, buildings and urban development have been associated with environmental impacts [6–9]. In the process of sustaining population growth and meeting the rising demand for materials and energy during rapid urbanization [10–12], there have been increasing conflicts between resource supply and demand, along with an accumulation of pollutants and a rise in waste emissions [13,14]. Additionally, solid waste accumulation has contributed to the deterioration of air and water quality [15], and increased urbanization has further enhanced greenhouse gas emissions [16]. Environmental damage will hinder not only the economic development of China's cities but also their sustainable development [17,18]. In such situations, there is an urgent need to characterize the overall stocks of the construction sector and to find a refinement development model for cities, particularly for metropolises [19].

Mapping the spatial distribution of urban building stock through a certain method can provide building-data gridding, effectively improving the spatial resolution of building data and elucidating accurate information on the spatial distribution of buildings [20,21]. At present, the evolution of urban space has been studied by many scholars using building bottom projections [22], but different buildings are located at different locations, have different heights, and have different intensities of land use. Therefore, this study converts building bottom projections into a unified material accumulation and uses material quantities to study the evolution of space, guiding the study of urban space expansion. It is a theoretical supplement to urban space research and helps to better understand the potential of the circular economy, and it is key to informing low-carbon sustainable development [23]. The acquisition of updatable building information in the rapid development of urban areas is a challenge in current research [24]. This paper introduces a novel method for mapping urban housing stock that integrates multisource geographic data across temporal, spatial, network, and attribute dimensions. Unlike previous methods, which primarily focus on static data, this approach synthesizes diverse data streams to provide a dynamic, high-resolution visualization of urban material stock. This method not only enhances the granularity of building data but also offers an up-to-date framework for understanding the dynamics of urban development, addressing the urgent need for sustainable urban planning in rapidly growing cities.

The remaining paper is structured as follows: Section 2 provides a review of the relevant literature. Section 3 addresses the study area, data sources, and research methods. Section 4 presents the spatial distribution characteristics of the residential building stock. Section 5 focuses on the formation mechanism, innovations, and deficiencies. Section 6 presents the main conclusions.

2. Literature Review

In recent years, the research community has widely conducted modeling of urban building clusters to understand the flow and accumulation of resources in human societies [25]. The main research methods are divided into top-down and bottom-up approaches and their combined expansions [26]. For different research objectives and spatial resolutions, a variety of data sources are used, including remote sensing imagery, night-time light data, online map information, and statistical data, to estimate the stock of urban buildings.

Statistical data is primarily used in the top-down approach and is the most readily accessible source for estimating the stock of buildings. For instance, Bergsdal et al. (2007) estimated the building stock and material flow regarding dwellings in Norway from 1900–2100 using demographic data (2006) and floor information (2001) retrieved from Statistics Norway to determine the building area of houses, the average material intensity (MI) per floor space, and the building period [27]. In China, based on the gross domestic product (GDP) and housing floor area per capita, the building stock, material flows, and amount of concrete and steel were estimated and projected for all of China from 1900–2100 as well as for the city of Beijing from 1949–2050 [28,29]. Additional information such as the building age and the number of floors and structure is needed, which can be obtained by sampling buildings from architectural archives [30].

In addition, Kohler et al. (2002, 2007) adopted the population size and specific surface/network ratio per person as variables in studying material stocks [31,32]. The model originally developed by Müller, considering the population size and useful floor area per capita and involving two exogenous variables, was applied to estimate the housing demand, namely, the household size (the number of persons per family, which approximates the number of persons per housing unit) and the average floor area of housing units [33,34]. Sandberg et al. (2014) used the number of housing units as a parameter because they believed that the average building area data for each housing unit was highly uncertain. Therefore, it is assumed that housing demand depends on the population and housing occupancy rate [35]. Aided by Eurostat data, European housing statistical reports, and other national data sources (2003–2009), the time series of the annual completion and demolition of houses and the total house stock were analyzed by Wiedenhofer et al., and a dynamic method was then developed for the evaluation and impact assessment of the European construction flow [36]. Another study quantified the materials used in floors, roofs, and other components of single-family homes, multi-family residences, and apartment buildings from different construction periods, utilizing data provided by the H2020 European projects Hotmaps and AmBIENCe for each EU27 country [37]. However, statistical data are usually reported and documented by administrative regions (e.g., countries and provinces), which have very coarse spatial and temporal resolutions, particularly for urban areas [38]. This results in limitations for the more detailed quantification of the spatial distribution of material inventories.

With the development of urban information technology, the points of interest (POIs) from online maps such as Gaode and Baidu in China provide another route for extracting building information, which can be used to invert the in-use stock of urban buildings. Urban research has been carried out by referring to the GIS data of buildings in the central areas of major Chinese cities provided by Gaode maps (https://www.amap.com/), which include the shape, location, and number of buildings [39]. Such POI data are very useful for classifying buildings; for instance, Liu employed OpenStreetMap (OSM) road networks to identify parcel geometry and POI data to infer parcel characteristics. A vector-based cellular automata model and POIs were adopted to select urban parcels [40]. Nevertheless, this kind of data exhibits the characteristics of a difficult acquisition process, low update frequency, and a complicated processing method.

Night-time lighting (NTL) data serve as a significant source for extracting building information [41]. Since 1992, global NTL products have been provided by the Defense Meteorological Satellite Program's Operational Line-scan System (DMSP-OLS) [42–44]. Land-cover data from the International Steering Committee for Global Mapping (ISCGM) have been used to extract urban NTL data [45]. A notable application of NTL data was to estimate the steel stock in civil buildings across 102 countries [46]. Additionally, data from the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (S-NPP VIIRS) have been used to estimate the steel stock of urban infrastructure worldwide [47]. There is growing consensus that NTL data are particularly suitable for estimating steel and infrastructure material stocks at the national level. NTL data features include wide coverage, high update frequency, and simple processing methods, making it ideal for capturing spatial data over extensive areas with frequent updates. However, a significant issue with NTL data is the light saturation in urban centers with intense lighting, where the digital number (DN) value stops increasing despite higher ground-light intensity. Another limitation is the low data resolution resulting in the regulation of complex urban built environments, as well as the lack of observation capabilities in rural areas [48].

The datasets commonly employed in most studies do not permit the precise localization of material stocks. GIS data, utilizing building vector data, provide detailed spatial distribution information for individual buildings, thereby overcoming this limitation [49]. The use of materials and the subsequent flow of construction and demolition waste from the residential building stock in the city of Rio de Janeiro were assessed using GIS data [50]. The total material stock and demolition waste flow were estimated by a spatially explicit analysis in Padua, a medium-sized Italian city, over the period from 1902 to 2007 [51]. A study utilized a high-resolution decomposition method to model the geometry of buildings and was used to derive the building stock of all buildings in Melbourne, Australia [52].

Additionally, Tanikawa and Hashimoto developed a 4D-GIS, enhancing the accuracy of the building-stock model by incorporating time-series and geographic reference information [53]. A 4D-GIS model of Longwu Village in Shenzhen city was also established, and material flow and stock analysis (MFSA) and GIS methods were combined to reveal the spatiotemporal pattern and material consumption evolution of its buildings [19]. However, the lack of historical and high-resolution digitized maps complicates the determination of spatiotemporal patterns for specific buildings.

As noted, mapping the spatial distribution of urban buildings is a critical area of research in urban remote sensing. This mapping aids in assessing resource-related and environmental impacts, as well as indicating levels of urban economic development. Although building distribution statistics provide ongoing insights into the spatial characteristics of urban housing, demonstrating authority and sustainability, the process of determining building distributions is time-consuming, labor-intensive, and requires significant human intervention. Consequently, research on fine-scale architectural spatialization is substantially limited. The focus of domestic research primarily lies in developed cities such as Beijing and Shanghai, with limited attention given to underdeveloped western cities. Consequently, there remains a lack of comprehensive understanding regarding the current state of urban construction in our cities. An increasing number of authors are studying the spatialization of material stocks [54,55].

This research utilizes multisource geographic data encompassing temporal, spatial, network, and multi-attribute dimensions. Methods employed include data crawling, the acquisition of remote sensing data, the cleaning of duplicate and incorrect data, analysis of zoning statistical yearbooks, and verification through mathematical methods and on-site sampling. These processes enable the use of a variety of high-precision data as auxiliary sources. The study focuses on developing a spatialization method that achieves high accuracy across various grid scales while also allowing for the sustainable updating of spatialization results.

3. Materials and Methods

3.1. Case Study Description

As the capital city of Shaanxi province, Xi'an is a sub-provincial city on the Guanzhong Plain in Northwest China (34°16′ N 108°56′ E) and is rated as one of the top ten ancient capitals in the world by the American *Life Science* magazine. Like other cities in China, Xian has experienced rapid urbanization, with massive dynamics of material flow and stock associated with residential building construction and rehabilitation. In the late 1990s, Xi'an entered a phase of "mass demolition and renovation", with the transformation of shantytowns and urban villages prompting a rapid shift in the city's spatial layout. With the introduction of the national "Western Development" strategy in the 21st century, along with the establishment of various socioeconomic development plans like the Greater Xi'an Plan, Xi'an's urban status has continuously risen, and the city's scale has expanded accordingly. Considering the periodic nature of data collection and statistical reporting in China, along with comprehensive and consistent data records for the accurate analysis of urban development trends and material flow dynamics, this study selected the period from 1990 to 2020 as the research timeframe. The system boundary of this study is based on the delimitation of the central urban area in the Xi'an City Master Plan (2008–2020), which includes seven districts and 52 subdistrict offices in a total area of 690.8 square kilometers (Figure 1).

