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City-scale assessment of the material and environmental footprint of buildings using an advanced building information model

A case study from Canberra, Australia

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Abstract

As cities grow, demand for urban materials is set to rise. Meeting sustainability targets will require transformative changes to how cities are constructed. Yet, accurate information on embodied building materials and their environmental impacts at the city scale is still lacking. We use Light Detection and Ranging data, building archetype information, and statistical models to estimate the embodied materials in buildings in Canberra, Australia, and their energy, carbon, and water footprint. In 2015, 57 million tonnes (Mt) of materials were embodied in 140,805 buildings. By weight, concrete was the most used material (44%), followed by sand and stone (32%), and ceramics (11%). Current population growth and building construction trends indicate a need for 2.4 times the building materials stock of 2015 by 2060. Producing such materials would require 1.6 thousand TJ of energy and 793 thousand megaliters of water and emit 48 Mt of CO_2e—an environmental footprint 1.6 times the one in 2015. If the additional population were to live only in new single houses, material demand would be 4% higher than under current trends and the environmental footprint 5% higher. Housing new residents in low-rise apartments would reduce from current trends the material demand by 5% and the environmental footprint by 12%. Using only apartments of four or more stories would reduce material demand by 28% and the environmental footprint by 14%. This research can inform circular economy efforts to improve building materials management by helping estimate the implications of alternative configurations of the urban built environment.

KEYWORDS
building information model, building material footprint, circular economy, embodied GHG emissions, industrial ecology, material flow analysis

1 INTRODUCTION

1.1 Buildings and their impacts on the environment and climate

Building materials have a large range of environmental impacts, from accounting for most waste to landfills to depleting natural resources (Cao & Masanet, 2022; Purchase et al., 2022). From 2000 to 2017, global building material consumption tripled from 6.7 billion to 17.5 billion tonnes (Huang et al., 2020). From 1900 to 2010, global material stocks accumulated in buildings, infrastructures, and machinery rose 23 folds, reaching 792 billion tonnes (Krausmann et al., 2017). The buildings and construction industry have a substantial carbon footprint, accounting for 36% of global energy use and 37% of energy-related CO_2 emissions by sector in 2020. Additionally, around 10% of global energy-related emissions came from industries devoted to manufacturing building construction materials (International Energy Agency, 2021).

Sustainable material consumption in cities is critical for mitigating environmental impacts and achieving development goals, including carbon neutrality targets. In Australia, the construction sector accounts for 33% of the total waste to landfills, 25 million metric tonnes in 2020–2021 (Pickin et al., 2022), with emissions accounting for 18% of Australia's total carbon footprint in 2013 (Yu et al., 2017). Embodied materials in residential, commercial, and industrial buildings could double from 2016 to 2060, reaching 7.4 billion tonnes by the end of this period (Soonsawad et al., 2022).

Buildings technologies are crucial for addressing environmental and climate issues in urban areas (de Wilde & Coley, 2012). Each life cycle stage of buildings contributes to environmental impacts, including greenhouse gas emissions, waste, and energy and water consumption. Embodied environmental requirements refer to environmental impacts generated during the production of building materials and construction (Crawford et al., 2019; Stephan & Athanassiadis, 2017). Most studies on reducing buildings' environmental footprint have largely concentrated on operational environmental flows (Röck et al., 2020). In the past decade, research has increasingly focused on the environmental impact of embodied building materials, including emissions, energy, and water use (Hossain & Ng, 2018). Embodied carbon in buildings is increasingly viewed as crucial for net-zero emissions, especially as operational emissions are expected to decline due to the shift to renewable energy sources. For instance, in Australia, embodied and operational carbon comprised 16% and 84% of total building emissions in 2019, respectively. By 2050, projections indicate that embodied carbon may constitute 85% of Australia's total building emissions (GBCA & thinkstep-anz, 2021). Assessments of building stocks and their embodied environmental impacts can guide policy toward net-zero emissions and circular economy targets in the building sector.

1.2 Building material stock modeling

Recent studies have categorized methodologies for analyzing material stocks and flows in buildings and infrastructures —see reviews by Augiseau and Barles (2017), Lanau et al. (2019), Müller et al. (2014), Tanikawa et al. (2015), and Wang et al. (2020). This study adopted the methodological classification introduced by Lanau et al. (2019), which in addition to top-down and bottom-up approaches, includes a remote-sensing-based method and a hybrid approach.

The top-down approach calculates building stocks using net flows of materials data or the difference between inflows and outflows of materials (Müller et al., 2014). This method is useful for conducting analyses and modeling material stock dynamics at large spatial scales but is generally unsuitable for high-resolution assessments (Haberl et al., 2021; Heisel et al., 2022; Lanau et al., 2019). Notable implementations of the top-down method can be found in Fishman et al. (2014) and Tanikawa et al. (2015). Conversely, the bottom-up approach provides highly detailed calculations using spatially explicit data on building characteristics such as length, area, or volume (Haberl et al., 2021). With new technologies available for generating and processing high-resolution building data, bottom-up analyses are becoming more common (Haberl et al., 2021; Miatto et al., 2017; Schandl et al., 2020; Soonsawad et al., 2022).

Remote-sensing-based approaches utilize remote sensing technologies to estimate material stocks. A common example is using night-time lights (NTL) as a proxy for human activities and socioeconomic variables. The advantages of the NTL method include worldwide data availability and affordability. However, it has several limitations, such as not being representative of underground built stocks and non-light emitting structures and the inability to map high-resolution material information (Haberl et al., 2021; Lanau et al., 2019). Studies using the NTL method include Hattori et al. (2014), Liang et al. (2019), and Vilaysouk et al. (2021). Another remote-sensing approach uses Light Detection and Ranging (LiDAR) data to estimate material stocks based on three-dimensional (3D) models of above-ground structures from digital surface and digital terrain models (Huang et al., 2019). Although this newer method delivers high-resolution estimates, can substitute cadastral information, and has been used in combination with aerial images for building extraction (Huang et al., 2019), it is expensive and usually covers small areas (Haberl et al., 2021). Schandl et al. (2020) provide a recent example of the application of LiDAR in assessing building material stocks. There also exist hybrid methods, which calibrate top-down models using bottom-up results (Lanau et al., 2019).

