

Recycling potential of secondary resources in built environment stocks

Evidence from Hong Kong public rental housing

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Abstract

In urban environments, region-specific knowledge of building material intensities and stocks is vital for efficient resource recovery in the construction sector, especially for city regeneration and redevelopment. Previous studies often relied on generalized data, leading to inaccuracies due to local variations in construction practices, materials, and urban density. This study addresses these limitations by developing a locally refined inventory through a GIS-based, bottom-up material stock analysis that integrates archetype-specific building design data, demonstrated with evidence from Hong Kong's public rental housing (PRH). The results show that material intensities for Hong Kong PRH buildings range from 1567 to 2386 kg/m², with a total stock of 60.85 megatons as of 2022. Up to 46.95 megatons may have recycling potential over the next three decades, offering significant opportunities for sustainable resource management. Spatiotemporal and hotspot identification reveals a shift in material stock distribution toward the northern territories, reflecting urban development trends. This research enhances the accuracy of material stock assessments and supports strategic planning for achieving a circular economy, particularly in densely populated areas like Hong Kong. By promoting circular and generative city concepts and establishing benchmark archives for key construction materials, the study advances practical applications for sustainable urban resource management, aiding policy development for efficient spatial planning and urban mining strategies.

KEYWORDS

circular economy, industrial ecology, material stock analysis, resource management, sustainable development

1 | INTRODUCTION

Human activities, particularly fossil fuel combustion, release greenhouse gases, leading to global warming, rising sea levels, and extreme weather. Industrial processes contribute 58% of global emissions (Ritchie & Roser, 2024). In response, the United Nations' Sustainable Development Goals (SDGs) advocate for social, economic, and environmental sustainability (Lim et al., 2018). Industrial ecology (IE) emphasizes circular materials use,

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inspired by natural ecosystems (Korhonen, 2004; Lowe & Evans, 1995; Saavedra et al., 2018). Urban areas, consuming a large share of global resources and emitting substantial greenhouse gases, play critical roles in sustainable resource management efforts.

Understanding in-use material stocks (MS) within buildings and infrastructure is essential for sustainability (Barles, 2010; Kennedy et al., 2011; Li & Kwan, 2018; Sun et al., 2023; Zhang et al., 2015). These stocks represent secondary resources that can be reclaimed through urban mining, a key component of the circular economy (CE) (Bender & Bilotta, 2020). With urban population growth outpacing new construction, redevelopment and demolition are accelerating globally (Fernández, 2007; Ichimura, 2003). To optimize resource recovery and reuse, detailed knowledge of material stocks is needed (Hertwich et al., 2019; Li et al., 2023; Miatto et al., 2019; Wuyts et al., 2022). However, robust data on location-specific material inventories are often lacking (Pei et al., 2024), complicating circular economy initiatives in construction. Accurate material stock mapping, anchored in local building characteristics, is essential for advanced resource management.

Various approaches have been developed for quantifying building material stock (Arbabi et al., 2022; Augiseau & Barles, 2017; Lanau et al., 2019). Among these, material flow analysis (MFA) is a prevalent top-down method. It utilizes government data to track material inflows and outflows (Bergsdal et al., 2007; Hu et al., 2010; Müller, 2006; Wittmer et al., 2007). However, MFA's accuracy depends on the reliability of the data, which can vary between locations (Baars et al., 2022). In contrast, bottom-up inventory modeling offers an alternative approach by using dimensional floor areas in combination with material intensity (MI) factors. While both approaches have limitations, bottom-up modeling can be more precise when detailed spatial and material-specific data are available (Gao et al., 2020; Lanau & Liu, 2020; Mollaei et al., 2021; Ortlepp et al., 2016). Nighttime light satellite imagery has also supported methods that infer gross floor area (GFA) from radiance and combine it with material intensities (Haberl et al., 2021; Hsu et al., 2013; Liang et al., 2023; Peled & Fishman, 2021; Rajaratnam et al., 2023). To further refine estimates, archetype-based modeling has emerged as a significant advancement in estimating material stock by classifying structures into predefined typologies (de Tudela et al., 2020; Ergun & Gorgolewski, 2015; Mata et al., 2014). While this method requires extensive data collection to accurately define archetypes, it is increasingly recognized for its effectiveness in urban material bank estimation. Recent studies highlight that archetype use enhances the granularity of stock assessments by differentiating material used according to building type, age, and function (Akin et al., 2023; Alrasheed & Mourshed, 2024; Pristerà et al., 2023; Slavkovic et al., 2022). More recently, machine learning algorithms have shown promise for stock prediction at the individual building scale by applying regression analysis to easily accessible predictor variables (Yuan et al., 2023). Advances in MFA, such as deep learning and computer vision techniques (Dai et al., 2024; Raghu et al., 2023), highlight the evolving capabilities of machine learning in enhancing stock modeling accuracy and efficiency.

Collectively, these inventory methods afford diverse data sources and geographic coverages to quantify constructed material holdings. A comparison of these methods highlights the strengths and limitations of top-down versus bottom-up approaches. While top-down methods like MFA provide broad geographic coverage, they often lack the granularity offered by bottom-up techniques, which can leverage detailed spatial data from geographic information system (GIS) technologies. GIS-based methods, particularly when integrated with statistical analysis, offer enhanced precision and adaptability to local conditions. Despite these advancements, a key limitation across methods is the reliance on generalized material intensity data. Many studies adapt these intensities from different regions or times, potentially compromising accuracy due to regional differences in construction practices, climate, and regulations. Such variations impact material usage, leading to inaccuracies in stock assessments and land use planning. Therefore, addressing these data gaps through the development of regional-specific, up-to-date inventories and material intensity benchmarks is crucial for reliable stock estimates at finer geographic scales.

This study addresses these limitations with a GIS-based, archetype-enabled approach to develop a secondary resource inventory for public rental housing (PRH) in Hong Kong. The study considers the future recycling feasibility and circular use of these critical construction materials. It promotes the concepts of circular and generative cities, especially in densely populated areas like Hong Kong, where recycling is more necessary and challenging. Leveraging extensive data from the affordable housing sector, PRH structures are systematically classified into 24 distinct archetypes, which are further organized into eight age categories that reflect historical construction techniques and architectural styles. The material stocks are quantified based on design plans and geospatial data, establishing a benchmark archive for key materials, including steel, concrete, and timber. Hotspot identification further determines areas with high recycling potential, offering insights into recyclable waste quantities and locations. The findings will support policy development for more efficient spatial planning and urban mining strategies during PRH redevelopment, advancing both methodology and practical applications for sustainable urban resource management.