As stated before, the central focus of this study is only residential buildings and does not involve other building types such as commercial or industrial buildings. The residential building material stock is calculated, and its temporal and spatial evolution laws and characteristics are analyzed. The relationship between this analysis and urban development is considered, and then corresponding optimization strategies are proposed in the hope of achieving healthy and orderly city development from the perspective of material stock and avoiding waste and the unreasonable use of resources.

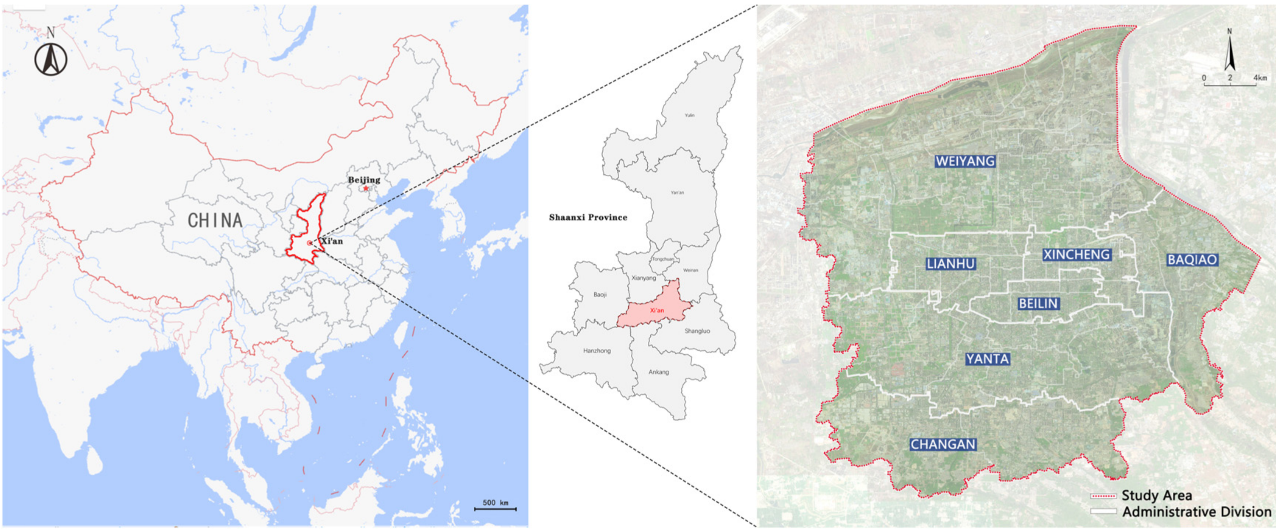


Figure 1. The location map of Xi'an city and its administered central districts.

3.2. Data Sources and the Processing Method

We obtained different data from diversified sources with rich types and a high degree of refinement. The central task was to merge different source data, such as building base data, residential area data and residential building strength data, and then develop a high-resolution database of urban residential material stock, which lays the foundation for the follow-up study of temporal and spatial evolution characteristics. The data were based on the acquisition of residential construction information from the internet and statistical yearbooks, and we used geographic information systems to establish a database of residential building inventories. In addition, satellite data were also used to study the relationship between the material stock of residential buildings and urban expansion. Therefore, in future research, it will be easier to update the construction and demolition status of buildings in real time.

3.2.1. Multisource Geographic Data

Specifically, the data used in the central research consist of building base data, residential area data, residential building strength data, street office population data and administrative division boundary data (Table 1). Necessary data mining procedures are needed to clean and calibrate the original data. The workflow of database processing and fusion is shown in Figure 2. Building contour data were acquired through OSM maps, and building attribute data were acquired through POI data. Then, we cleaned up the data, conducted spatial checks, and verified the maps on-site. At the same time, statistical data were used to determine the residential building material intensity, and a bottom-up material flow analysis method was used to calculate the inventory of building materials and to establish high-resolution data.

(1) Building contour data: Building contour data were obtained through OSM, which was founded by Steve Kester. OSM data mainly include the building contour area and the height, land area, roads, subways, etc. This database has been proven to be accurate and is widely applied in urban planning. A total of 139,874 valid surface data points of Xi'an building data were obtained through OSM (Figure 3).

Table 1. Data types, content, and sources employed in mapping urban building stock dynamics.

Type of Data	Data Content	Data Sources (Accessed on 23 March 2024)
Building contour data	Longitude and latitude: contour, story height	OSM (www.openstreetmap.com); www.gscloud.cn; "The historical atlas of Xi'an"; "Xi'an Statistical Yearbook"
POI (point of interest)	Longitude and latitude of the building: age, areas, structure.	https://xa.lianjia.com; https://xa.anjuke.com; https://xa.58.com; https://xian.fang.com
Residential building material intensity	Steel, cement, lime, gravel, glass, good, brick, et al. from 1990 to 2020	"Xi'an Statistical Yearbook" (1990–2020); database of Guanglianda
Demographic and economic data	Population data of community; gross domestic product et al. from 1990 to 2020	Statistical departments of each subdistrict office
Administrative division map of Xi'an	Administrative district boundary and street office boundary	"Urban master plan in Xi'an (2008–2020)"
Remote sensing image data	Used for extracting information on urban built-up areas	http://www.gscloud.cn

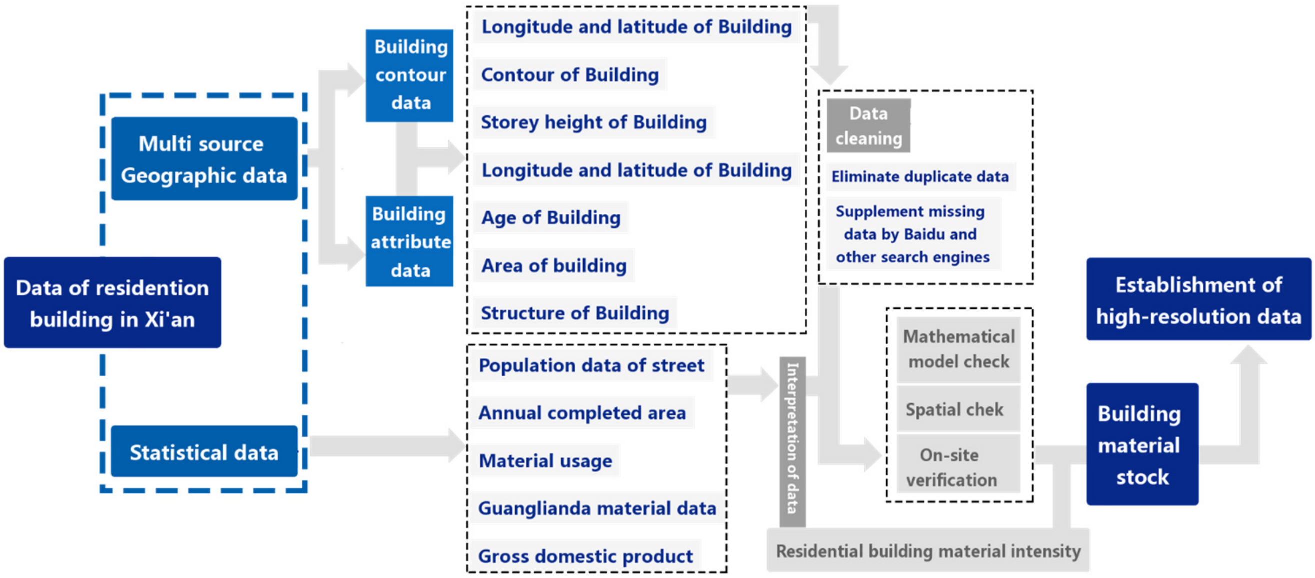


Figure 2. Working flow chart of the database processing and multisource data fusion.

(2) POI data: POI data were obtained through the LocoySpider collector. The LocoySpider collector was employed to retrieve data from various websites, such as Soufun, Lianjia, 58TongCheng, and Anjuke. Taking Lianjia as an example, by identifying the web structure and entering the included URL (uniform resource locator) and variables during website acquisition, the URL was tested, and data were obtained. In this way, POI data such as residential area, number of households, latitude and longitude, building age, and building structure can be obtained. Building spatialization information was acquired based on OSM data (Figure 4).