Advances in information technology, such as 3D city models, geographic information systems (GIS), Digital Twins, and remote sensing, have facilitated the digital transformation of urban planning. Such technologies aid in collating local infrastructure information and bridging data gaps in material stock and flows (Gil, 2020; Seto & Christensen, 2013; Steadman et al., 2020; Tanikawa & Hashimoto, 2009).

Three-dimensional digital models have been mainly used for visualization (Biljecki et al., 2015; Steadman et al., 2020). However, their use has been expanding to other areas. Several building stock models focus on assessing energy consumption to promote efficient use of energy in buildings (Evans et al., 2017; Guo et al., 2019; Heisel et al., 2022; Österbring et al., 2016). Other applications focus on informing planning urban resources (Padsala et al., 2021); assessing urban water demand (Bao et al., 2020); forecasting the growth of employment and population retention and transport and land use planning (The Mid-Region Council of Government, 2022; UrbanSim Inc., n.d.); analyzing outdoor thermal comfort (Hosseinihaghighi et al., 2020); and assessing global urban settlements and agglomeration by generating a global 3D map of buildings (Esch et al., 2022).

Here, we used a combination of bottom-up and remote-sensing-based approaches for creating 3D building models from high-resolution LiDAR data linked to building archetypes to quantify, map, and project building material stocks and flows as well as their environmental impacts.

1.3 | Purpose of the study

Whereas a significant number of studies on building stock modeling are available, most of them have a coarse spatial resolution, thereby not providing high accuracy in material stock estimates. Also, their applications for decision making in urban planning decisions are still limited. Using existing methods to estimate the tonnes of embodied materials and environmental impact at the urban scale is often impractical for urban planning due to cost, time constraints, or insufficient detail. We attempt to bridge this gap by developing a stock and flows model that allows the estimation of embodied building materials and their emissions, energy and water footprint for single building assessment or whole-of-city analyses. Such a model starts with the generation of level of detail 2 (LOD2) 3D building polygons derived from high-resolution LiDAR data collected in Canberra, Australia, in 2015. Building polygons were categorized into various types such as residential, commercial, and industrial. Then, each building was linked to a construction technology archetype to estimate its embodied materials. Australian-specific coefficients were used to calculate the environmental footprint of the embodied materials in Canberra's building stock. This model was also used to estimate the material demand and environmental footprint for replacing buildings as they reach the end of their useful life and for covering the building needs of a growing population while accounting for material use efficiency trends. This model could be used as a support tool for urban planning decisions to map high-priority areas for improving the sustainability and resilience of the built environment. Model components could be substituted for more cost-effective or accurate data. For instance, for regions without LiDAR data, 3D models from aerial photography could be used. The approach can also be useful for informing strategies toward net-zero emission cities and for estimating building materials' waste flows and the potential for the circular economy of the construction sector.

2 | RESEARCH DESIGN

2.1 | Study area

Canberra, located in the Australian Capital Territory (ACT), is the capital of Australia. Despite being established in 1913, it is a relatively young and compact city with around 432,000 residents in June 2021 and an urban footprint of around 37,000 ha (Australian Bureau of Statistics, 2017, 2021). The ACT Planning Strategy, 2018 emphasizes urban compactness to accommodate population growth (ACT Government, 2018). In 2020, the city achieved 100% renewable energy supply, with ongoing efforts to decarbonize other sectors. The ACT aims for net-zero emissions by 2045 by setting out key priorities related to energy, buildings, and urban development, including improving requirements for new buildings' energy performance and climate resilience characteristics. However, building materials and their environmental and climate implications, such as embodied carbon and energy, are not explicitly included in the city's climate change strategy (ACT Government, 2019). Recently, demand for extra residential and commercial floor area has risen, coinciding with urban redevelopment in various city sectors (Schandl et al., 2020). The materials needed for refurbishing old buildings and construct the infrastructure needed by a growing population will have considerable implications for carbon emissions and energy and water use in this city.

2.2 | Method

For estimating baseline and projected materials embodied in buildings, we used LiDAR data to generate two-dimensional (2D) and 3D building footprints of all buildings in Canberra (Figure 1). Then, all the building polygons were classified into different archetypes (e.g., single houses and

FIGURE 1 Process followed to estimate material demand for urban buildings in the ACT and their environmental footprint.

apartment buildings) that account for differences in the number of stories and construction periods. This information was used to estimate the tonnes of materials embodied in Canberra buildings in 2015. We used environmental footprint indicators (CO_2 emissions, water, and energy use) to estimate the environmental implications of the materials embodied in city buildings. With estimates of the useful life expectancy of the 2015 building stock, we estimated the material demand to replace and expand the gross floor area (GFA) of buildings to cover the demand of a growing urban population.

2.2.1 | Generating 3D building data

We used classified LiDAR point cloud data (8 points per m^2) collected in 2015 (available at https://elevation.fsdf.org.au/) to generate 3D models of all building envelopes in Canberra. This process starts with generating 2D polygons of ground-level buildings, that is, building footprints. Artifacts in the boundaries of such building footprints, for example, kinks, and incorrect corners, were removed using Gribov's (2019) polyline compression algorithm in ArcGIS Pro 2.9. Then, we used LiDAR data to generate a Digital Elevation Model (DEM), a Digital Surface Model (DSM), and a Normalized Digital Surface Model (nDSM). A DEM indicates the elevation of the bare Earth, that is, all natural and built features are removed. A DSM includes data about the land cover's elevation, that is, all natural and constructed features. In contrast, an nDSM indicates the height of land cover features, for example, trees or building heights. These elevation surface layers were combined with the building footprints to estimate roof characteristics such as type (e.g., flat and gable roof) and roof direction. This step allowed the production of the LOD2, 3D building models. Each 3D building model includes information about its 2D and 3D surface area and the height of different roof parts (e.g., eave and ridge height).