2 | METHODS

2.1 | Analytical scope

Given the increasing demand for housing units and the emphasis on sustainable construction, Hong Kong's PRH sector presents a typical area for assessing construction material stocks and exploring the potential for recycling secondary resources through urban mining and strategic waste management (Sections 1 and 2 of Supporting Information S1). This study focused on analyzing the built environment stock of PRH in Hong Kong as of the end of 2022, encompassing 238 estates and over 2000 building blocks (including demolished and reconstructed buildings), housing more

than 2 million individuals, as illustrated in Figure S2 of Supporting Information S1 (HKHA, 2023a, 2023b). In this context, the term “built environment stock” refers specifically to buildings within the PRH sector, excluding infrastructure like roads or utilities. The analysis quantified building stocks and critical construction materials in terms of dimensional floor area and mass, with results presented at both district-level and region-level spatial resolutions. Material stocks were assessed based on the superstructure designs of PRH buildings, with a particular emphasis on the vertical distribution of materials above ground.

2.2 | Bottom-up material stock mapping

To accurately assess and map material stocks, a GIS-enabled bottom-up approach was implemented, allowing for precise spatial distribution of material stocks across the study area. Bottom-up stock mapping overcomes deficiencies in top-down methods reliant on aggregate material flow data (Augiseau & Barles, 2017; Schiller, Müller et al., 2017). It involves disaggregating the built environment into constituent building samples before quantifying stocks based on parameterizing each sample. Recent advancements have further refined this approach by integrating GIS with remote sensing data, such as nighttime light imagery, to enhance material flow and stock analysis (Haberl et al., 2021; Liu et al., 2023; Peled & Fishman, 2021; Rajaratnam et al., 2023; Wang et al., 2025; Wurm et al., 2021). These studies demonstrate the efficacy of combining spatial data with material intensity factors for more accurate assessments. This study utilized GIS databases of building footprints, heights, and addresses as key data sources. Material intensities, calibrated against primary building plans, provided essential composition parameters for quantifying stocks in archetypes and synthetic building groups. A hybrid archetype modeling technique was applied, classifying PRH structures into predefined typologies to capture variations in dimensional attributes, material specifications, and intensities. Material stocks are calculated following Equation (1):

$$MS_{ij}(\text{PRH}) = FS(\text{PRH}_{\text{synth},j}) \times MI_i(\text{PRH}_{\text{synth},j}) \quad (1)$$

where MS is the overall material stock mass in megatonnes (mt); i represents the collection of construction material aggregation; j is the collection of synthetic PRH buildings according to different age categories; PRH is public rental housing; FS is dimensional floor space in square meters; and MI is the material intensity indicator (kg/m^2 or t/m^2 FS).

2.2.1 | Archetype classification, synthetic building groups, and samples selection

An in-depth investigation into the PRH building stocks was conducted, spanning from its initial establishment in 1950 through to the end of 2022, covering a significant number of individual building blocks. In material stock and flow analysis, classification typically relies on building use (residential/non-residential) and construction type (Augiseau & Barles, 2017). For residential buildings, construction type and age serve as primary classification criteria. Due to the demonstrable relation between archetypes and period of construction, age is the most frequent and reliable factor considered in material flow and stock analysis (Kleemann, Lehner et al., 2017; Schiller, Gruhler et al., 2017).

To systematically analyze PRH material stocks, buildings were classified by age categories and archetypes, reflecting construction techniques and styles from different historical periods. This framework categorized all building stocks into 24 archetypes and grouped them into eight age categories for detailed assessment (Section 3 of Supporting Information S1). Within each age category, representative building samples were selected as case buildings (CBs), covering dominant archetypes and different construction styles from each period (Mohammadizazi & Bilec, 2022). The chosen case buildings were curated to represent the dominant architectural styles, structural configurations, and technical specifications characteristic of their respective eras, sharing the inherent homogeneity prevalent in the construction techniques. The analysis notably benefits from the relatively fixed building layouts characteristic of PRH (e.g., trident, harmony, slab, etc.), which maintain stability over defined periods, thereby enhancing the reliability of the findings. To underpin this comprehensive analysis, a detailed quantification of material stocks for the selected CBs was performed through the examination of architectural, structural, and technical documentation sourced from the online building archives of the Hong Kong Housing Authority (HKHA) (HKHA, 2014). The weighting factors applied to the selected CBs for creating the synthetic building groups are determined by the frequency with which each specific archetype occurs (Section 3 of Supporting Information S1). In this approach, the resulting material stocks represent the weighted average stocks of the analyzed CBs. Figure 1 depicts the overall concept of investigation.

2.2.2 | MIs per floor area and PRH building stocks

Material intensities are fundamental for quantifying the average quantities of construction materials embedded per unit floor area, forming a basis for bottom-up stock quantification. This study advances the understanding of MIs by refining age-category archetype-specific values derived from sampled PRH buildings, enabling comprehensive estimation of total stock holdings across the entire PRH portfolio. By aligning overall floor areas with assigned archetype classifications, it was possible to systematically apply the relevant average MIs' multipliers, facilitating the calculation

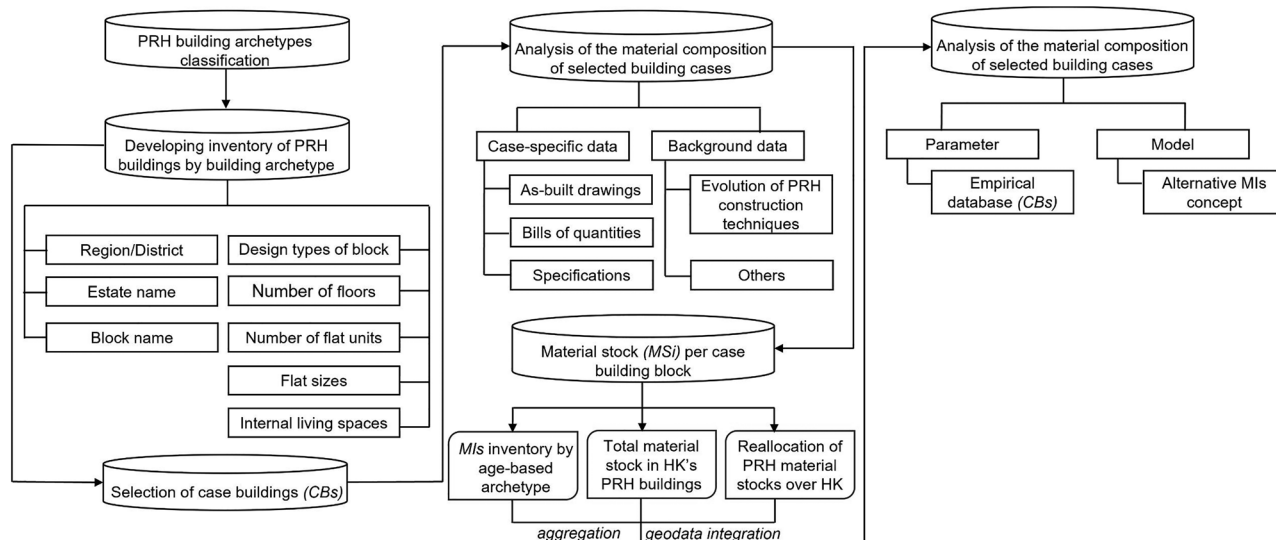


FIGURE 1 Concept for investigation of material intensities (MIs) and material stocks (MS) for public rental housing (PRH).