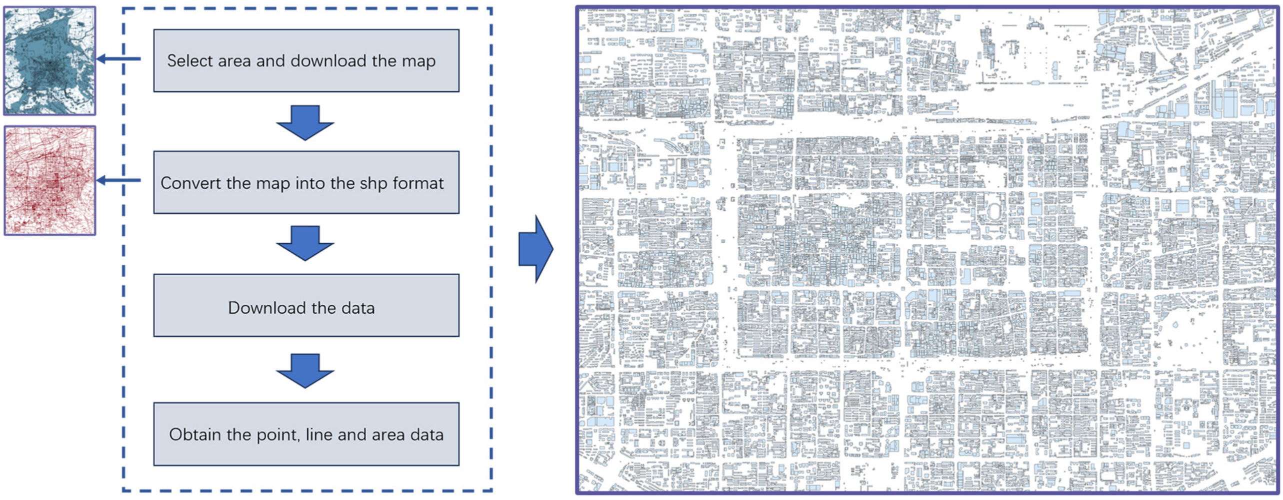


Figure 3. Crawl OSM map data based on QGIS and displayed in ArcGIS.

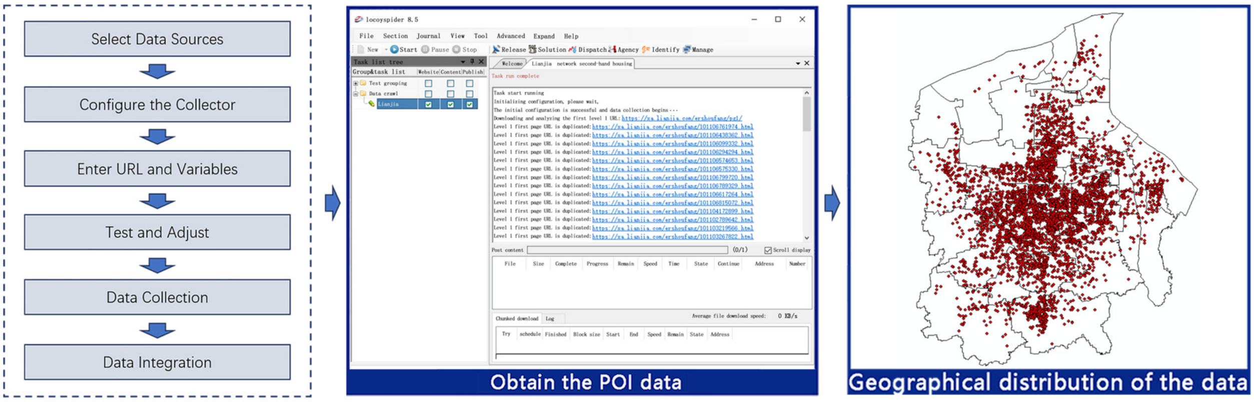


Figure 4. Residential building distribution and data collection using LocoySpider 8.5.

Through data statistics and the preliminary deletion of duplicate, abnormal, and incorrect data, 6238 valid residential community data points in Xi'an from 1990 to 2020 were obtained.

(3) Over time, residential structures have evolved, transitioning from multistorey buildings to small high-rise and high-rise structures. Consequently, the proportion of materials used in different structures varies, leading to variations in both the material stock per unit area and the material strength coefficient. To obtain a more accurate estimation, it is necessary to identify houses with different ages and to calculate the strength coefficient of residential buildings regarding periods.

MI refers to the average mass per unit of the building volume. By consulting the *Xi'an Statistical Yearbook* and related references, the advantages and disadvantages of various research methods were compared. After communicating with experienced scholars, the MI was determined according to the actual use of residential materials in Xi'an. The main components of the residential building system were steel, cement, lime, gravel, glass, wood, and brick. According to the different ages of residential buildings, the study period was divided into six periods: 1990–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, and 2016–2020. The MI of the residential buildings in Xi'an in the different years was obtained (Table 2).

Table 2. Material intensity of residential buildings considering age.

Year/Material	Steel	Cement	Lime	Gravel	Glass	Wood	Brick
1990–1995	12.5	200	100	600	1.9	16.7	220
1996–2000	12.9	180	90	600	1.9	15.9	140
2001–2005	23	360	145.43	700	2	15.4	88
2006–2010	28	360	145.43	700	2.1	14.9	88
2011–2015	33	360	145.43	700	2.2	14.4	88
2016–2020	37	360	145.43	700	2.3	13.9	88

(4) Population and economic data: Population and economic scales determine the growth trend of urban development and building material stock. In this study, a field survey of the seven districts was conducted, and the registered residence population and permanent population, the completed housing area, and the data of various materials and GDP were collected for approximately 52 communities in Xi'an from 1990 to 2020.

(5) Remote sensing image data: The remote sensing images used for the extraction of information on urban built-up areas in this article were from the Landsat series of the United States, and all remote sensing image data had a spatial resolution of 30 m. Based on the time scale of residential material inventory research and the clarity of the remote sensing data, a 5-year time span was used to select remote sensing images of the central urban area of Xi'an in 1995, 2000, 2005, 2010, 2015, and 2020 as the main research objects. At the same time, to ensure the accuracy of the data, relevant remote sensing image data with similar times and less than 10% cloud cover were selected for the remote sensing image data over the years. Before extracting the information on urban built-up areas, preprocessing operations such as image correction, cropping, radiometric calibration, and atmospheric correction were performed on the selected Landsat remote sensing images. To make the research more targeted, this study extracted only information on urban built-up areas within the research scope and cropped remote sensing image data based on the research scope.

3.2.2. Data Cleaning and Checking

Data cleaning: To ensure the accuracy and completeness of the data, multiple sources were explored; for instance, Lianjia, Anjuke, and Fangtianxia were searched for POI information. The acquired multisource data were compared and reorganized, and obvious erroneous or duplicated data were removed. The data were repeatedly screened with different similar sounding terms to ensure that the data pertaining to the same residential area appeared only once, thus guaranteeing the unity and accuracy of the data. Any residential area lacking data was supplemented; namely, Baidu or other search engines were employed to fill residential area data gaps. After data cleaning, a total of 4998 data points were obtained.

Data checking: After data cleaning, there may still be many errors associated with residential building attributes. To further ensure the data quality, the crawled residential data must be evaluated at individual point and spatial levels.

(1) Mathematical model check: The boxplot option in the R language model was adopted to evaluate the building-stock data of each residential area in Xi'an from 1990 to 2020. Boxplots (box–whisker plots) are generally used to intuitively determine whether data exhibit symmetry and to obtain the data dispersion degree. The time and material stock are defined as the horizontal and vertical coordinates, and then boxplots of the obtained residential stock data are obtained. Residential areas occurring far above the average are denoted as outliers, which need to be further assessed by locating their position using the Baidu map. Then, the total building stock is recalculated and compared to the crawled data. The ratio of the corrected data to the total data is considered when evaluating the accuracy of the data and determining whether

the data can be used. The total number of abnormal data points obtained was 215 (Figure 5).

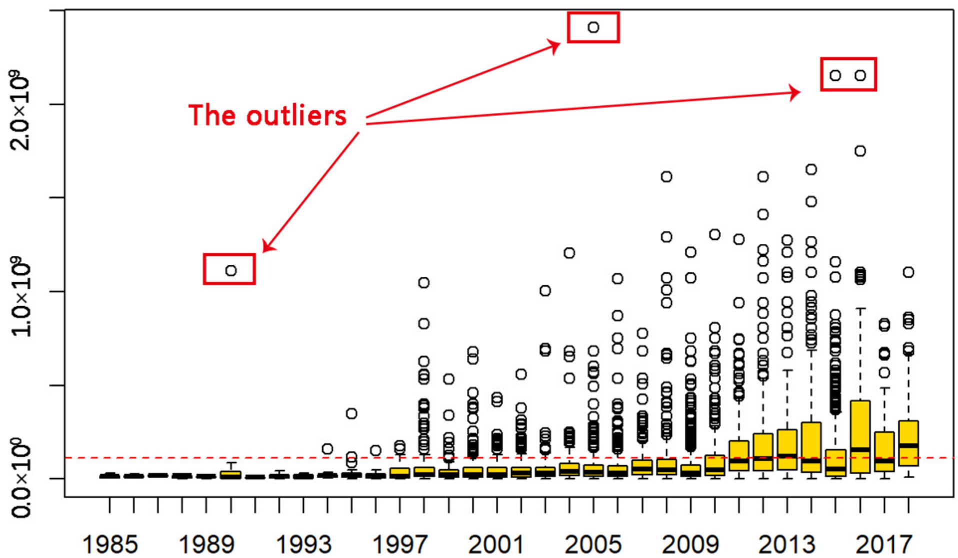


Figure 5. Using boxplots to filter outliers in building-stock data from 1990 to 2020.

(2) Spatial check and calculation: Accurate spatial location plays an important role in analyzing the spatial development characteristics of residential material stock. As mentioned above, the building contour data and POI point data were integrated to compile a high-resolution dataset with spatial dimensions. The Gaode map was used to check the point data and building contours and to accurately check the spatial position of the POI. As shown in Figure 6, the position of the "Weifeng garden villa" is in an abnormal location, and the spatial check returns it to the correct position. After the spatial verification of the obtained data, 215 incorrect data points were found; therefore, the data error is less than 5%.

