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MaterialCities: mapping building material stocks and floor area of the world's 1.8 million settlements by structures and functions

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Abstract

MaterialCities is a dataset of the gross floor area and the mass of eight construction materials of the world's buildings in high resolution and detail. It differentiates floor area and material stocks by three building functions and five load-bearing structural types with region-specific construction archetypes using variant material intensity ranges that capture buildings materials' inherent uncertainties and variabilities. The data is available in five spatial resolutions, from its native data-driven delineation of individual settlements, towns, and cities to two levels of subnational administrative boundaries, individual countries, and two levels of global regional aggregations. It is the first global-scale high-resolution dataset of its kind to provide floor-area derived material stock estimates for detailed building archetypes. The data are provided in the GeoPackage format for use in geographic information systems (GIS) and as comma-separated value (CSV) tables to be easily filtered and recombined for ease of use. MaterialCities has many use cases including comparative assessments of buildings' service provisioning, material requirements, energy consumption, and environmental impacts, quantifying the urban mine of secondary materials or building stocks at risk from disasters, and as baselines for future development scenarios.

Background & Summary

Material stocks form the basis of modern society, foundational to the creation and maintenance of shelter, transport, energy transmission, manufacturing facility and other societal services. Recent decades were marked by steady growth in global in-use material stocks and the extraction of raw materials required to support this expansion^{1,2}. Material stocks embodied in buildings, infrastructure, and other products deliver many tangible services to society, accounting together for over 90% of anthropogenic material stocks². Yet material extraction and production also generate negative impacts to environmental systems and human health³⁻⁶.

Studies of material stocks have become increasingly common, supported by more comprehensive and openly available spatial datasets of buildings and transport infrastructure⁷. As buildings are immobile and their locations can be captured through various surveying and remote sensing techniques, many studies can now spatially map their material stocks at increasingly high resolutions. The value of material stock estimates mapped at high spatial resolutions, or ‘resource cadasters’⁸, derives from their potential to provide improved local estimates of material stocks, urban resource mines, and material inflows and outflows for closing material cycles at the local level⁹. Resource cadasters that include building attributes such as function, age, or vacancy inform assessment of their roles in environmental impacts¹⁰, local socioeconomics and disparities^{11,12}, and urban form¹³⁻¹⁵. The inclusion of such attributes enables more informed estimates of evolution of building and material stocks into the future and recreation of historical patterns^{16,17}. The growth of spatial resource cadasters¹⁸ can support assessment of approaches for more efficient lifetime extension and re-use of existing materials, and reduction of primary material requirements and associated environmental impacts.

Material stock studies cover widely varying scopes and levels of details, prioritized by the individual study’s objectives and data availability limitations. Building archetype classification is one example^{19,20}. Some studies²¹⁻²³ differentiate buildings by their functions (e.g. residential, commercial, industrial) at various levels of classification detail, which is important for the assessment of the roles of buildings in society. Other studies^{24,25} focus more on engineering issues and differentiate buildings by their construction technology or load bearing structure, and these different ways to categorize buildings and their materials have already been pointed out as limiting transferability and comparability²⁶. Though some studies correspond specific structure types to specific end-use functions^{27-30,15}, only a few studies cover a full possibilities space of function and structure type combinations^{31,32}. Another dimensionality of detail is buildings’ material compositions by age or period of construction^{21,29,32,33}, which can improve

assessments of the urban mine and forecasts of renovation and demolition waste flows. However, many studies cannot make that differentiation^{9,12,27,28,30,34–36} even when covering a time series of the evolution of the building stock^{27,37,38}, often due to data limitations.

On the spatial dimension, there are wide variations in both scale (the scope and geographical boundaries) and resolution (the level of spatial detail captured within the boundaries being studied). The varying resolutions across studies is exemplified by Germany's building material stocks, which have been assessed as a single object of the entire country^{39,40} through its subnational administrative regions¹⁰ and built-up areas⁴¹ to fine-scale grid resolution⁹. These material stock estimates are not always in full agreement, and the importance of more exact mapping of where are the material stocks for assessments of future developments has been noted¹⁰. Indeed, material stock studies range in scope from neighborhood and city districts material stocks^{37,42}, individual cities^{11,30,31,33,35,36,43–45}, entire countries^{15,28,34,46–53}, to continents^{17,41,54}, in varying levels of resolution. There have been many more high-resolution material stocks studies of developed economies including China compared to locations in the Global South^{8,19}.