of material stock tonnages for each age-category PRH building. These intensities, which indicate the quantity of construction materials required per square meter during specific periods, serve as the foundation for detailed stock quantification. The aggregation of building-scale results yields portfolio-scale MIs, expressed as the total amounts of constituent resources per square meter of PRH constructed floor space. This approach not only enhances comparability across different contexts but also assists in identifying potential hotspots for resource recycling initiatives. To ensure the accuracy and contextual relevance of the MIs to the Hong Kong setting, calculations were conducted using detailed PRH architectural and structural drawings, construction specifications, and local standards, with detailed assessments conducted for different components. This process ensured that the calculations accurately reflect the unique characteristics and requirements of the region by cross-referencing local building codes and guidelines. It also provides a reusable benchmark for monitoring changes as the PRH building stock evolves. Due to the diversity in building component designs, structures with identical architectural designs may exhibit different structural elements across periods, such as variations in roof coverings and facade designs. Therefore, ideally, comparisons should be conducted at the level of individual building sections and components. To fully utilize the data on building floor area, number of floors, and units, above-ground buildings are conceptually divided into three parts for calculating MIs (Lanau & Liu, 2020): (1) the “upper section,” including roof coverings and roof structures; (2) the “vertical section,” including external walls, internal walls, windows, and doors; (3) the “horizontal section,” including the slab of intermediate floors and beams. The specific calculations on materials consider basic structural elements such as frame (slab, beam, and column), roof, structural walls, stairs and landings, balustrade and handrails, structure sundries, as well as non-structural elements such as external walls (non-structural), windows, and doors. The intensity of critical materials stocked in each case building was modeled as Equation (2):

$$MI_{iCB} = \frac{MS_{iCB}}{FS_{CB}} = \frac{\sum MS_i}{FS_{CB}} = \frac{\sum_i (MS_i^{US} + MS_i^{VS} + MS_i^{HS})}{FS_{CB}} \quad (2)$$

where MI_{iCB} is the intensity of specific material i stocked in the case building in kg/m^2 ; MS_{iCB} is the mass of specific material i in kg ; MS_i^{US} is the upper section's material stock of material i in kg ; MS_i^{VS} is the vertical section's material stock of material i in kg ; MS_i^{HS} is the horizontal section's material stock of material i in kg ; FS_{CB} is the overall dimensional floor space (overall internal living space) of the case building in m^2 .

To enable comparison with previous studies and enhance result transferability, age-related MIs are expressed in kilograms per square meter of floor area. These material intensity values are determined by aggregating the intensity results for each case building across different archetypes through respective weight factors. With increased detail, the material stock results are deemed more reliable. The built environment of PRH reflects typical residential building techniques in Hong Kong and their evolution, providing the possibility for future MIs to be directly transferred to the entire residential building sector.

2.3 | Hot-spot material stock recycling potential

Hot-spot identification was conducted to reveal spatial patterns of material recycling potential across the PRH building stock. This is a useful technique for identifying statistically significant spatial clusters of high and low values that warrant further investigation (Cheng et al., 2018; Jana &

Sar, 2016; Wang & Varady, 2005). In this study, detailed building blocks were used as the analytical index. The Getis-Ord G_i^* statistic was then applied to these intensity figures mapped across urban areas, evaluating whether aging building blocks and construction materials are intensely stocked or sparsely stocked in non-random spatial patterns, following the Equation (3) (Getis & Ord, 1992). Identified hot and cold spots revealed where intensification or relaxation of aging targets which potentially to be demolished and recycled through planning adjustments. This afforded empirical evidence to better target policies promoting sustainable construction adapted to local urban densities.

$$G_i^* = \frac{\sum_{j=1}^n w_{ij}x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S \sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - (\sum_{j=1}^n w_{ij})^2}{n-1}}} \quad (3)$$

where G_i^* statistic represents the z-score, x_j is the attribute value for feature j , w_{ij} is the spatial weight between feature i and j (years), n is equal to the total number of feature, and

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (4)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (5)$$

The building age is used as attribute values for the variable x (in years) and applied weights based on the distance factor. Within this approach, if the building age shows average high values in the study area, the target feature will be labeled as a hot spot. The clustering of hot spots signifies the presence of aging buildings with substantial demolition, redevelopment, and recycling potential.

2.4 | Data preparation

To develop a robust urban secondary resources inventory and conduct spatial analyses, a comprehensive integration of various complementary data sources was necessary. A hybrid GIS-based and bottom-up building archetype modeling approach was employed for material stock analysis (MSA), which relied on two primary data categories. First, spatial inventory data included property databases and census shapefiles from local planning authorities, offering high-resolution details such as building footprints, precise addresses, and housing unit counts for PRH structures (Esri China, 2022; LD, 2022). Second, archetype-based building information like dimensional attributes, structural plans, architectural plans, technical documentations, and material take-offs was derived through the assessment of selected case buildings of PRH buildings, complemented by archival records, to characterize compositions underlying the typological classification (HKHA, 2014).

3 | RESULTS

3.1 | Material intensities and material stocks

3.1.1 | Intensity inventory of critical construction materials

MI are coefficients utilized to determine total material stocks and flows by multiplying them with building dimensions, such as floor space in square meters, serving as input data for bottom-up MFA/MSA. In this research, MIs are empirically examined for case buildings and assessed by applying weighted factors to age-category building archetypes. This approach determines (1) specific material stock and intensity for case buildings, and (2) general MIs for age-category building archetypes, calculated using weighted factors, as shown in Figure S5 of Supporting Information S1. The MIs for different age categories are classified by construction material groups, as shown in Table 1.

The MIs in PRH buildings range from 1567 to 2386 kg/m² of floor area. Although variations in reference areas impede detailed comparisons, these values align with MIs of similar building structures, such as apartment buildings and multifamily houses from other studies (Cheng et al., 2018; Gontia et al., 2018; Lanau & Liu, 2020; Liang et al., 2023; Ortlepp et al., 2018; Teng & Pan, 2019). By considering concrete grades, the study provides an understanding of differences in aggregates and cementitious materials composition, highlighting the future implications for recycling feasibility and circular management in the construction industry.

Higher MIs compared to other Asian regions are due to reference floor area being internal living space rather than gross floor area. Additionally, low brick material intensities can be attributed to PRH practices, where concrete block walls are used between kitchens and bathrooms, and bricks

TABLE 1 Age-categories critical construction material intensities (MIs) inventory.