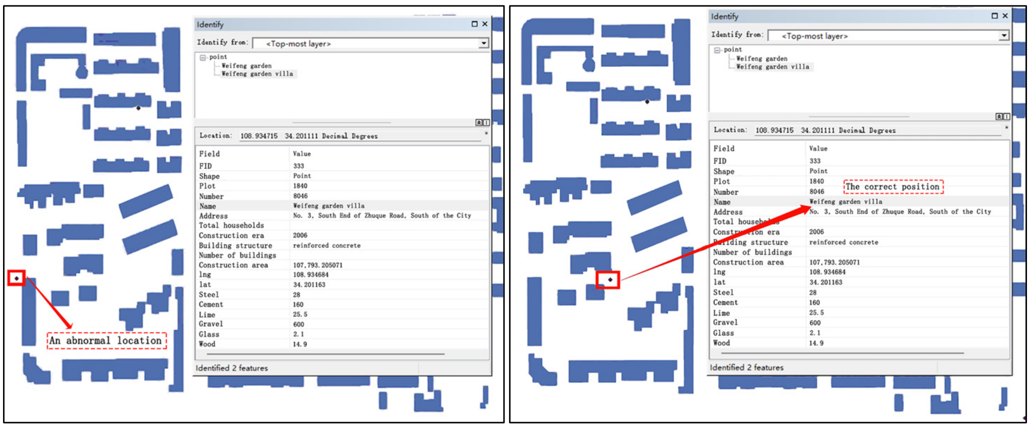


Figure 6. Space location check of Weifeng Garden.

(3) On-site investigation and verification: After the above data and spatial verification, our team was divided into 6 groups, 200 residential areas were randomly selected for manual investigation and verification, and the base area and height of residential buildings were measured. At the same time, supplementary surveys were conducted on residential buildings that lacked area data in the early stages. In addition, the building age and structure of a given residential area were determined through communication with the property owners. During the verification process, the base area data were shown to be highly accurate and could be used directly, while a small

deviation occurred in the building completion data. The difficulty and workload of this work were much higher than those required for the data and spatial evaluation steps. The obtained data were considered effective and could be used.

After data cleaning, mathematical method verification, spatial verification and manual verification, the results show that a total of 4758 residential areas were built in the central urban area of Xi'an from 1990 to 2020.

3.2.3. Building Material Stock Estimation

At present, there are two different methods of material flow analysis for estimating the material stock in buildings: the top-down method and the bottom-up method. In this study, a bottom-up approach is used to calculate the material stock in residential buildings within the study area. The calculation of the residential building stock requires two parameters, namely the area of residential buildings and the coefficient for material strength. This estimation can be achieved by utilizing Equation (1).

$$Mz_q = \sum_{i=1}^{n} X_q \times Y_q \tag{1}$$

where Mz_q is the total residential area in Xi'an, q denotes the buildings in the district, n is the total number of buildings, X_q is the base area of building q, and Y_q is the height of building q.

$$M_j = \Sigma_{Mz}^{n} \tag{2}$$

where M_j is the total residential area of Xi'an, n denotes all communities in the study area, and M_z is the total residential area in Xi'an.

$$Ms_{o,T,q} = \sum_{q=1}^{p} Mz_{q,t} \times C_{o,t,q} \tag{3}$$

where $Ms_{o,T,q}$ is the aggregate stock of residential building materials in Xi'an for a given year T. T is the construction year of a given building, t is the construction year for residential building q, p is the amount of materials, o is the residential building MI coefficient for materials including steel, wood, lime, gravel, cement, glass, and brick, $Mz_{q,t}$ is the total residential area of all communities in Xi'an city in year t, and $C_{o,t,q}$ is the MI coefficient of residential building o in a certain year.

$$Ms_T = \sum_{q=1}^{p} Ms_{o,T,q} \tag{4}$$

where Ms_T is the total quality of the residential buildings in year T.

We apply the above equation to calculate the housing stock of Xi'an city during the different periods and then sum the calculated data to obtain the total housing stock of Xi'an city.

3.2.4. High-Resolution Data Results

After obtaining the vector data of the aircraft and point data, we utilized the fishnet and connection tools within the ArcToolbox of ArcGIS Desktop 10.8 (Esri, Redlands, CA, USA) to integrate these datasets. Consequently, a material stock dataset with a resolution of 250 × 250 m was established. The color intensity in this map increases proportionally with the growth in the inventory, enabling us to discern the spatiotemporal evolution of residential material stock by sequentially overlaying vector diagrams from different years (Figure 7).

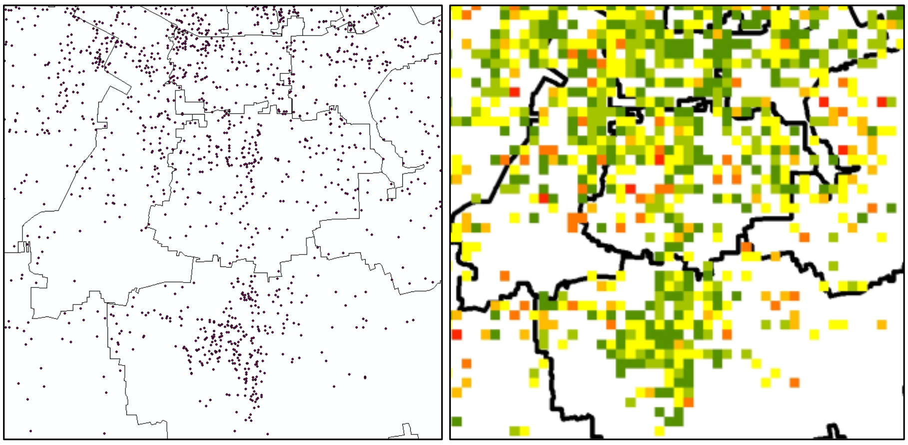


Figure 7. Gridding of small point data.

3.2.5. Extraction of Urban Built-Up Areas

This study adopts the supervised classification method of the support vector machine (SVM). SVM is a machine learning method based on statistical learning theory. It can automatically find a support vector with a great discrimination ability for classification and then construct a classifier, which can maximize the difference interval between various samples and has high classification accuracy. We selected a certain number of training samples for each land type based on meeting the classification requirements of each subcategory. Then, we used the training decision function to classify other data to complete the classification of the entire image.

We mainly refer to the corresponding relationship between the Kappa coefficient and classification accuracy and use a confusion matrix to verify the classification accuracy. In supervised classification problems, the most common evaluation indicator is accuracy (acc), but in practical problems, the sample size of each category is often uneven. Acc results often tend to lean toward large categories and cannot display accuracy for small categories. The Kappa coefficient corrects "bias" in measuring classification accuracy: 0.8–1.0 signifies highest accuracy, 0.6–0.8 high, 0.4–0.6 moderate, 0.2–0.4 average, and 0.0–0.2 extremely low. This study refers to high-resolution images and image classification results and constructs a confusion matrix calculation to study the accuracy of classification. In the classification results of 1995, 2000, 2005, 2010, 2015, and 2020, the Kappa coefficients were all greater than 0.8, with values of 0.9547, 0.8272, 0.8657, 0.8284, 0.8148, and 0.8326, respectively. This indicates that the classification accuracy is high and the final classification results are relatively reliable. The final interpretation result is shown in Table 3.

Table 3. Historical urban built-up area of Xi'an's city center.

Year	1995	2000	2005	2010	2015	2020
built-up area (km^2)	138.70	203.40	266.94	394.90	506.57	631.32

4. Results

4.1. High-Resolution Material Stock Maps

According to the map of residential material stocks in Xi'an, the darker the color is, the greater the stocks and the higher the spatial material strength. In contrast, the lighter the color, the smaller the stocks and the lower the strength of the space materials (Figure 8). Before 2000, the number of building grids was small and was mainly concentrated in the central region of Xi'an. The color was mostly light, and the residential material stocks were generally less than 50,000 tons. By the end of 2005, with the rapid development of the city, the density of the central area and the stock intensity of residential materials in the grid had increased, and the grid distribution began to expand to the north–south and east–west, showing an irregular enclave expansion and development. Due to the existence of historical sites, there is no residential material stock in the northwest of the city. By the end of 2010, the growth rate of residential material stocks in the central urban area was stable; there were many areas with a high intensity of residential material stocks in the city, mainly concentrated in the south and east, and no obvious residential material stocks in the west and north. By the end of 2015, dark grids appeared in the north and south of the city, forming a regional distribution, and the residential density distribution and intensity distribution in the central area of the city were lower than those in the peripheral areas. By the end of 2020, the strength of urban residential building materials had further increased. Compared with 2015, the residential distribution had further expanded, the expansion trend in the north and south was obvious, the peripheral material strength was higher than that in the central area, and the urban residential distribution tended to be saturated.