Material stock assessments that cover the entire world tend towards optimizing one level of detail over others. For example, some remain at a coarse spatial resolution of entire global regions or major countries but capture the growth of global building material stocks over long time periods^{55–57}. On the other hand, high spatial resolution assessments at the global scope exhibit a tradeoff with other levels of detail. Traditionally, such research assesses where and how much material stocks through conversion of remote sensing data, benefitting from the high spatial resolution of such data sources, but not distinguishing the specificities of the materials' end-uses, i.e. in what types of buildings and infrastructures^{58–62}. Recently, extremely high resolution mapping of building material stocks were achieved with their own tradeoffs. Haberl et al.⁴⁶ achieved an of 90m² of material stocks distinguishing five types of building functions, yet linked to the volume (m³) of buildings, not to floor area – buildings' fundamental unit of service provisioning – and by extension to the societal services they provide. Foong et al.'s 10m² resolution does link to floor area yet covers only the residential building stock, omitting certain classes such as non-residential uses⁶³. Both of these studies' building typologies focus on functions without discerning structural types, and their primary results are point estimates rather than ranges of values, dimensionalities that can better capture the variability inherent to buildings.

Though not an exhaustive review of the state of the art, these works demonstrate the diversity of material stock studies, pointing to tradeoffs in levels of detail and a gap of global data describing magnitude, variance, and spatial distribution of construction materials in buildings linked to their floor area as the key service provisioning unit⁶⁴, and distinguishing buildings by both function and structural types – key factors determining the utility, lifespan, and material efficiency of buildings^{65,66,20}.

Here we describe MaterialCities, a new dataset of the floor area and construction materials embodied in buildings with global coverage, detailing three building functions, five building structural types, and eight construction materials. The estimates are provided in multiple spatial resolutions, with the highest resolution covering 1.8 million contiguous human settlements. Within building function-structure type combinations, the masses of construction materials are estimated independently five times using material intensity variants that produce a distribution of values of material stocks, detailing the inherent variability and estimation uncertainties related to building material intensities. The temporal coverage is circa 2020, reflecting the coverage of its data sources. This dataset is based on fully open data and can be recreated with the computational power of a standard personal computer, so that it can be updated once its data sources receive updates. Numerous applications of the dataset are envisaged, including comparative assessments of material stocks across geographical entities and regionally dominant construction methods and materials, hazard assessments estimating construction rubble from natural disasters and human conflicts, estimating the material basis of service provision in buildings, and inequalities within and across regions in per-capita material stocks. While material stocks are the primary focus of this dataset, the calculations of floor area in various structure types and for different functions are themselves valuable datasets. Built floor areas are important indicators for understanding a range of social, economic and environmental measures from housing service provided to infrastructure value^{67,68} – including vulnerability to natural and human made extreme events^{69–71}, cost to energy use⁷², consumption of consumer goods⁷³, and their future developments⁷⁴. The methods and data herein provide valuable information to these fields as well.

Methods

Spatial units of data

The basic geographical units of MaterialCities are data-driven spatial polygon units that correspond to the shapes of built-up areas, termed Nighttime Light Cells (NLCs). Under this approach, nighttime lights – and darker areas around them – are used for edge detection to identify the cores and define the boundaries of independent spatial units. By applying hydrological analysis tools commonly used for identifying watersheds, the lights levels data are treated as topographic landscape features, with low and high values representing inverted ‘craters’ and ‘mountains’ of building intensity, respectively. ‘Watersheds’ are then identified, each of which corresponds to a distinct built-up core and its surrounding area of related human activity. This approach to defining spatial units for settlements’ material stock assessment is described in further detail in Peled et al.⁴¹.

Each of the resulting NLC polygons therefore represents an individual built environment, independent of political administrative boundaries. In some cases, a big city might be

identified as multiple NLCs of its various local cores, and in other cases two conjoined municipalities might be identified as a single NLC reflecting natural conurbation processes. The one-to-one representation of a settlement as an NLCs thus attempts to minimize avoidable spatial boundary definition issues such as the modifiable areal unit problem and scale effects which could deteriorate estimation accuracy and precision. This characteristic also makes NLCs preferable over uniform fixed-sized spatial grids (e.g. raster cells) whose arbitrary sizes and boundaries lead to similar issues of cutting through settlements or artificially aggregating them.

The nighttime lights data are sourced from the Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light datasets from the Earth Observation Group (<https://payneinstitute.mines.edu/eog/>). Annual VIIRS nighttime light (VNL) values were derived from the Annual VNL V2 product⁷⁵. Preprocessing of the data involved countering any potential outliers and reduction of temporal variability by using median annual values for the years 2014-2021 with a global correction algorithm⁷⁶. The nighttime light values were log-transformed in order to enhance the discernment of built-up areas⁷⁷. The NLCs were created using the Watershed Segmentation algorithm using the SAGA software⁷⁸. In total, 1,790,264 NLCs representing individual centers of human activity and settlements were created, with an average area of 6.16 km² and covering a total of over 11 million km² of land area. In MaterialCities, the nighttime lights data are solely used for the demarcation of the NLC polygon shapes, unlike previous studies^{41,79,80} which also used the radiance values of the nighttime lights to estimate the amount of floor area or other material stocks within the spatial units' boundaries.