Critical construction materials (kg/m ²)	PRH Buildings in Different Age-categories							
	1950–1959	1960–1969	1970–1979	1980–1989	1990–1999	2000–2009	2010–2019	2020–pres
Total	1587	1567	1586	1597	2235	2386	2174	2066
Concrete*	1493	1483	1506	1519	2137	2283	2073	1970
Aggregate	813	799	965	892	1077	1110	1016	976
Cementitious	209	209	201	209	312	344	325	308
Steel	75	66	64	61	85	87	84	80
Glass	1.85	1.85	1.85	1.85	1.85	1.85	1.85	1.85
Timber	5.09	6.38	6.04	6.42	4.77	6.47	6.32	5.87
Brick and tiles	11.34	9.95	8.25	8.65	7.22	8.30	8.71	7.68
Bricks	4.88	1.11	1.00	0.58	0.52	0.46	0.53	0.46
Ceramic tiles	3.49	4.90	4.33	4.28	3.83	4.53	5.80	5.67
Roof covering	2.96	3.95	2.91	3.79	2.87	3.30	2.38	1.55

Concrete*, concrete block walls (internal walls) are included.

are used mainly in mechanical rooms. Lower wood intensities are due to the exclusion of wood formworks. A notable increase in MIs from 1990 onward is attributed to improved structural strength. Concrete has been the primary building material in Hong Kong since the 1950s, particularly for building frames, roof flat slabs, stairs, and intermediary floors in multifamily buildings. Construction evolved from reinforced parapets to shaped concrete facades and from in-situ casting to precasting methods. A decrease in MIs is observed beginning from 2010, compared to the previous age categories. This trend is primarily attributed to advancements in construction technologies, such as the development of high-performance materials and the implementation of prefabrication techniques, which have facilitated more efficient building practices. The increased adoption of sustainable materials, including recycled aggregates and low-carbon cement, has further contributed to the reduction in MIs. Additionally, stricter regulations and an emphasis on sustainability have driven the optimization of material usage, promoting the adoption of resource-efficient designs.

3.1.2 | Material stocks of PRH

Material stocks for CBs are derived through an empirical review of construction documents (Sections 3 and 4 of Supporting Information S1). Material descriptions were analyzed at the level of building elements such as frames, external walls, windows, internal walls, doors, staircases, and roofs. When documentation was inadequate, especially for aging buildings, assumptions were formulated based on local practices and regulations. All assumptions are documented in SI_1.4.3. Material stocks were typically quantified based on MIs using key metrics such as floor area or gross volume. Although gross volume closely relates to the overall size of a building, floor area is the metric that is more prevalently reported. Given the prevalence of floor area and its widespread inclusion in previous studies, this study will leverage the relationship between material stocks and dimensional floor area as a reliable indicator for conducting future analyses with consistency.

The development of building MS illustrates the timeline of major PRH construction in Hong Kong, spanning age categories from 2 to 74 years. Between 1952 and 2022, 60.85 megatons of material stocks accumulated, reaching an average of 28.73 tonnes per capita, with significant increases in 1980 and 2001. Buildings from the 1950s and 1960s contribute minimally, while those from the 1980s and 1990s formed the second and third largest stocks. New constructions in the 2000s account for the highest material stocks. During the past decade, the growth in PRH flats and the authorized population led to a reduction in average household size, while material stocks per capita rose, highlighting ongoing expansion and intensification in PRH construction (see Figure S7 of Supporting Information S1). As shown in Figure 2b, 58.06 megatons of concrete make up more than 90% of the total stock. Steel and bricks account for 2.31 and 0.25 megatons, respectively, while timber and glass together account for 1%. Concrete stock in PRH is noticeably higher than in other studies because concrete blocks are used for internal partitions, compared to clay bricks used elsewhere. Urban stocks differ from primary ores as they become available only at the end of a building's lifecycle (Lederer et al., 2016). Figure 2a shows that older resources become available sooner, and over the next decade, about 1.36 megatons of secondary resources could be extracted from buildings over 50 years old. Long-term, up to 46.95 megatons of construction materials in PRH buildings may become extractable over 30 years.

Figure 3 provides a detailed view of the locations, quantities, and densities of material stocks accumulated, highlighting the involved relationship between these stocks and the surrounding infrastructure. The data reveal a strong positive correlation between the densities of material stocks and the road network, as well as bus stop densities within the PRH environment (see Figures S8 and S9 of Supporting Information S1). In regions like

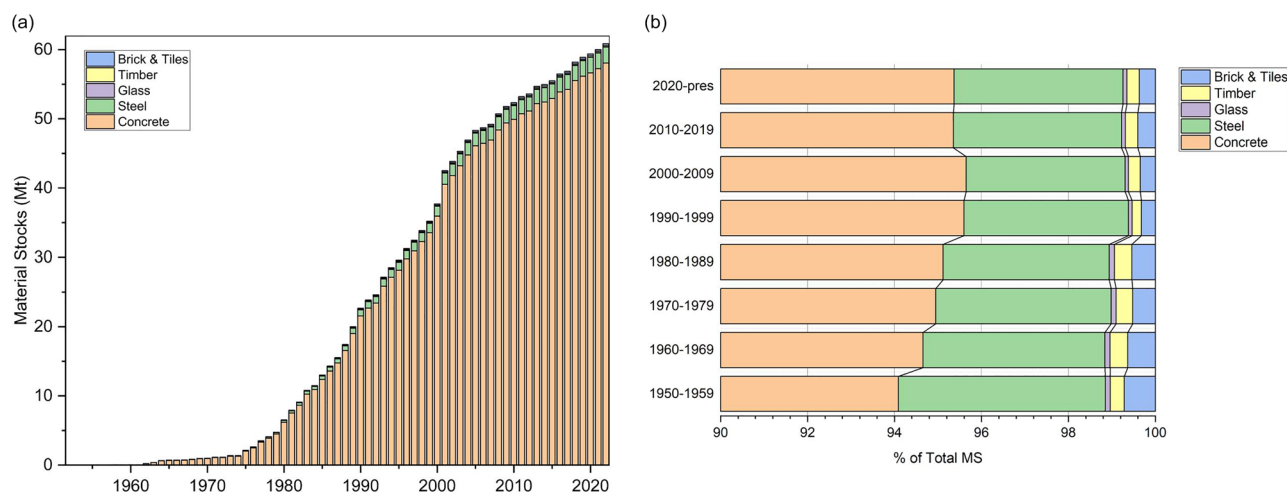


FIGURE 2 (a) Accumulated construction material stocks of public rental housing (PRH) from 1952 to 2022, highlighting potential extractable secondary resources over decades; (b) evolution of critical construction material compositions in PRH across different age categories (underlying data for this figure are available in Table 1 of Supporting Information S3). MS, material stocks.