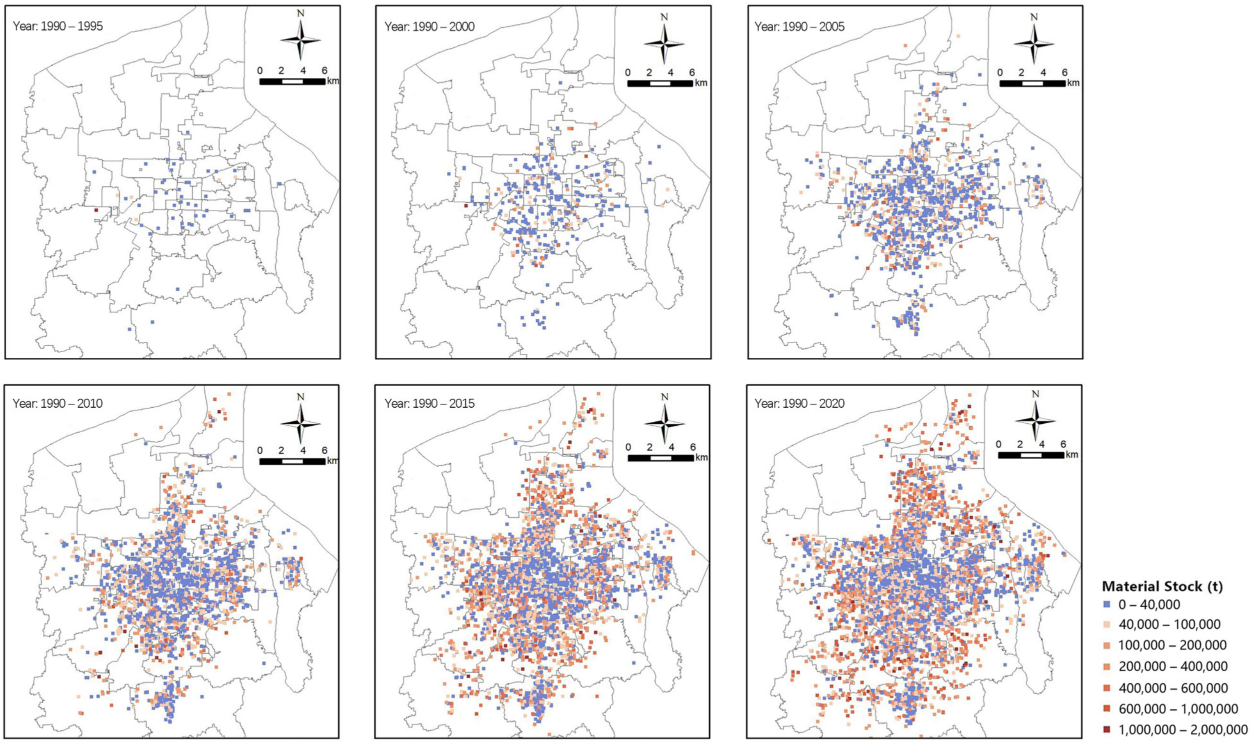


Figure 8. High-resolution material stock maps.

In general, the aggregation of material stock can reveal the center and corresponding scale of human activities and socioeconomic development. From the perspective of environmental sustainability, material storage agglomeration areas tend to consume more material resources and emit more greenhouse gases, resulting in urban-heat-island effects. Based on the obtained residential material stock information in the central urban area of Xi'an, the study area was divided into a grid of 500 m $\times$ 500 m, and the cumulative total amount of residential material stock in the grid area was counted to generate the intensity distribution map of residential material stock (Figure 9). At the level of urban space, it is possible to visually display the areas with high development intensity and the material accumulation of residential buildings. Identifying these areas with high material accumulation intensity will provide accurate quantities and spatial locations of material materials for the recycling and utilization of future material stocks. At the same time, this process provides the necessary research basis for resource managers and urban ecologists to study urban resource consumption, solve urban environmental problems such as the urban-heat-island effect, and realize the sustainable management of the urban building environment and the sustainable development of cities.

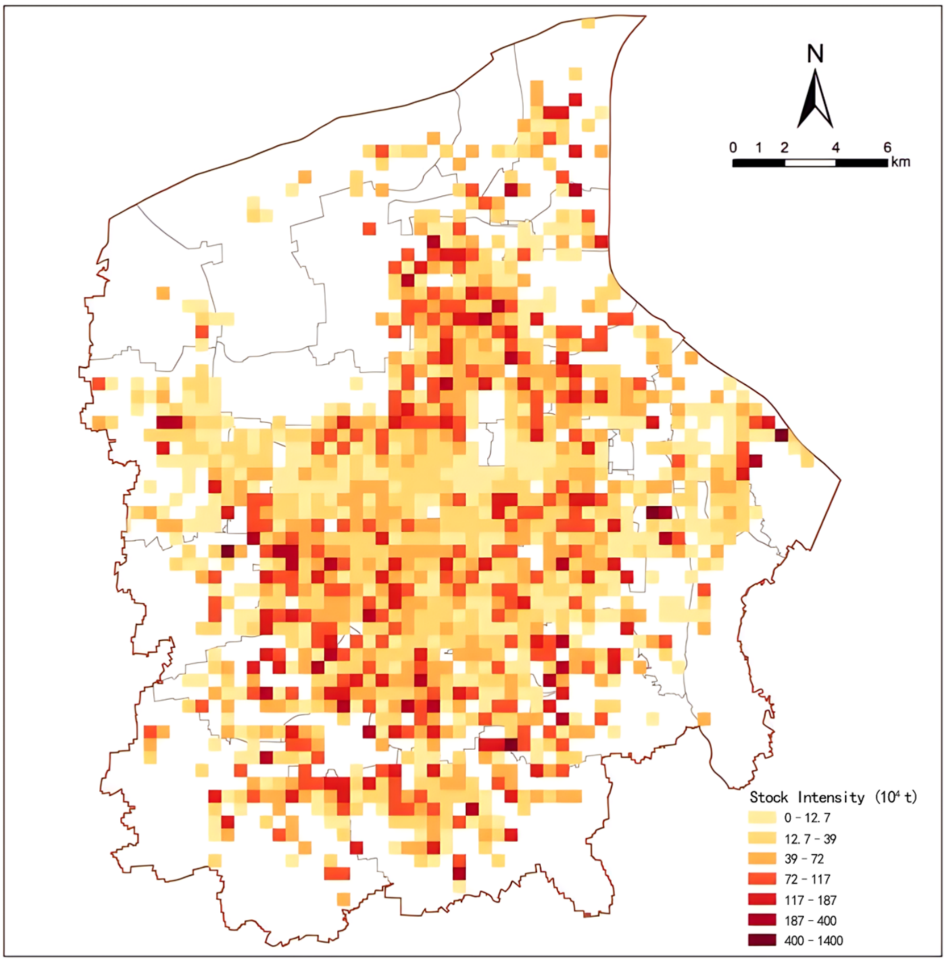
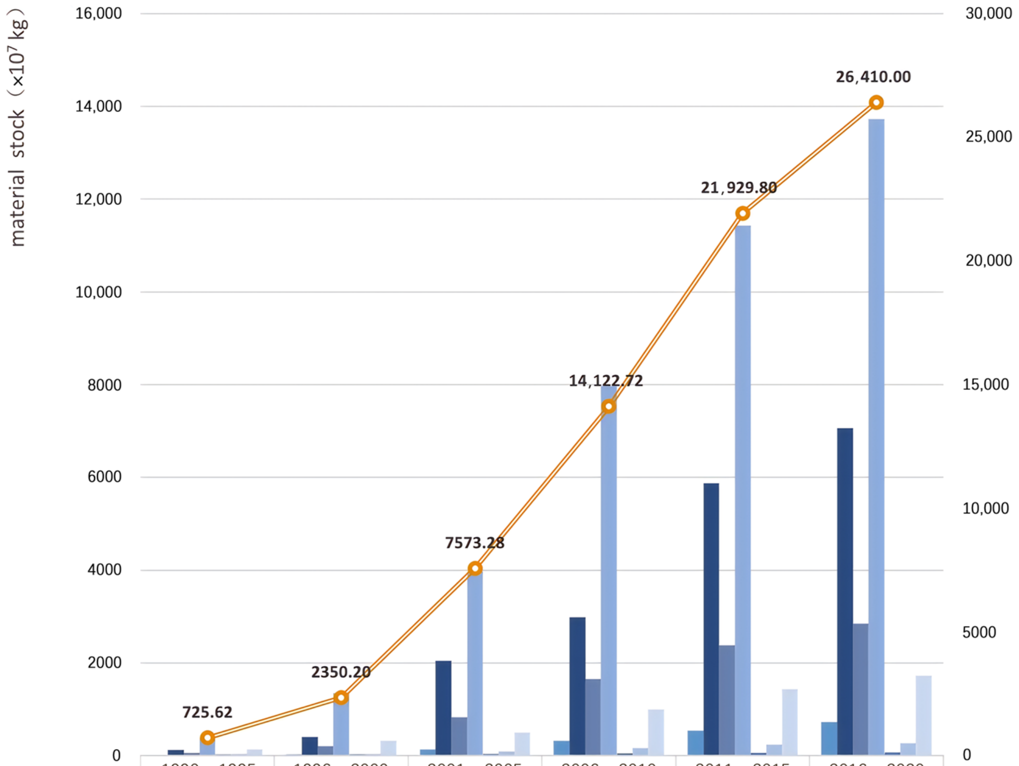


Figure 9. Distribution diagram of residential building stock.

4.2. Dynamics of Urban Residential Building Material Stock

The consumption of different types of building materials and the total material stocks of Xian city from 1990 to 2020 are presented in Figure 10. The residential building material stocks reached 7.31 × 108 t in 2020. During the period of concern, all the kinds of materials used exhibited a rising trend but at different rates. Among the seven main building materials, gravel is the largest, reaching 388 million tons, followed by cement, with glass exhibiting the smallest portion of 0.012 million tons and bricks exhibiting a relatively stable portion.