2.2.2 | Classifying building polygons and estimating buildings' construction period

A supervised rule-based algorithm was used to classify buildings into five types: residential, commercial, industrial, designated, and community buildings, with each type having different stories (Figure 2). The building classification by stories was based on the National Exposure Information System (NEXIS) database version 11 (Geoscience Australia, 2020), which reports aggregated census data. This approach relied on heuristics based on land-use zoning rules, such as maximum story limits and building-to-plot area ratios, coupled with polygonal geometric data like building height and 2D footprint area. For example, a building in a residential zone with a single address and occupying less than half the plot area, per building codes, was classified as a single house.

We refined classification rules (e.g., height thresholds for multi-story buildings) using 618 manually labeled polygons. This sample was generated using high-resolution imagery, Google Street View data, real estate information, and on-site observations. We ensured that the sample represented the shares of different building types of Canberra and the characteristics of a government city dominated by its suburban landscapes and absence

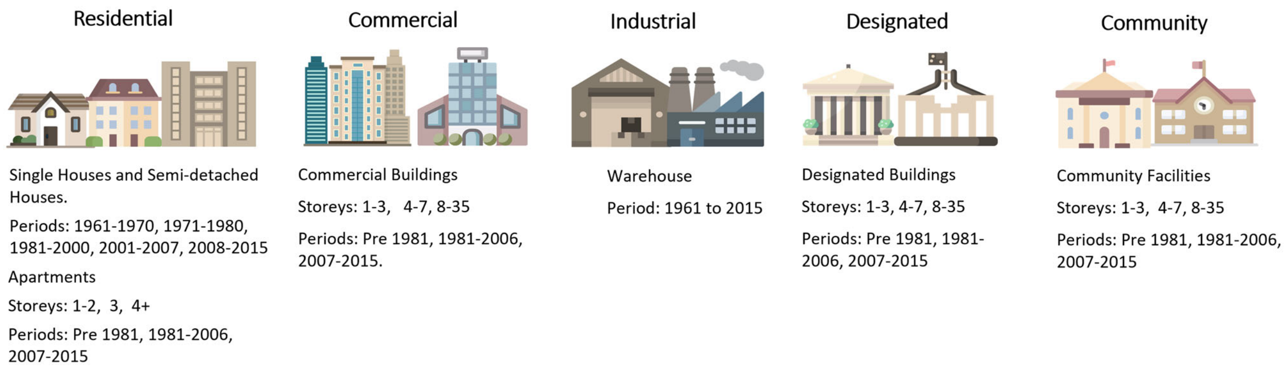

FIGURE 2 Building types and construction periods used to estimate building stocks in 2015.

of significant industry and manufacturing locations. The methodology achieved an accuracy rate of 83% (Cohen's Kappa coefficient = 0.66), with most inaccuracies in mixed-use commercial areas. These errors were manually corrected in a GIS, cross-referencing with Google Street View and real estate information. Rule calibration was accomplished in 3 days, while manual corrections took approximately 5 days for the entire city.

The construction period for 2015 standing buildings was estimated using suburb establishment years (ACT Government, 2009) and building lifetime distribution assumptions. For each suburb, we used a Weibull distribution (shape = 1.97 and scale = 67.34) to estimate the proportion of building materials needing replacement per year. The decision to use a Weibull distribution was guided by previous analysis of the influence of the distribution function on the results of building decommission (Miatto et al., 2017). The Weibull distribution yields very similar results to a log-normal distribution and is superior to normal or Gompertz distributions. Such a distribution assumes an average lifetime of 60 years, aligns with the global average life of buildings as indicated by Deetman et al. (2020) and the reported average life of buildings in Australia (Australian Bureau of Statistics, 2000).

Buildings were classified by construction period to align them with construction archetypes developed by Stephan and Athanassiadis (2017) for Melbourne. The construction technologies in Melbourne and Canberra are similar since they follow the Australian construction code (Soonsawad et al., 2022). And the building archetypes are representative of Australian construction technologies during different time periods (Stephan & Athanassiadis, 2017, 2018). Buildings standing in 2015 in suburbs older than 60 years are likely to be newer or significantly refurbished buildings. To account for building replacement and renewal in those suburbs, we used data on the proportion of buildings constructed before and since 1981, at the mesh block level,[1] from NEXIS. This year marked construction technologies and regulations changes in Australia (Geoscience Australia, 2020). For instance, after 1981, there were stricter requirements for building components (e.g., windows and roofs) to resist strong winds (Boughton et al., 2011). Commercial and residential building materials were assumed to align with technologies prevalent during specific periods (Figure 2). For buildings in newer suburbs, construction archetypes were derived from technologies prevalent post-suburb establishment. For instance, single houses in a suburb established in 2009 used construction technology data from 2008 to 2015. This location-sensitive approach enables estimation of the embodied materials in buildings and their remaining useful life while controlling for differences in construction technologies. This results in 42 unique building typologies (Figure 2).

2.2.3 | Estimating embodied materials in buildings and their environmental footprint

The estimation of the material composition and weight of each building classified in Figure 2 relied on building archetypes developed by Stephan and Athanassiadis (2017). These archetypes provide an approximation of the structural and material composition of various building types and construction periods in Melbourne, Australia, with an error margin of ±10% compared to the actual quantities (Stephan & Athanassiadis, 2017). We used each building's polygonal geometry data to estimate the area, volume, or linear measurements of different building assemblies, such as outer and inner wall area, based on their construction period and building type. A comprehensive list of the building assemblies considered in our analysis is provided in Table 1. Each archetype contains information regarding the primary materials needed for constructing various building assemblies, considering factors such as building type, area, height, and construction period. For instance, each archetype includes a ratio of windows to wall area to estimate the total window area and information on materials required per m^2 of windows, such as kilograms of aluminum, glass, and so on. Stephan and Athanassiadis (2017) describe in detail the assembly and material composition of the building archetypes used in our analysis. This approach allowed us to estimate the tonnes of concrete, aluminum, steel, timber, ceramics, plasterboard, glass, copper, plastics, sand and stone, bitumen, paint, insulation, and carpet embodied in each building.