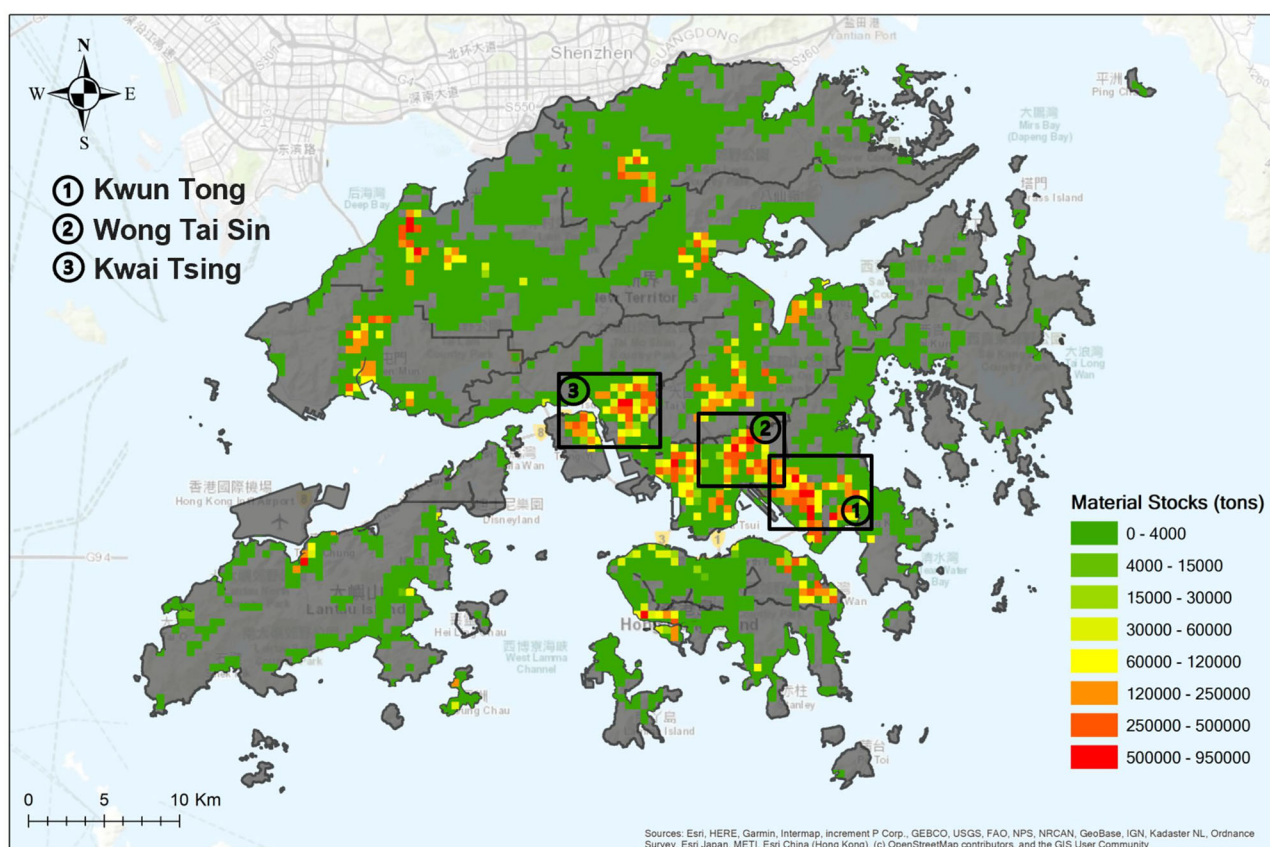


FIGURE 3 The densities of accumulated material stocks in public rental housing (PRH) buildings across Hong Kong, highlighting the relationship between stocks and the surrounding infrastructure (underlying data for this figure are available in Table 2 of Supporting Information S3).

Kowloon and the New Territories, particularly in Kwun Tong (9.84 megatons), Wong Tai Sin (6.10 megatons), and Kwai Tsing (7.38 megatons), the abundance of secondary resources is supported by flat terrain and efficient transport links, facilitating easy access and distribution. Western New Territories, such as Tuen Mun and Yuen Long, also host numerous stocks due to their available land and lower prices, reflecting the government's strategy to alleviate urban housing pressures. On Hong Kong Island, although with well-developed transportation networks, stocks are sparse, constrained by high land prices and limited land availability driven by its commercial and financial role. Material stock distribution in PRH buildings has

shifted from aggregation to dispersion over decades, as depicted in Figure 4, mirroring Hong Kong's urban development. Growth initially focused on the center of Hong Kong Island and Kowloon, later expanding to the New Territories, shaping the current urban layout by 2022. This trend highlights potential future urban mining locations.

3.2 | Hot-spot identification

Using spatial analysis, this study identifies clusters of aging PRH buildings, particularly those over 50 years old, as prime areas for potential short-term urban secondary resource extraction. As shown in Figure 5, red hotspots signify clusters of older secondary resources, while blue cold spots represent newer ones. Regions with clustered hotspots are identified as potential urban mineral deposits. Specific buildings are classified into different levels based on material stocks per block, as depicted in the small diagram in Figure 5. Hong Kong Island (Southern, Eastern, Central, and Western), Wong Tai Sin, and Kwun Tong District are especially rich in extractable urban secondary resources, with 0.45, 0.35, and 0.32 megatons of construction material stocks, respectively. Wong Tai Sin's material stock density is about 38,153 tons per square kilometer, 3.82 times that of the Southern District, suggesting more efficient extraction. In the mid-to-long term, material stocks in Kwai Tsing, Sha Tin, and Yuen Long, are expected to grow, while Kwun Tong District will remain the richest in resources, with a projected 6.75 megatons (see Figure S13 of Supporting Information S1). This information is valuable for Hong Kong's recycling facilities, given the potential for material recovery from concrete demolitions. The richest urban secondary resource areas will shift over time, providing planners with insights into suitable areas for future exploitation based on demand.

3.3 | Uncertainty analysis

Material stock assessments often depend on assumptions and approximations that may introduce inaccuracies, particularly in urban settings where precise data are critical. Therefore, uncertainty analysis was performed to ensure the reliability of the MS estimates in the study. To enhance the robustness of the findings, the analysis focuses on two key types of uncertainties: parameter uncertainty and model uncertainty (Laner et al., 2014). Parameter uncertainty examines the accuracy of the input data, specifically MIs, and whether the chosen case buildings accurately represent the overall stock. Model uncertainty evaluates the assumptions made in the model, particularly the use of MIs categorized by building age, and how this approach compares to using a single average MI for all building types. The goal is to systematically identify and minimize these uncertainties to provide robust and reliable results for MSA (Darius & Burström, 2001; Wang & Ma, 2018).

3.3.1 | Parameter uncertainty

Parameter uncertainty is introduced when selecting input data, such as MIs for construction materials. In this study, MIs are assessed by evaluating case buildings (CBs) selected based on the assumption that their average material content mirrors that of buildings constructed during the same period and with similar architectural forms. To validate this hypothesis, the MIs are compared with values calculated from other data sources within the same target area and time frame (Yang & Kohler, 2008). Differences in the definition of "building area" between case buildings (which include total internal living area) and tested buildings (which include gross floor area) introduce some variation. Living space accounts for about 64% of gross floor area in PRH buildings, leading to a 1.56 times difference between the two. After adjusting for these differences, the uncertainty in material content is estimated to be lower than 5%. Despite these variations, there is convergence in material composition between tested buildings and case buildings constructed between 1990–2009, confirming the robustness of the input data (Section 7 of Supporting Information S1).