Overall, a total of 4758 residential areas were built in the central urban area of Xi'an during the considered period from 1990 to 2020, and the growth rate of residential material stocks initially grew and then stabilized (Figure 10). With regard to different time intervals, the first period from 1990 to 1995 witnessed relatively small housing-material consumption, with a cumulative housing input of 7.263 million tons. At that time, collective housing with 2–3 floors was the dominant residential building type, and the per capita housing area was relatively small. The value of the cumulative housing input changed to 23.5 million from 1996 to 2000. During this period, Xian's housing was gradually developing from family building units to commercial housing. The number of newly built communities increased gradually, but the city was still small in size. Rapid development of urban housing occurred in the period of 2001–2005, when the residential material input was 75.73 million tons, which was 3.22 times that in the last period, and the commercial housing market developed further. Between 2006 to 2010, Xi'an's residential material input reached 141.23 million tons, an increase of 1.86 times that of 2001–2005. From 2011–2015, the residential material input reached 21.20 million tons, an average annual increase of more than 40 million tons, representing an increase of 15.41 times that of 2004–2008. From 2016–2020, residential material input reached its peak, with an increase of 264.1 million tons per year. The increase by more than 50 million tons every year was mainly due to the rapid increase in the urbanization rate, which increased the demand for housing, and the introduction of a series of policies that promoted housing development in Xi'an.



	1990 – 1995	1996 – 2000	2001 – 2005	2006 – 2010	2011 – 2015	2016 – 2020
Steel	7.88	29.13	130.59	318.67	538.84	725.64
Cement	126.07	406.49	2044.02	2987.12	5878.3	7060.29
Lime	63.04	203.25	825.73	1655.15	2374.67	2852.16
Gravel	378.22	1354.97	3974.49	7966.77	11,430.03	13,728.34
Glass	1.2	4.29	11.36	23.9	35.92	45.11
Timber	10.53	35.91	87.44	169.58	235.13	272.61
Bricks	138.68	316.16	499.65	1001.53	1436.91	1725.85
Stock	725.62	2350.20	7573.28	14,122.72	21,929.80	26,410.00

Figure 10. Increased residential building material stocks in Xi'an from 1990 to 2020.

4.3. Residential Building Stock and Urban Expansion

To demonstrate the direction and intensity of the expansion of the built-up area in the central urban area of Xi'an more intuitively, this study focuses on the Bell Tower in Xi'an, with a buffer distance of 2 km, and generates 9 circles. Starting from 22.5° due north by east, it is divided into 8 directions at 45° intervals, for a total of 72 regions. The urban built-up areas in 72 regions in each period were counted, and a radar chart was drawn (Figure 11a). At the same time, the newly added urban built-up areas in different directions and circles within each period were counted. Based on the proportion of newly added areas in each circle to the total areas of circles in each direction, a circle chart of urban built-up area expansion was drawn (Figure 11b–f), which can clearly show the main directions and areas of the newly added urban built-up area.

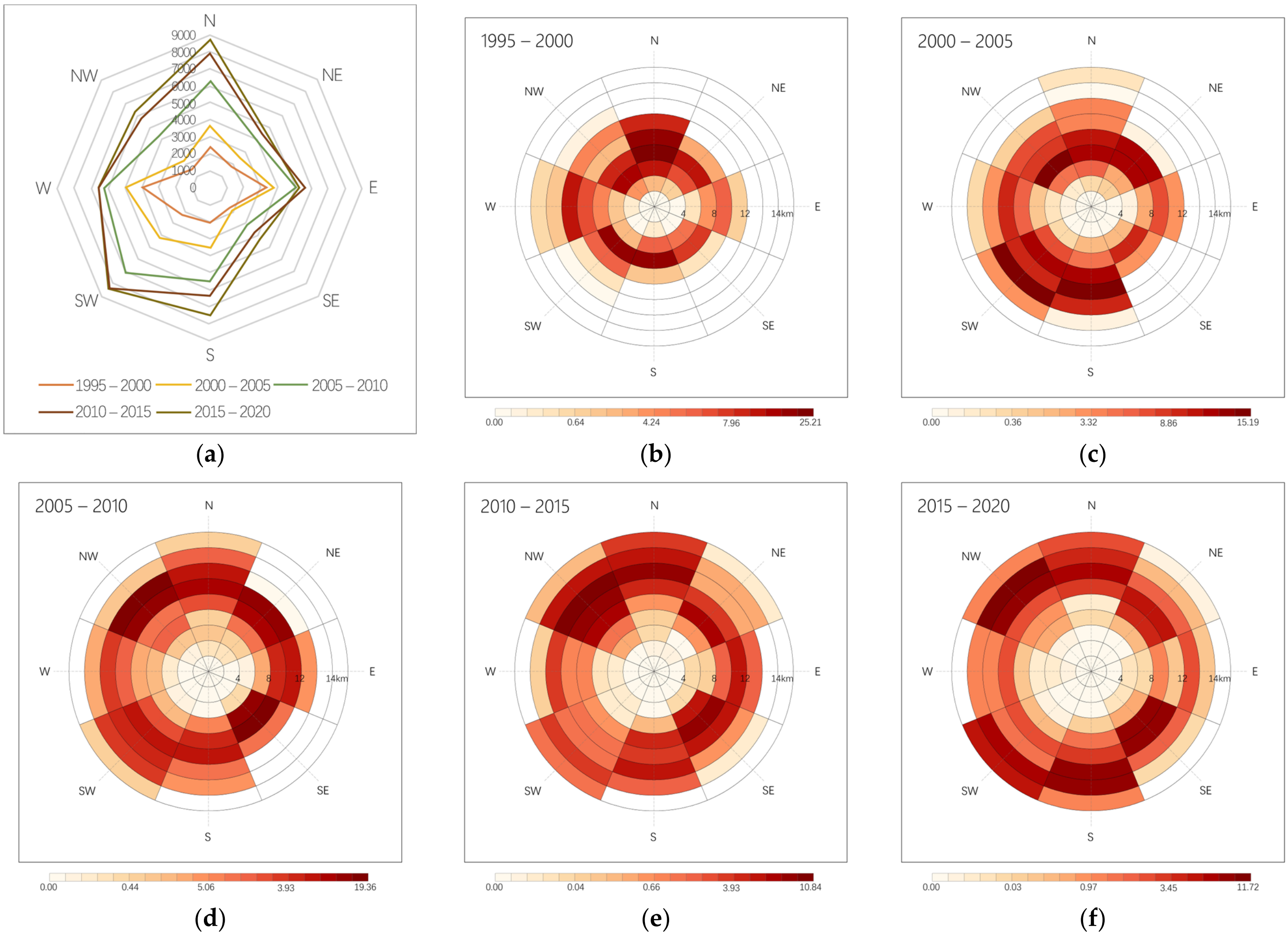


Figure 11. Urban spatial expansion in the central urban area of Xi'an from 1995 to 2020. (**a**) Radar chart of urban built-up areas from 1995 to 2020; (**b**–**f**) Expansion circle map of urban built-up areas in different periods.

Overall, the expansion direction of the central urban area of Xi'an has undergone a transition from mainly expanding in the east-west direction to gradually expanding in the north-south direction. The expansion degree in the north, south, and southwest directions is much greater than that in other directions. The expansion speed of the built-up area in the central urban area gradually accelerated from 1995 to 2010, with particularly significant expansion in the north and southwest directions. However, after 2010, the expansion speed of the built-up area in the central urban area gradually slowed. By comparing the expansion of urban built-up areas and the growth of residential material stock in the central urban area of Xi'an at the spatial level, the study found that from 1995 to 2020, the outer edge of the central urban area of Xi'an had been in a high-speed development period, while the internal development was in a slow development period, which parallels the development law of residential material stock. This indicates that in recent years, Xi'an has focused on the expansion of the outer suburbs and the integration and reconstruction of the internal central urban area. Currently, the development of the city is still in the stage of expanding to the periphery. The development speed in the north and southwest directions of the urban built-up area in the central urban area of Xi'an is much faster than that in other directions, which is basically consistent with the expansion trend of residential material stock in the northeast–southwest direction. The expansion of the built-up area in the northeast direction of the research area is limited by the geographical factors of the Ba River; thus, the expansion intensity of the built-up area in the northeast direction is relatively weak. The expansion of urban built-up areas in the central urban area is basically consistent with the spatial expansion characteristics of the growth of residential material stock, indicating that there is a mutually promoting effect between the growth of residential material stock and urban expansion.

5. Discussion

High-resolution mapping is very useful for better describing the spatial distribution of residential building material input in the city than single-material data (iron, bricks, gravel, etc.) and can be used to study the spatial evolution of high-resolution spatial residential building-stock data and material inventories [27]. In addition to its coupling relationship with urban population expansion, land-use change, economic development, and environmental impact, the data results are better able to explore the essence of urban expansion. This research not only refines the acquisition of high-resolution spatial data but also explores the process and mechanism of the spatial evolution of the urban residential building stock, as well as the relationship with population expansion and economic development. It provides a new research perspective for more reasonable resource allocation, intensive and efficient land use, and compact urban development during the process of urban construction.