The Environmental Performance in Construction (EPiC), using life cycle inventory methods, quantifies emissions, energy, and water use during the production of Australian building materials (Crawford et al., 2019). Our analysis prioritized the production stage, identified as

TABLE 1 Materials used in building assemblies.

Material	Assembly	Present in/used for
Aluminum	Doors, outer walls, roof, windows	Door handles, reflective foil, gutter, frame or sill
Bitumen	Roof	Weather proofing
Carpet	Floors	Nylon carpets
Ceramics	Floors, internal and outer walls, roof, windows, and minor finishes	Tiles, clay bricks (100 and 110 mm), terracotta roof tiles (20 mm), basin or toilet suites
Concrete	Columns, ground and upper floor(s) slab, door and windows lintels, internal and outer walls, roof	15 or 25 Megapascals (MPa), mortar, precast
Copper	Wires and pipes	Electrical wires, plumbing items, built-in appliances
Glass	Windows, minor finishes	Clear float (4 mm) window pane
Fiberglass/expanded polystyrene	Outer walls, roof	Insulation
Paint	Columns, doors, internal and outer walls, roof, ground and upper floor(s) slabs	Water-based paint
Plasterboard	Internal and outer walls, roof, ground and upper floor(s) slabs	10 mm plasterboard for internal lining
Plastics	Floors, ground floor slab, minor finishes, pipes, windows, wires	Plastic membrane (1 mm), bath (acrylic), PVC water pipe (20 mm), wire coating, general PVC
Sand and stone	Ground floor slab, outer walls	Screenings, sand
Steel	Beams, columns, doors, ground and upper floor slab(s), internal and outer walls, roof, minor finishes, windows	Structural frame, door accessories, reinforcement, stainless sinks, gutter
Timber	Floors, ground and upper floor(s) slabs, internal and outer walls, doors, roof, windows, minor finishes	MDF/particleboard or softwood (framing), hardwood (structural)

Source: Schandl et al. (2020) with information from Stephan and Athanassiadis (2017).
Notes: Minor finishes include toilet and kitchen components such as basins, toilet suites, and sinks.

having greater environmental impacts compared to other stages (Crawford et al., 2016; Omrany et al., 2021; Petrovic et al., 2019). We used EPiC data to quantify the environmental footprint of Canberra's building materials in 2015, focusing on energy, emissions, and water per tonne.

2.2.4 | Projecting the building material and environmental footprint under urban planning scenarios

Projections from 2020 to 2060 area consider materials for building replacement and new construction to meet the demands of a growing population in residential, commercial, and industrial sectors. We assumed that the per capita demand of non-residential buildings would follow similar patterns to those observed in the baseline building stock modeling. Accounting for changes in labor markets and other economic indicators would require a more complex modeling approach that is currently unavailable in the literature. As in the baseline analysis of 2015 buildings, we assumed an average lifespan of 60 years for new buildings, with replacement rates following a Weibull distribution (shape = 1.97 and scale = 67.34) and remaining useful life estimates dependent on the suburb's establishment year.

Based on historical trends, replacement buildings were assumed to be constructed using technologies that led to gradual improvements in resource efficiency. Between 1981 and 2015, Canberra experienced a 3.68% decline in tonnes of building material per capita. Therefore, we assumed a 0.11% per annum reduction in material used to account for potential improvements in material use efficiency.

We estimated the material demand for new buildings using district-level population projections from 2018 to 2060 (ACT Government, 2018) and per capita estimates of material demand per building archetype. We explored the material and environmental impacts of four scenarios that assumed the new population in Canberra would be living only in the following:

1. Single or semi-detached houses (low residential density scenario).
2. Apartments of 1 to 3 stories (medium residential density scenario).
3. Apartments of 4 or more stories (high residential density scenario).
4. A similar building type split like the one observed in 2015 (Business as Usual, BAU, scenario).

The BAU scenario assumes that the building needs of a growing population are fulfilled using the same mix of building types observed in 2015, which may not persist due to urban intensification. Therefore, we explored the material demand of extreme case scenarios, where all new population lives in a single type of residential building. This helps to identify minimum and maximum levels of material demand and how those levels compare to BAU conditions. Using NEXIS data (Geoscience Australia, 2020) we calculated the average occupancy for each residential building type in 2015 to estimate future building needs. We assumed these averages would persist through the projection period.

The material demand for commercial, industrial, designated, and community buildings was projected using the corresponding 2015 per capita building material estimates. The per capita estimates were multiplied by the annual increase in population to estimate the total materials required for each of those non-residential building types. We also assumed a 0.11% per annum reduction in material used in the construction of those buildings.

Material flows for replacement buildings were calculated for 2015–2060, while materials for new constructions were estimated for 2018–2060 since population projections were only available for such a period. For brevity and alignment with local urban strategies, the focus was narrowed to the 2020–2060 period. Estimates of the material demand for new and replacement buildings under each scenario were multiplied by the per-tonne environmental footprint data from EPiC (Crawford et al., 2019) to assess the emissions, water, and energy of projected material demand. Since we assumed continuation of historical material efficiency trends, replacement buildings require slightly less materials than old buildings. Hence, each year, a portion of the historical embodied emissions are removed and replaced by a new, smaller level of embodied emissions.

We used ArcGIS Pro for LiDAR data and R (R Core Team, 2017) for classification and material and environmental footprint calculations.