3.3.2 | Model uncertainty

Model uncertainty in this study arises from the assumptions made when calculating MIs based on the age of buildings. Buildings constructed in different periods often use varying types and amounts of materials due to changes in construction practices, architectural designs, and materials availability (Kleemann, Lederer et al., 2017; Ortlepp et al., 2016, 2018). This study adopts an age-based approach to categorize MIs, as it is believed to provide a more accurate representation of the actual material stocks compared to using a single, generalized MI for all buildings. To test this assumption, the study compares the results from the age-based model to those obtained using a simplified, single average MI set (Fishman et al., 2014; Tanikawa et al., 2014). The findings show that the age-based method results in more accurate estimates, with a total material stock of 60.85 megatons, compared to 57.98 megatons using the generalized approach—showing a difference of 5%. However, the uncertainties vary by material group: Concrete shows a difference of 5%, timber 13%, and bricks and tiles 7%. These results suggest that accounting for building age provides a more precise assessment of material stocks, as it reflects historical changes in construction practices that affect the types and quantities of materials used over time.

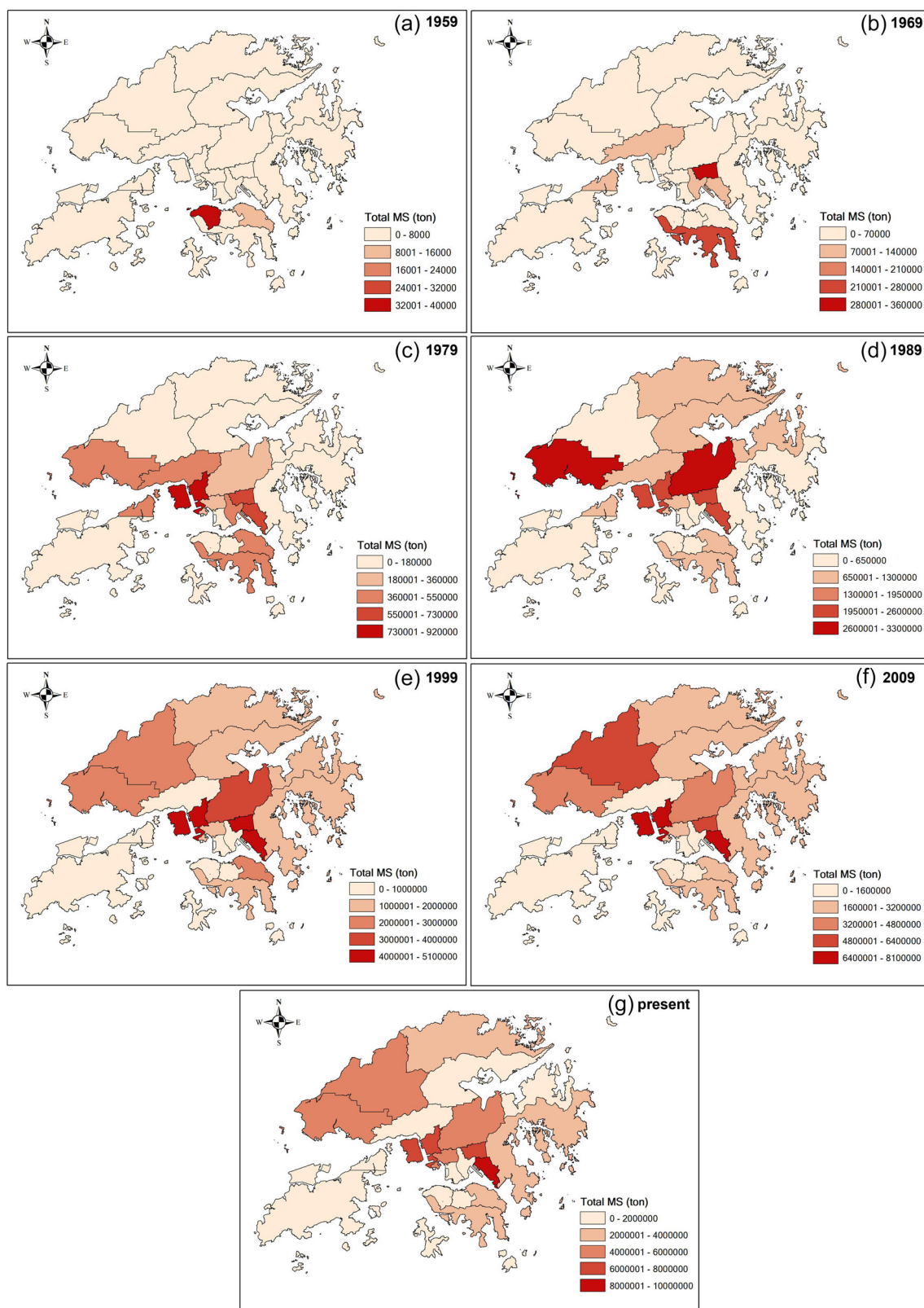


FIGURE 4 The evolution of the distribution pattern of material stocks in public rental housing (PRH) buildings from 1950 to 2022 illustrates a shift from central aggregation to broader dispersion, with the color gradient from dark to light representing dense to sparse stocks over time (underlying data for this figure are available in Table 3 of Supporting Information S3).