5.1. Residential Building Stock and Population Expansion

By analyzing the data on population growth and the inventory of residential materials from 1990 to 2020 (Figure 12), a significant upward trend is evident in both variables. Notably, since the year 2000, the growth rate of the residential material inventory has consistently exceeded that of population growth. The trend in population growth exhibits a stable linear pattern, while the growth in the residential material inventory follows an "S-shaped" curve, characterized by accelerated growth starting around the year 2000 and continuing until approximately 2015. This growth pattern reflects the direct impact of population increases on housing demand, as a rising population necessitates more living facilities, thereby driving the expansion of urban land and urban functions [56]. The complexity of cities increases with their size, which, in turn, drives the demand for building materials. However, between 1990 and 2000, the growth in the residential material inventory was markedly slow, failing to meet the housing demand spurred by rapid urbanization. This lag is likely due to a delay in the expansion of population growth and construction sites relative to economic development [57]. Since 2015, a rapid increase in the residential material inventory has begun to balance this demand, gradually meeting the housing needs driven by population growth. Overall, population growth has played a lasting and profound role in driving the increase in the residential material inventory. Furthermore, recent studies indicate that the overall and spatial coupling relationship between urban expansion and population growth is becoming increasingly tight [58].

5.2. Residential Building Stock and Socioeconomic Factors

Socioeconomic factors exhibit a strong correlation with the material stock of urban areas [59,60]. In this study, we employ the IPAT equation to scrutinize the growth of driving factors. The IPAT model, widely employed in material flow research, is a tool for decomposing environmental impacts and analyzing various permutations. The calculation formula is presented as follows:

$$MS = P \times A \times T = POP \times \frac{GDP}{POP} \times \frac{MS}{GDP} \tag{5}$$

MS represents the stock of residential materials, P (POP) denotes the resident population, A stands for per capita GDP (at constant prices in 1990), and T represents the technological factor, which is the intensity of material use (GDP/POP). T also indicates the amount of material stock required to generate one unit of GDP and can be used to measure the efficiency of current material utilization. A decrease in T indicates an improvement, while an increase in T signifies a decline in efficiency.

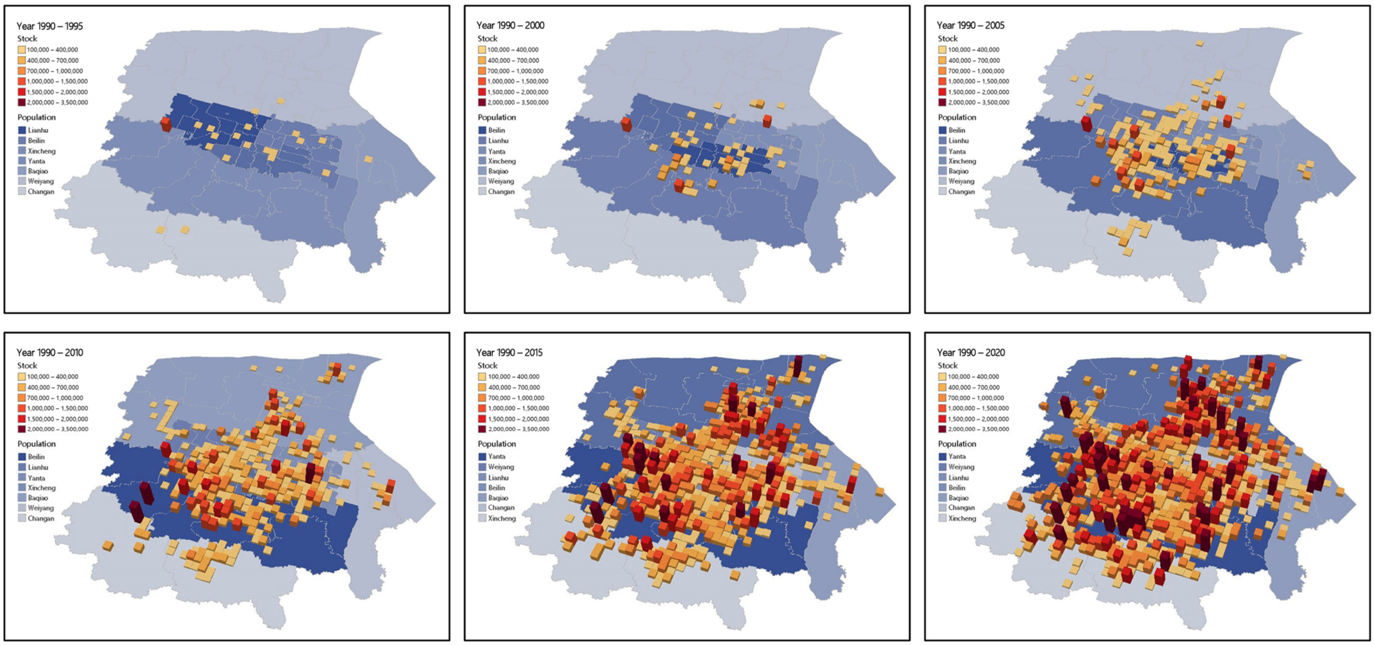


Figure 12. Residential building metabolism and demographic changes from 1990 to 2020.

In this study, the LMDI method is employed to convert Equation (5) from a multiplicative form into an additive form, facilitating the analysis of the contributions made by three driving variables toward variations in the residential material stock. According to Equation (6), the contributions of population factors, economic factors, and technological factors to changes in the residential material stock from 1990 were calculated as depicted in Figure 13. A positive contribution enhances the growth of the residential material stock, while a negative contribution hinders its growth.

$$\begin{aligned}\Delta MS = \Delta P + \Delta A + \Delta T \\ &= \frac{MS_{t'} - MS_t}{ln(MS_{t'}) - ln(MS_t)} \times ln\left(\frac{P_{t'}}{P_t}\right) \\ &+ \frac{MS_{t'} - MS_t}{ln(MS_{t'}) - ln(MS_t)} \times ln\left(\frac{A_{t'}}{A_t}\right) + \frac{MS_{t'} - MS_t}{ln(MS_{t'}) - ln(MS_t)} \times ln\left(\frac{T_{t'}}{T_t}\right)\end{aligned} \tag{6}$$

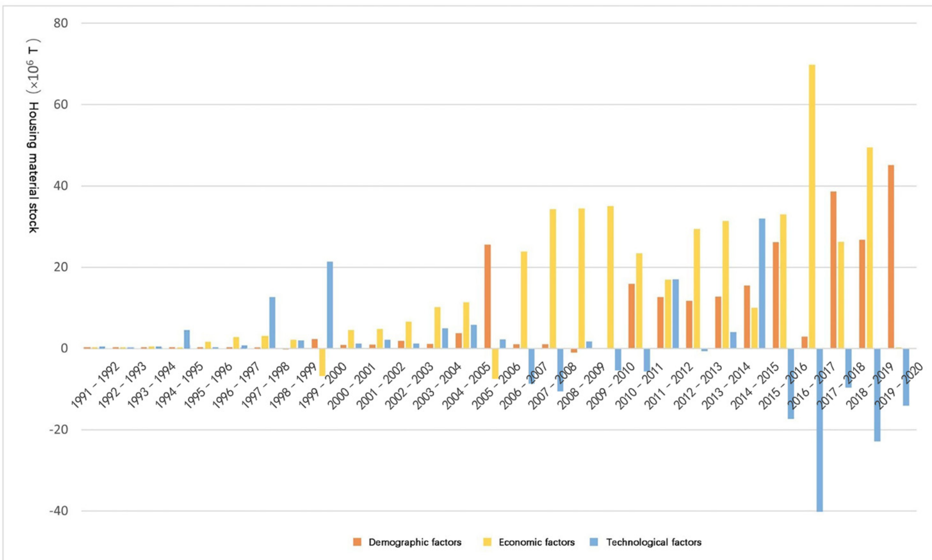


Figure 13. Contribution of various factors to changes in residential stock over time.

ΔMS represents the change in MS from year t to $t\prime$ ($t\prime > t$); ΔP, ΔA, and ΔT reflect the contributions of changes in the resident population, economic factors, and technological factors, respectively.

Overall, both population and economic factors have a positive impact on the growth of the residential material stock, with their influence increasing alongside the growth in the urban population and GDP (Figure 13). This trend is likely due to population growth directly increasing the demand for housing, while economic growth enhances the purchasing power of residents and the quality and efficiency of housing construction. Additionally, urbanization accelerates the concentration of populations in urban areas, facilitating the development of new residential zones and the renovation of old urban districts [2,56]. However, the impact of material use intensity has varied significantly. Prior to 2006, it contributed positively to stock growth, but in the past five years, it has turned negative, indicating that improvements in material use efficiency are now starting to constrain the growth of residential material stock. The decrease in material use intensity also reflects a relative decoupling between economic growth and material stock growth as cities develop and economies evolve.

Statistical analysis and calculation of the driving effects of different influencing factors on residential material stock across six time periods are conducted (Figure 14). The contribution of population factors to residential material stock was relatively low from 1991 to 2010, but since 2011, their role in promoting the growth of residential material stock has significantly increased. The intensity of material use had a suppressive effect on the growth in residential material stock during the periods 2006–2010 and 2016–2020, and since 2001, the impact of material use intensity (in absolute terms) on residential material stock has gradually intensified. In downtown Xi'an, the expansion of residential material stock is primarily fueled by economic development, with population growth being a secondary driver. Additionally, advancements in material efficiency or decreases in material utilization intensity have somewhat counterbalanced the rise in residential material stock. Related research also confirms the impact of material efficiency in residential construction on the building stock [61].