3 | RESULTS

3.1 | Baseline building stock and environmental footprint

3.1.1 | Gross floor area and baseline building stock

The algorithm identified 140,805 buildings in 2015, integrated by: single houses (79.5%), semi-detached houses (13.1%), apartments (1.3%), commercial buildings (2.7%), community facilities (1.4%), industrial structures (1.1%), and designated buildings (0.9%). The total GFA of those buildings was approximately 77 km^2 covering around 43 km^2 of land. Single houses represented 56% of the GFA, followed by semi-detached houses (17%), commercial buildings (12%), and community facilities (5%). Other types, including apartments, industrial, and designated buildings, accounted for 10% of the GFA. Materials embodied in buildings in 2015 weighed around 57 million tonnes, resulting in 0.75 tonnes of material per m^2 of GFA. Those materials required around 400 thousand TJ of energy, 500 thousand megaliters of water, and produced about 29.4 million tonnes of CO_2e emissions.

Our analysis allowed the exploration of the spatial heterogeneity of material intensity indicators in the city. We estimated the tonnes of material per GFA, per capita, and per residential dwelling at the mesh block level (Figure 3). Areas with a high density of high-rise buildings or that have undergone significant redevelopment have lower material use per m^2 of GFA (Figure 3a). The spatial patterns of tonnes per capita (Figure 3b) and tonnes per dwelling (Figure 3c) show higher material use in regions with a significant proportion of commercial and industrial buildings. Regions with less than 1 tonne of material per m^2 of GFA, between 1 to 50 tonnes of material per capita, and between 1 to 200 tonnes per dwelling correspond to areas primarily covered by single and semi-detached dwellings. Mesh blocks with few residents or dwellings, such as areas with many new constructions in 2015 or predominantly office facilities, showed the highest per capita and per dwelling material tonnage (darker areas in Figure 3b,c).

3.1.2 | Embodied environmental impacts of building stock

In terms of weight, concrete was the most used material (44%) in buildings standing in 2015, followed by sand and stone (32%), ceramics (11%), timber (6%), plasterboard (3%), steel (2%), and others (2%) (Table 2). However, ceramics (e.g., tiles, clay bricks, and terracotta roof tiles) cause the highest environmental impact, including 27% of the greenhouse gas (GHG) emissions, 29% of embodied energy, and 19% of embodied water (Table 2). Concrete accounted for 21% of embodied emissions, 16% of energy, and 19% of water. Timber had the third largest environmental footprint, accounting for 14% of the total embodied emissions, 18% of water, and 16% of energy. Despite sand and stone representing 32% of the tonnes of embodied materials, the corresponding environmental footprint is 4% on average.

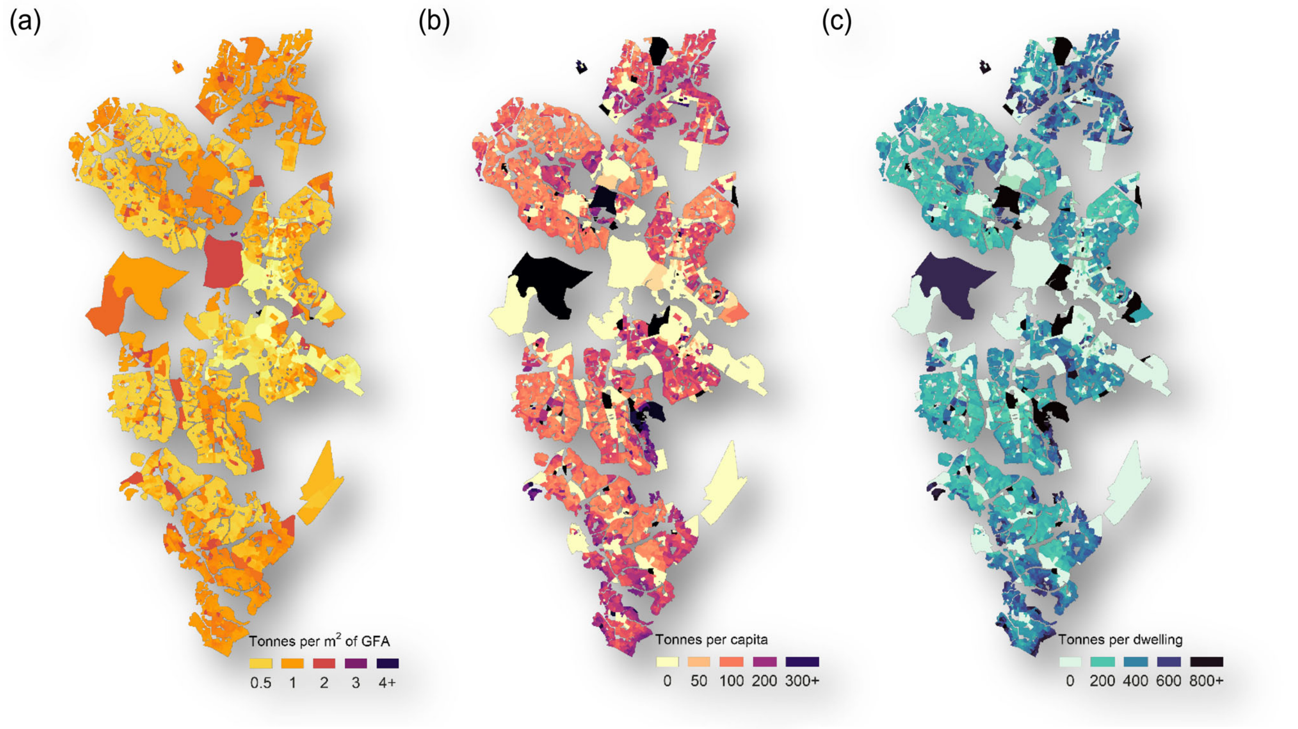

FIGURE 3 (a) Material use per gross floor area (GFA), (b) per capita, and (c) per dwelling in Canberra by mesh block level. Mesh blocks with a large share of high-rise buildings, significant redevelopment, or without residential dwellings are shown in light colors. Areas with a large share of old buildings and low GFA, population, or dwellings are shown in darker colors.