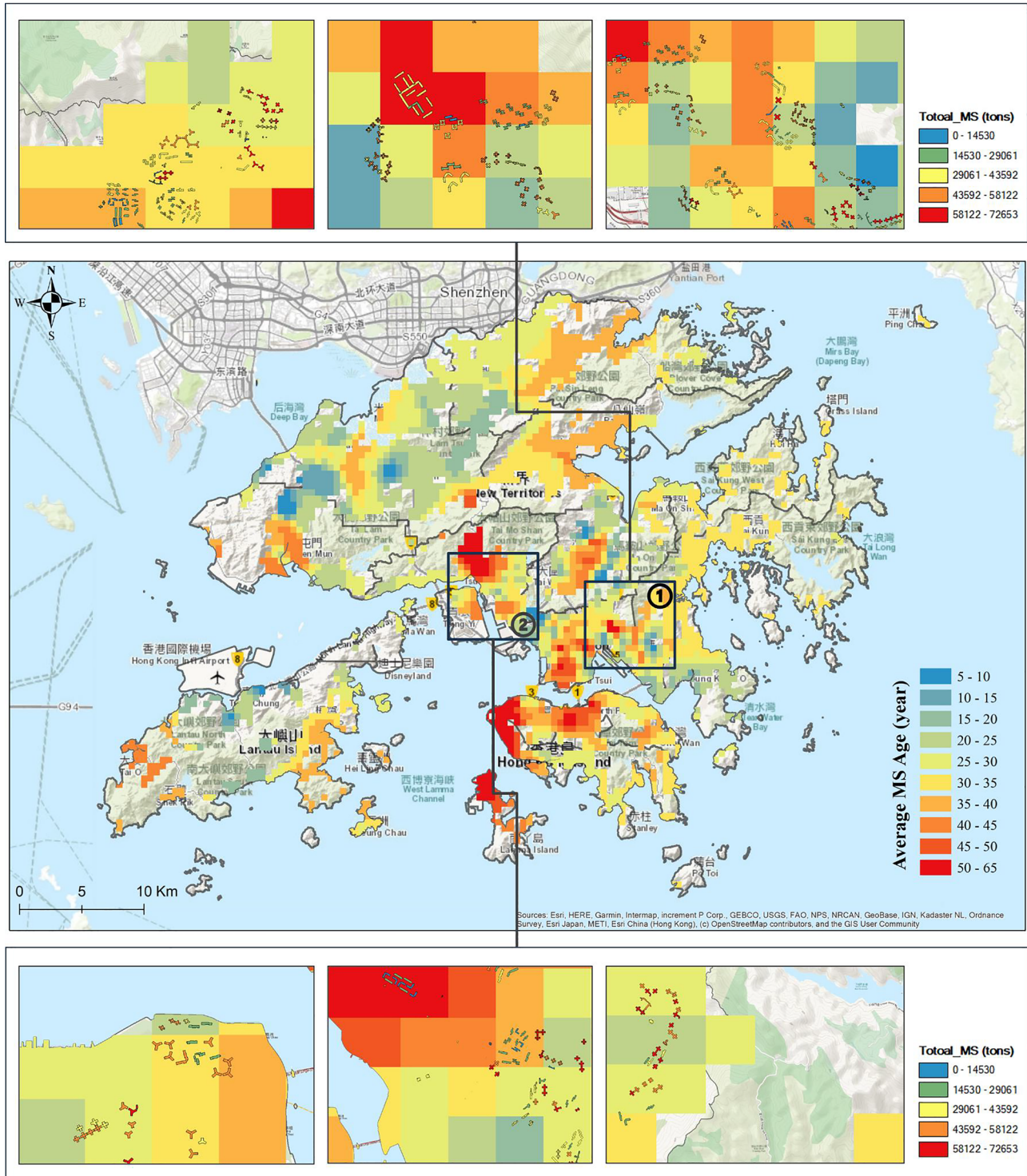


FIGURE 5 Hot spot identification for the urban mineral deposits, with high extraction potential in clustered red hotspots (underlying data for this figure are available in Table 3 of Supporting Information S3). MS, material stocks.

4 | DISCUSSION

4.1 | Comparison with other studies

This study compares total MS in PRH buildings, using age-associated MIs calculated from the research, with estimates from several existing studies in similar regions. These studies employed various methods and data. For instance, Cheng et al. (2018) estimated urban ores in Taipei using statistical and spatial analysis. Teng and Pan (2019) assessed material composition and embodied carbon in typical Hong Kong's prefabricated buildings with a five-level framework. More recently, Liang et al. (2023) mapped building material stock in China's coastal areas using nighttime light data. Li

et al. (2023) used a bottom-up approach for estimating material stocks in Chinese cities, while Song et al. (2021) evaluated provincial stocks with integrated data. Sun et al. (2023) created pixel-level datasets from existing studies for nationwide coverage and Huang et al. (2024) used big geodata and machine learning to analyze built environment stocks in 50 Chinese cities, revealing per capita patterns driven by rapid urbanization. In examining buildings with comparable structural forms in constrained urban contexts (Cheng et al., 2018; Liang et al., 2023; Teng & Pan, 2019), the results indicate varying differences in total and major construction material stocks (Section 6 of Supporting Information S1). The differences in total stocks with Liang's study are minimal due to similar reference metrics, particularly in the definition of floor area. However, discrepancies arise in specific materials due to differences in construction techniques. Aligning the reference metrics with the other two studies on a similar scale reduces the overall stock differences, though significant discrepancies remain in individual materials. This is primarily because the MIs in this study are derived from different age categories rather than an average value, as well as the adjustment of the reference key metrics based on an average empirical value. When compared to other large-scale studies (Huang et al., 2024; Li et al., 2023; Song et al., 2021; Sun et al., 2023), the observed differences increase due to variations in methodology and data sources. Nevertheless, the average discrepancies are maintained within 20%, suggesting a general alignment of the findings with the existing literature. This variation emphasizes the impact of urbanization and economic development on MS estimates, advocating for tailored approaches in different urban scale environments.

The bottom-up MSA offers a detailed representation of MIs across different age groups, considering architectural designs, structural forms, and primary materials. Selected case buildings encompass most of the reference total areas within the target time frame, ensuring methodological reproducibility. The MIs represent the weighted average of PRH building types, reflecting the technical and social development of affordable housing. Although these MIs are not directly transferable to other regions, the approach provides a foundation for adaptation. Future studies can adapt MIs based on similarities in design, structure, and floor area, using similar methods to analyze uncertainties and determine applicability.

4.2 | Validation and uncertainty

Accurately estimating MIs is sometimes challenging due to the lack of detailed records in official statistics. To confirm the robustness and accuracy of MS estimates in this study, identifying and reducing these uncertainties is essential. Methods for addressing uncertainty include examining the uncertainty caused by input parameters and model design, as mentioned in Section 3.3. Typically, parameter uncertainty is estimated by comparing data from independent sources or through sensitivity analysis. To evaluate the robustness and accuracy of MS estimates, a sensitivity analysis was further conducted, with details in Section 7 of Supporting Information S1. By adjusting MIs for certain materials by 10% while keeping other parameters constant, the analysis aimed to observe the impact on total MS quantification. Generally, these adjustments resulted in minor variations, typically less than 1%. However, significant deviations were observed for concrete (9.539%), separately with an aggregate of 5.029%, and cement of 1.392%, indicating more substantial effects. These results underscore the robustness of the findings against variations in input parameters, enhancing the credibility of the employed methodology. Detailed results of the analysis are provided in Table S5 of Supporting Information S1.

4.3 | Transitioning to circular economy

Figure 6 illustrates the carbon emissions associated with material flows in PRH buildings over the next decade (2022–2032). It captures both the inflow of 2.4 megatons of construction materials required for an additional 43,000 residential units and the outflow of approximately 2.15 megatons from the demolition and rebuilding of around 32,400 old units. The figure also reflects the environmental impact of these material flows, including critical construction materials, such as concrete, steel, timber, glass, bricks, and tiles. Disposal and recyclable rates of construction and demolition (C&D) waste, essential for estimating recycling potential, are sourced from local government reports and literature specific to Hong Kong to ensure regional alignment. Emission factors are primarily drawn from the Ecoinvent database (Wernet et al., 2016), ensuring methodological rigor. Key parameters are detailed in Table S6 of Supporting Information S1, aligning with regional standards to provide a robust foundation for estimating recycling potential and environmental impact.

Without considering any specific strategies for C&D waste management, as shown in Figures 6c,d, these inflow and outflow activities will result in $6.163\text{E}+05$ tons of carbon emissions. When considering the current recycling rate for C&D waste in Hong Kong, carbon emissions are reduced to $6.159\text{E}+05$ tons, indicating that recycling has only a minimal impact on reducing carbon emissions. This limited impact is primarily due to the significant embodied carbon of newly added construction materials and the energy-intensive nature of the collection, sorting, disposal, and recycling processes for demolished materials. The energy consumption and greenhouse gas emissions associated with recycling processes further diminish the carbon-saving potential.

However, compared to landfilling, increasing the recycling rate does lead to a reduction in carbon emissions, with further mitigation achievable through the utilization of end-products derived from recycled C&D waste. To facilitate a transition toward a circular economy, future research should prioritize the development of efficient sorting systems, the amplification of recycling proportions, and the promotion of recycled materials in new construction. This study employs a bottom-up analysis of PRH buildings, underscoring the practical implications for development and management. By focusing on the sector related to people's livelihoods, it aims to better promote the concepts of circular construction and generative cities while attending to the needs of the populace.