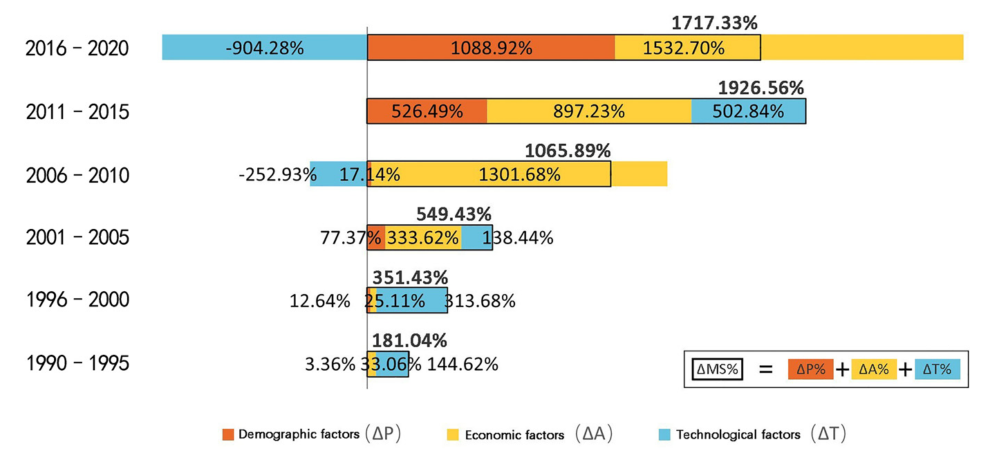


Figure 14. Contribution of factors to residential stock changes in different time periods.

5.3. Residential Building Stock and Housing Policy

The study analyzed the evolution of urban residential construction within Xi'an, utilizing a nuclear density map to elucidate the spatial distribution of residential building materials as depicted in Figure 15. Prior to 2000, residential development in Xi'an focused on historic urban centers and the National High-tech Industrial Development Zone. The 1992 "General Plan for Urban Housing System Reform in Shaanxi Province" aimed to commercialize housing and boost the real estate market. Further propelled by a 1998 State Council notice and Shaanxi's initiative to increase affordable housing, these reforms enhanced residential construction across Xi'an, markedly increasing the consumption of building materials like concrete, steel, and glass.

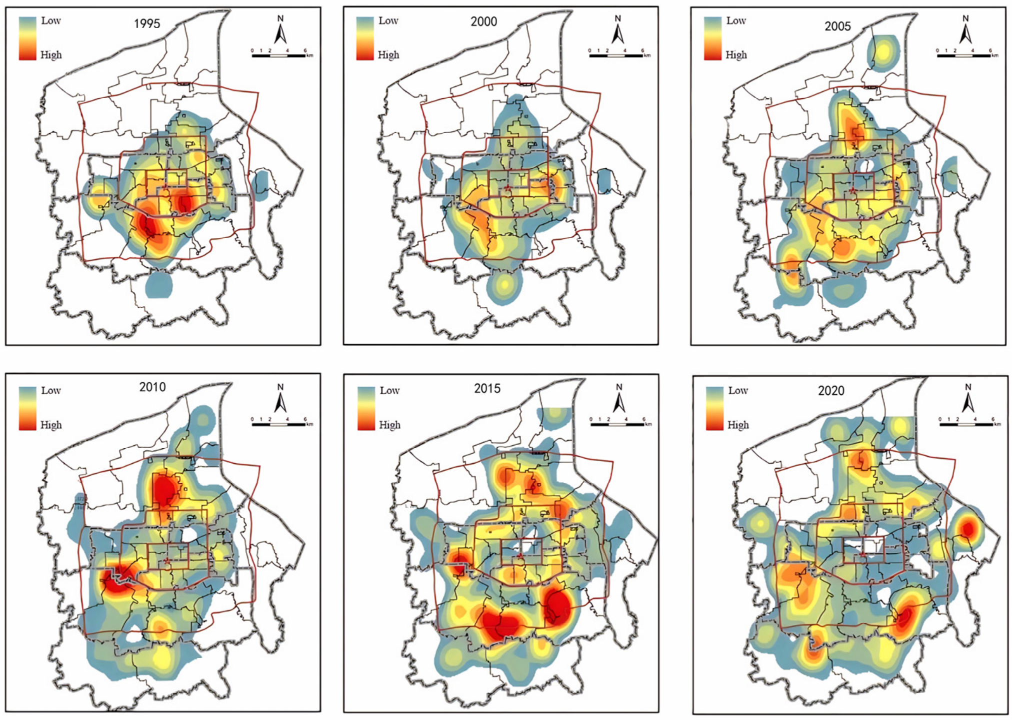


Figure 15. Nuclear density map of housing material distribution.

Between 2000 and 2005, the creation of University Town in Xi'an spurred the southward migration of higher education institutions, increasing housing demand in the southern districts. From 2005 to 2010, the development of the Qujiang New Area and Chanba Ecological Area led to significant residential construction, necessitating a substantial supply of urban infrastructure and building materials. In 2008, the opening of Xijing Hospital and the northward move of the Xi'an Municipal Government significantly boosted the housing supply in Weiyang District. Between 2010 and 2015, enhancements in rail transport infrastructure stimulated residential growth along the north–south axis, and the approval of the port area introduced a new development nucleus, diversifying the use of construction materials across different districts.

Post-2015, the northward shift of Xi'an's municipal government led to a surge in residential development, creating multiple density centers. Simplified construction processes, due to relaxed shantytown redevelopment and affordable housing policies, boosted residential sector growth. However, 2017 policy adjustments in housing transactions, which imposed waiting periods on property sales, curbed speculative activities, moderating price inflation and industry growth. Additionally, a new residence registration policy in 2017 attracted more settlers to Xi'an, significantly increasing housing demand and expanding the residential building stock.

Since 2020, the Xi'an government has implemented stricter regulations and control measures on the real estate market, such as increasing down-payment ratios for commercial loans used to purchase second homes, raising down-payment ratios for provident fund loans, and improving access conditions for pre-sale permits of commercial housing. This has effectively suppressed the demand for housing, particularly the investment and speculative demand. By strategically regulating market dynamics, these policies have been pivotal in controlling the rapid growth of the residential building stock, thereby averting excess supply-induced market risks.

To promote responsible resource consumption and recycling in the construction environment in the future, the study proposes the following targeted policy recommendations:

introduce mandatory construction regulations that require the use of recycled materials; provide incentives for developers using sustainable materials and for recycling enterprises handling construction waste; implement stringent green building standards that require new residential buildings to meet criteria for energy efficiency and low resource consumption; adopt policies for a full lifecycle assessment of construction projects; and implement strict regulatory measures on the real estate market to ensure sustainable development practices.

5.4. Strengths and Limitations

The main limitation of this study lies in the investigation of the driving factors behind housing material stock, which only focuses on relatively macrolevel factors. Therefore, it is necessary to incorporate mesoscale and microscale urban spatial elements to further explore other factors that influence the distribution of housing material stock.

Another limitation of the study is that only the input of housing material stock is considered. From the perspective of urban material metabolism, matter and energy encompass both input and output processes within the city. The output refers to the quantity of waste generated subsequent to building demolition. In future studies, incorporating the average lifespan of buildings can be employed to estimate the overall volume of construction waste and to enhance research on material stock outputs. Furthermore, the study of residential building materials offers insights not only into urban sprawl but also waste generation, environmental impacts, and land-use efficiency. Future research should thus encompass material consumption patterns for new constructions and existing infrastructures to devise sustainable urban development strategies.

Additionally, while this study provides valuable insights into the dynamics of urban material stocks within Xi'an, its findings are primarily contextual to the local urban setting. Recognizing the potential for broader applicability and generalizability, future research should consider expanding the scope of investigation to include other cities and countries. By examining diverse urban contexts, the study could offer a more comprehensive understanding of material consumption patterns and their implications for sustainable urban development across different global settings. This expansion would not only enhance the relevance of the findings but also contribute to the development of more universally applicable urban planning strategies.

6. Conclusions

This study utilized multisource geographic data, encompassing temporal, spatial, and network dimensions, and integrated a variety of complementary data collection methods, including data scraping, the spatial acquisition of remote sensing data, and analysis of statistical yearbook data, to establish a high-resolution visualization system for sustainably updating the inventory of residential building materials in space. Taking into account the strength coefficients of seven types of residential materials, the inventory of residential building materials from 1990 to 2020 was calculated. The results showed that the material inventory increased from 1.53 million tons to 731.12 million tons, with the spatial distribution of materials steadily expanding. Over the past 30 years, residential construction has grown rapidly, with urban ecological spaces being occupied by reinforced concrete spaces. By combining the spatial distribution characteristics of residential material inventories, the study explored the relationship between the growth of residential material inventories and urban expansion, showing a mutually reinforcing effect over time and space. Additionally, the study innovatively analyzed the spatial distribution of building material inventories in Xi'an in relation to population, economic development, and policy-making, revealing that population growth, economic development, and policy formulation have promoted the increase in residential building materials. These results endorse the monitoring of building stock behavior with respect to material demand, energy consumption, and waste generation, thereby promoting sustainability across various construction-related sectors.

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Data Availability Statement: All data, models, and code generated or used during the study appear in the submitted article.

Conflicts of Interest: Author Qi Yang was employed by the company CCCC First Highway Consultants Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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