TABLE 2 Material composition of the 2015 building stock of Canberra and its embodied environmental footprint.

Materials	Tonnes	Energy (TJ)	Water (Megaliter)	GHG (tonnes CO_2e)
Aluminum	135,834	40,071	21,733	3,626,778
Bitumen	17,234	72	50	3447
Carpet	43,018	5001	12,357	335,539
Ceramics	6,185,881	116,913	94,025	8,041,645
Concrete	25,337,403	65,877	93,748	6,080,977
Copper	19,981	2997	5774	201,807
Glass	284,945	8121	9175	569,890
Insulation	266,403	15,212	16,570	1,012,330
Paint	119,476	14,815	23,537	752,698
Plasterboard	1,611,075	18,801	19,236	1,272,749
Plastics	59,331	7535	26,283	456,845
Sand and stone	18,483,425	8133	34,564	554,503
Steel	1,157,401	34,143	51,273	2,430,542
Timber	3,436,636	65,605	91,621	4,089,597
Total	**57,158,041**	**403,297**	**499,948**	**29,429,347**

3.2 | Scenario analysis of material demand: Population projection and replacement of buildings

If Canberra's growing population uses a similar building composition as observed in 2015 (BAU scenario), the cumulative material demand by 2060 could be approximately 135 million tonnes (Figure 4a). This is about 2.4 times the building materials stock of 2015 (57 million tonnes). This material demand could produce 47.6 million tonnes of CO_2e emissions, 1.62 times the 2015 levels, require 631 thousand TJ, 1.57 times the baseline embodied energy, and 793 thousand megaliters of water, 1.59 times the water embodied in buildings in 2015.

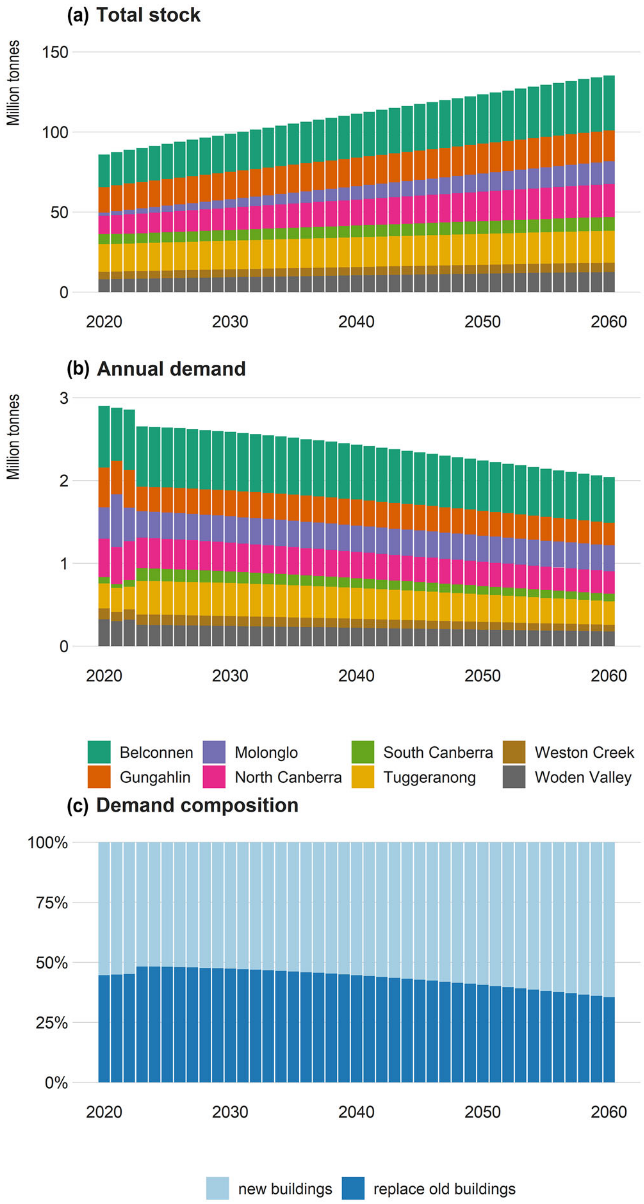

FIGURE 4 Total material stock and annual material demand from 2020 to 2060 by district. (a) Total stock, (b) annual demand, (c) demand composition. The underlying data can be found in the Supporting Information S1.

At the district level, Tuggeranong and Belconnen have a relatively high share of cumulative demand, while Weston Creek and South Canberra have the smallest shares (Figure 4a). This is partly due to the high baseline material stock in those districts, which would need to be replaced or refurbished within the projection period. Also, Belconnen's population projection by 2060 is the highest of all districts. Similarly, the Belconnen district accounts for the largest share of annual material demand, around half a million tonnes per year, followed by Tuggeranong and Gungahlin (Figure 4b). The share of new materials required for buildings to accommodate increasing populations and materials for replacing old buildings are similar, being close to 50% from 2020 to 2040. After 2040, material demand for buildings in new locations gradually increases, reaching 60% in 2060 (Figure 4c). The variability in annual demand from 2020 to 2023 in Figure 4 is due to projected population growth in new suburbs in the Molonglo district.