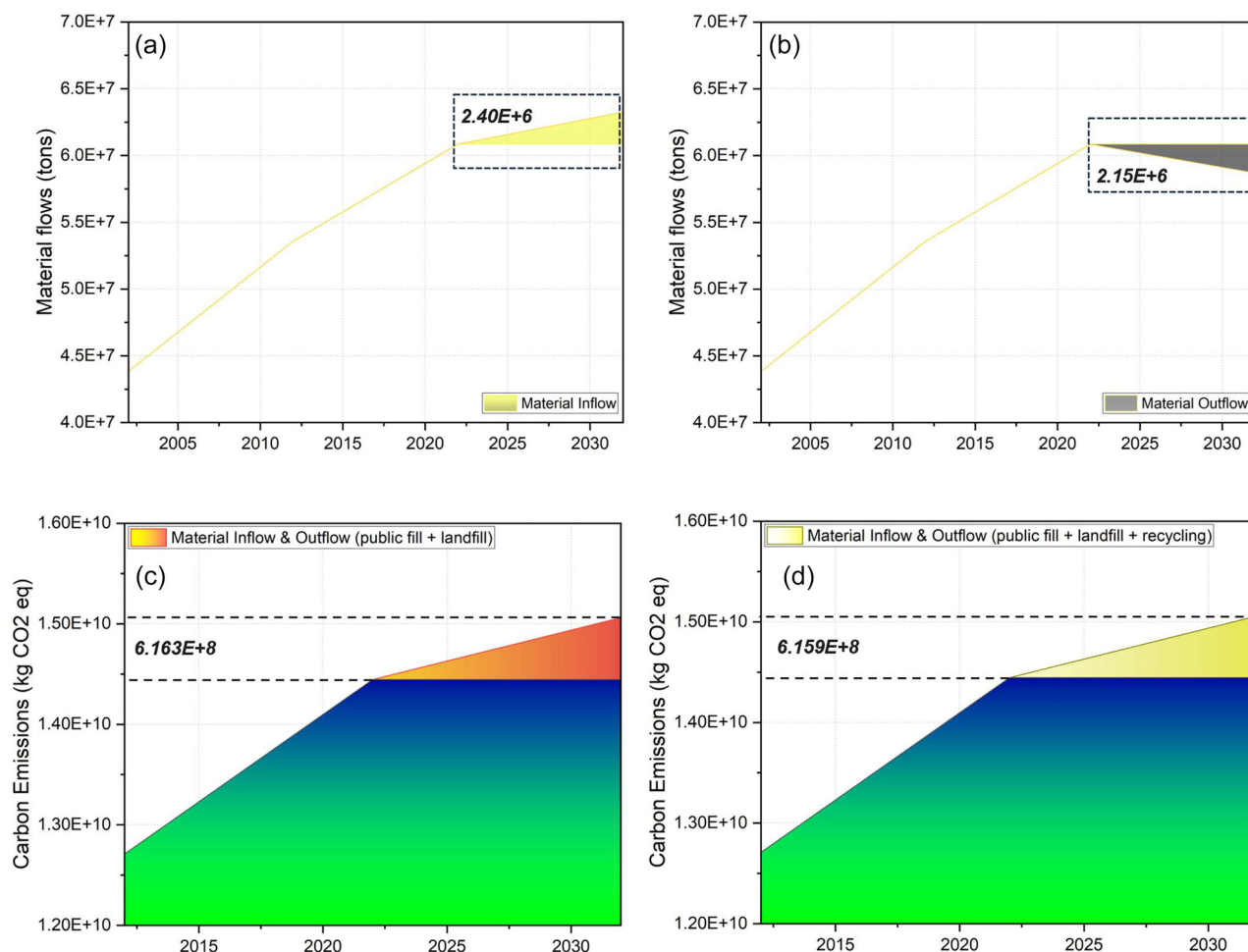


FIGURE 6 Carbon emissions contributed by material flow activities (inflows for new construction and outflows for demolition and renovation) for the period of the next 10 years (underlying data for this figure are available in Table 4 of Supporting Information S3).

5 | CONCLUSION

This study establishes a secondary resources inventory for PRH buildings in Hong Kong using a GIS-enabled bottom-up MSA method. This method integrates empirical data from case buildings with weighted factors based on age-category building archetypes. This hybrid approach enabled a detailed quantification of material stocks and intensities across various construction periods, providing a robust framework for assessing the sustainability of the built environment.

The findings reveal that the material intensities (MIs) in Hong Kong's PRH buildings range from 1567 to 2386 kg/m², which are higher than those in other Asian regions. These MIs align with similar building types in Europe and Asia, reflecting both regional construction practices and the unique characteristics of Hong Kong's built environment. Since the 1950s, concrete has been the dominant building material, comprising over 90% of the material stock, followed by steel, bricks, timber, and glass. Advances in construction techniques, such as the transition from in situ casting to pre-casting methods and the use of shaped concrete elements for facades, indicate both functional and aesthetic improvements in building design.

The material stock distribution in Hong Kong's PRH buildings has shifted from central aggregation to broader dispersion, highlighting potential sites for future urban mining. Over the next three decades, up to 46.95 megatons of construction materials may have recycling potential from older PRH buildings. Given the critical role of PRH as a public welfare component in Hong Kong, understanding the evolution and quantity of its stock is crucial. This knowledge informs policy-making by ensuring efficient resource allocation and enhancing housing sustainability, ultimately benefiting the socio-economic well-being of residents.

However, uncertainties in building area definitions and measurement errors pose significant limitations in estimating MIs. The hybrid bottom-up MSA method developed in this study provides detailed and region-specific MIs, yet applying this framework to other regions requires careful adjustments to account for local construction practices and building characteristics. Material inflow and outflow activities in Hong Kong's PRH sector will result in significant carbon emissions over the next decade. Although recycling can reduce emissions compared to landfilling, the impact is limited by the emissions associated with the recycling process itself. More efforts are needed to improve sorting systems, increase the recycling rate, and utilize recycled materials to advance circular economy goals.

While this study makes significant contributions in providing region-specific material intensity data for Hong Kong's PRH, advancing the hybrid bottom-up MSA methodology, and offering practical insights into sustainability and the circular economy in the construction industry, there are areas for improvement. The results are specific to Hong Kong, and the transferability of the material intensity framework to other regions is limited by differences in construction practices, regulations, and material usage. Additionally, the study relies on available data and certain assumptions that may not fully capture the complexities of older buildings or future construction trends. Future research could expand the geographic scope of material intensity studies, improve data availability or reduce data requirements, and refine methodologies to better address uncertainties. For a more effective circular economy through secondary resource reuse, efforts should also focus on developing more efficient sorting systems, increasing the proportion of recycled materials, and promoting the use of recycled construction materials to achieve true circularity.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The detailed data related to building blocks are available upon request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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