3.3 | Scenario analysis of material demand

According to the NEXIS database, the average occupancy of single and semi-detached houses in the study area was 2.5 people, 19.9 for apartment buildings of 1 to 3 stories and 133.1 for apartment buildings of 4 or more stories. This information was used to estimate the number of buildings needed for new residents under low-, medium-, and high-density housing scenarios, respectively. In 2015, single and semi-detached houses

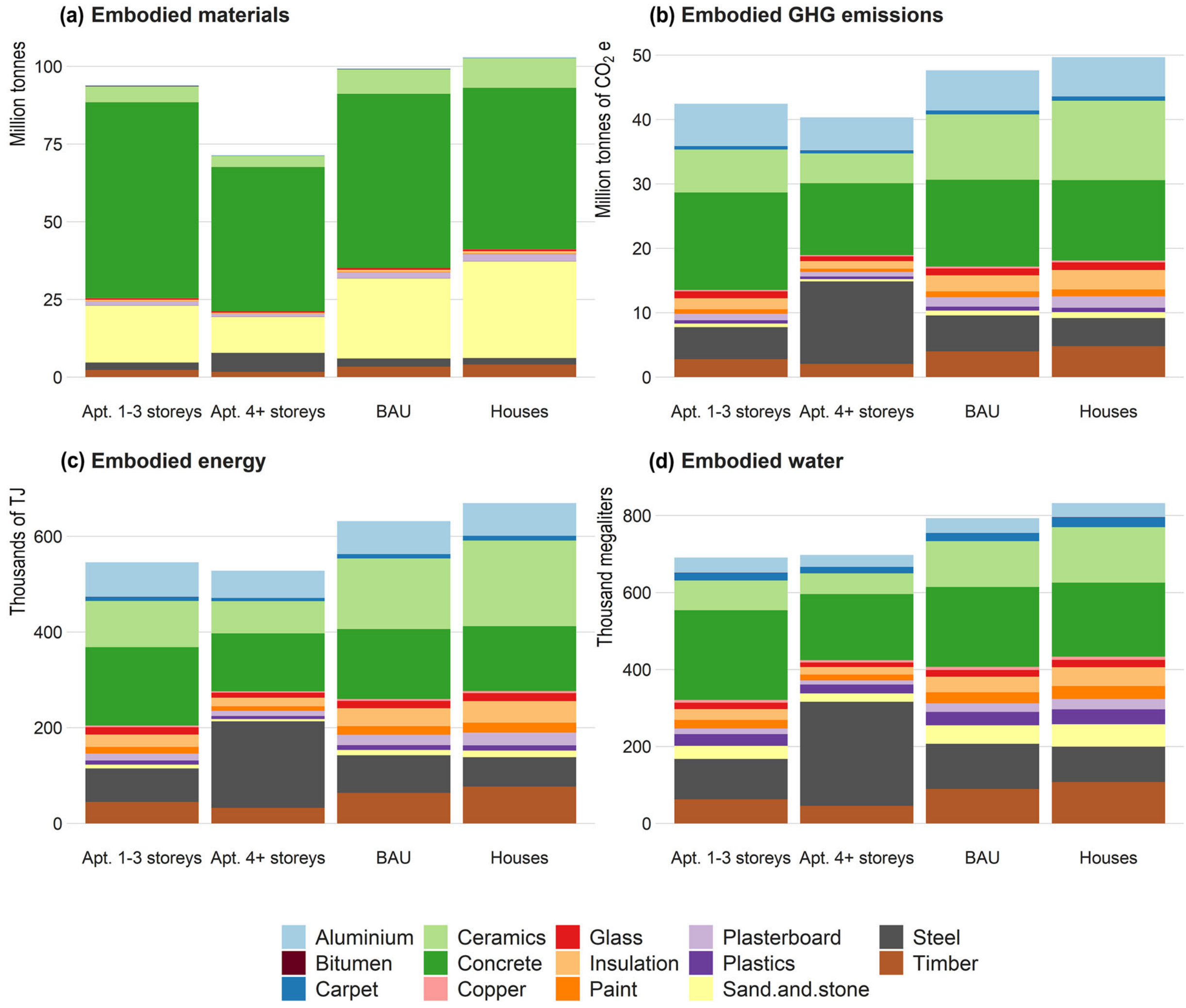

FIGURE 5 Materials and corresponding environmental footprint for new buildings and replacing old buildings (accumulated for the period 2020–2060). (a) Embodied materials, (b) embodied GHG emissions, (c) embodied energy, and (d) embodied water. The underlying data can be found in the Supporting Information S1.

accounted for 98.65% of the building stock, apartment buildings of 1 to 3 stories 1.32%, and the share of buildings of 4 or more stories was 0.02%. This building mix was projected to continue in the BAU scenario.

The projected cumulative material demand from 2020 to 2060 was 103 million tonnes for single or semi-detached houses, 99 million tonnes for BAU, 94 million tonnes for low-rise buildings, and 71 million for high-rise buildings (Figure 5a). In all scenarios, concrete, sand, and stone accounted for the largest proportion of embodied materials. Timber use was more extensive in scenarios based on single homes, while the share of steel use was higher in the high-rise buildings scenario than in other projections. Cumulative emissions ranged from 40.3 million tonnes of CO_2e in the high-rise building scenario to 49.6 million tonnes of CO_2e in the single houses scenario. Concrete, aluminum, steel, and ceramics accounted for 71% of all cumulative emissions in the single houses scenario and 84% in the high-rise building scenario (Figure 5b). Similar results were observed for embodied energy (Figure 5c). The large water footprint of steel meant that the high-rise buildings scenario had more embodied water than the low-rise buildings projection (Figure 5d). The scenario based on single and semi-detached houses had the most extensive land footprint, 39 km^2, followed by the BAU scenario, 35 km^2, while buildings of 4 or more stories required the least land, 11.5 km^2 (Figure 6).

4 | DISCUSSION

4.1 | Methodological contributions

This study contributes to advancing knowledge in the field of material stocks and flows by offering a modular, hybrid bottom-up and remote-sensing methodology for analyzing building materials at a city scale. Our approach uses a highly disaggregated representation of the building stock of

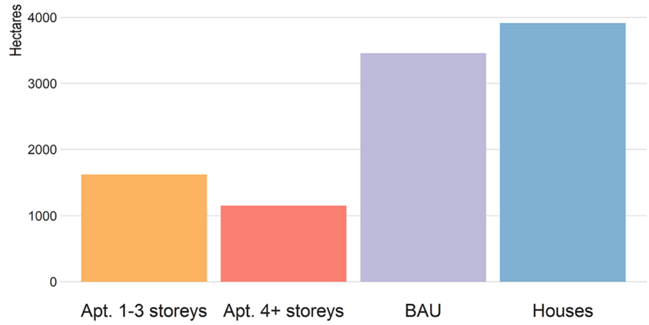

FIGURE 6 The land footprint for new buildings and replacing old buildings (accumulated for the period 2020–2060). The underlying data can be found in the Supporting Information S1.

Canberra in 2015, modeling seven major building types and subtypes based on the number of stories and construction periods, a total of 42 building archetypes. LiDAR data enabled the generation of highly realistic 3D building envelopes, thereby enabling more accurate calculations of polygonal geometry and GFA compared to non-spatial analytical approximations (Schandl et al., 2020). This helped capture more accurately the spatially heterogeneous patterns of building types, construction materials, and construction periods in the study area. Overall, this method provides insights that can inform sustainable urban planning, resource management, and decision-making processes, such as cities' targets toward net-zero emission and a circular economy.

Working with LiDAR data for generating building footprints is computationally demanding. Advancements in computing, automated 3D workflows, and cheaper LiDAR surveys, are making large-scale digital representations of cities increasingly accessible (Bonczak & Kontokosta, 2019). For instance, photogrammetry science is introducing alternatives for highly accurate 3D modeling of urban features using cost-effective sensors (Dostal & Korth, 2022). However, our modeling approach allows the replacement of model components when better or cheaper information becomes available.

4.2 | Applications and implications

Our algorithm can estimate spatial patterns, composition, and age of the urban building stock. With such information cities can create more targeted policies to promote sustainable configurations of the built environment and identify areas of intervention. Intra-city material demand variation calls for tailored policies. Areas with high material stock may benefit from policies on refurbishment, whereas those with rising populations may necessitate sustainable practices in new developments. Our model could help inform the environmental and material implications of urban footprint changes, such as transitions to compact or net-zero emission cities.

The findings indicate that Canberra's building stock largely consists of single and semi-detached houses, collectively contributing to a high material and environmental footprint. Thus, stakeholders in the residential building sector should consider measures to mitigate embodied environmental impacts.

Population growth and building renewal in Canberra will heighten demand for materials like ceramics, concrete, steel, and timber, which dominate the city's material and environmental footprint. Governments at various levels could incentivize carbon reduction in building materials through abatement incentives (Green Building Council of Australia & Property Council of Australia, 2019). Promoting sustainable materials, eco-friendly construction methods, and efficient land use can help decouple urban growth from environmental harm. For instance, using low energy-intensive construction materials such as "green steel" could help significantly reduce buildings' emissions (Muslemani et al., 2021; Wang et al., 2020).

Our analysis shows how urban growth patterns, such as urban sprawl and compact cities, could impact urban material and environmental footprints. It suggests that urban intensification could mitigate the environmental impact of building stock expansion. Urban intensification is often promoted as a way to reduce travel times, car dependency, energy and material consumption, and pollution, facilitate social interactions and spare green areas (Bibri et al., 2020). Dense cities may alleviate certain sustainability concerns but could adversely affect others, like per capita access to city services or green spaces (Neuman, 2005; Schandl et al., 2020; Williams, 1999). Urban intensification could strengthen urban heat island effects, increasing ambient temperature more than climate change (Huang et al., 2019). Therefore, adequate management of urban intensification impacts and infrastructure and associated services is needed to ensure net benefits for urban dwellers (Williams, 1999).

4.3 | Limitations and future research

While our estimates aim for robustness, greater accuracy could be achieved with more detailed information on each building's construction period or significant refurbishment dates. Our projections omit recurrent embodied materials—such as carpets with short service lives—that require multiple replacements over a building's lifespan. This could notably influence life cycle estimates of embodied material and environmental footprints (Rauf & Crawford, 2015).

Our analysis excludes operational and end-of-life impacts like demolition and waste management, which have notable implications for energy consumption and greenhouse gas emissions (Martínez et al., 2013). Our analysis implicitly considers material reuse and recycling by assuming a continuation of historical material use reduction trends. Explicitly modeling circular economy strategies across various life stages of buildings could further mitigate resource use and environmental impact (Hossain & Ng, 2018). Future scenarios could explore the effects of shifts in building codes, regulations, lifestyle, and demographics on building designs and their associated material and environmental footprints (Ucci, 2010).

Although LiDAR data is costly and often limited to small areas (Haberl et al., 2021), such technology allows highly accurate generation of building models and GFA estimation (Schandl et al., 2020). Our approach could be adapted to use 3D building models derived from digital aerial photography or satellite imagery (Caccetta et al., 2016; Esch et al., 2022). Material use and environmental footprint data based on local building information could also improve the accuracy of our results.

5 | CONCLUSION

We demonstrated a methodology for high-resolution, city-wide mapping of buildings and their material and environmental footprints. This approach allowed a baseline assessment of material stocks and projection of material flows for several urban growth scenarios. The algorithm enabled the exploration of spatial patterns of material intensity indicators, for example, material use per capita, GFA, at any spatial scale within city boundaries and for different building materials.

Growth patterns, such as urban sprawl and compact cities, impact the material and environmental footprints of cities. Most of Canberra's building stock is composed of single and semi-detached houses, which collectively have a high material and environmental footprint. This points toward the need for mitigation measures in the residential building supply chain. The analysis indicates that, under current construction and usage trends, Canberra's material stock could double by 2060, even when accounting for material use efficiency trends. The results also show that urban growth based on high-rise buildings has a lower material and environmental footprint than development based on low-rise buildings or single and semi-detached houses. Urban intensification could help reduce the environmental burden of expanding the building stock, but it also requires careful management to balance other sustainability concerns. Our modeling approach can serve as a support tool in urban planning decision making for other local authorities. It can help them spatially identify high-priority areas of policy intervention and support improvements in building regulations, building material selection, urban planning, and waste management.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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NOTE

[1] Mesh blocks are the smallest geographic area used by the Australian Bureau of Statistics to report population and housing data across land uses such as residential, commercial, primary production, and parks.

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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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