Material stock estimation using buildings inventories and material intensities

The material stocks MS in each NLC are classified by material m , variant intensity p , within buildings of function f and structure type s . These material stocks, in kg, are the product of each NLC's inventory of buildings' gross floor area (GFA), expressed in m², and corresponding representative regional material intensities (MI), expressed in kg/m²:

$$MS_{NLC,f,s,m,p} = GFA_{NLC,f,s} \times MI_{R,f,s,m,p} \quad (1)$$

The data requirements, sources, and calculations of the floor area inventories and MIs are described in the following sections.

Buildings floor area inventory

Reference and validation datasets of gross floor area

We compiled 16 local built-up gross floor area datasets for reference with our world-encompassing gross floor area estimation. 12 of these were used for calibration of the

estimations, and 4 for validation. These 16 reference datasets were chosen based on the following criteria, and their sources are listed in Table 1:

1. Derived from separate sources: in order to test the robustness of our estimation, we chose building datasets that were compiled using different methods (e.g. Governmental building registers, LiDAR)
2. Minimal Level Of Detail (LOD) of 1.1, corresponding to the outline of individual buildings and/or building parts for enhanced accuracy ⁸¹.
3. Temporal coverage as closely as possible to the years of the data used in our estimation (2014-2021).
4. Representing different settings across the world including urban, suburban, and rural areas of various sizes and geographic and socioeconomic characteristics. While many building datasets are from developed economies, an effort was made to cover a diverse extent while maintaining the aforementioned criteria.

Table 1: local GFA reference datasets for calibration and validation

Location	Sources	Comments	Temporal coverage	No. of NLCs covered
Reference datasets				
Bordeaux, France	⁸²	LOD1.3	2021	770
Chicago, USA	^{83,84}	Height and building footprints originate from separate sources	2017	14
Edmonton, Canada	⁸⁵	LOD1.2	2019	62
Flanders, Belgium	⁸⁶	LOD1.2, based on LiDAR data gathered from the DHMV II dataset.	2013-2016	1,304
Los Angeles, USA	⁸⁷	LOD1.2	2017	481
Lyon, France	⁸²	LOD1.3	2021	32
Medellín, Colombia	⁸⁸	LOD1.2	2023	7
Nagoya, Japan	⁸⁹	LOD1.2	2020	15
New York City, USA	⁹⁰	LOD1.3	2014	83
Osaka, Japan	⁹¹	LOD1.2	2020	11
Sapporo, Japan	⁹²	LOD1.2	2020	25
Tallinn, Estonia	⁹³	LOD1.3	2021	259
Validation datasets				
Bogotá, Colombia	⁹⁴	LOD1.2	2021	36
Montpellier, France	⁸²	LOD1.2	2021	38
Warsaw, Poland	⁹⁵	LOD1.2	2017	218
Yokohama, Japan	⁹⁶	LOD1.2	2020	34

The 16 data sources listed in Table 1 contain buildings' ground footprints and heights. Structures with a height below 2 meters (such as sheds) were deleted from the datasets. To convert them into gross floor area reference datasets, the heights were divided by a

floor-to-floor height factor of 3.7 meters. This value was calculated from the building height and number of floors of a random sample of 10,000 buildings of different sizes and uses from across the world that contain both of these data attributes in OpenStreetMap⁹⁷. We then overlaid the NLC boundaries that spatially correspond to the areas of each reference dataset (cf. the right column of Table 1), and calculated the sum of gross floor area of all buildings in each NLC:

$$GFA_{NLC,reference} = \sum_{i=1}^n A_i \times \frac{H_i}{3.7} \quad (2)$$

where i is an individual building in a *reference* dataset inside the boundaries of a *NLC*, A_i is its ground area in square meters and H_i is its height in meters. Where buildings straddle the boundaries between two or more NLCs, the shares of GFA of the building was allocated by the relative ground area of each building within each of the neighboring NLCs.

Estimation of global gross floor area

For the global-scale dataset, the inventory $GFA_{NLC,f,s}$ is the total m² of gross floor area of each NLC's buildings, differentiated by their function class f and structure types s . First we calculated GFA_{NLC} , the total gross floor area of all buildings in each NLC, and then split this by each NLC's unique ratios of functions and structure type combinations.

The total undifferentiated gross floor area of all buildings in each NLC, GFA_{NLC} , was estimated with equation 3:

$$GFA_{NLC} = BUFRAC_{NLC} \times H_{NLC,h} \times \alpha_h \quad (3)$$

Where $BUFRAC_{NLC}$ is the horizontal factor of the ground footprints of buildings within each NLC, $H_{NLC,h}$ are the vertical average building height factors within each NLC, and α_h is a conversion and rescaling factor.

The source data for $BUFRAC_{NLC}$ are a global 10m resolution built-up surface area dataset for the year 2018, the GHS-S raster dataset⁹⁸ from the Global Human Settlement Layer (GHSL) project. We used its built-up fraction (BUFRAC) estimates which represent the percent of built-up surface within each grid cell. For calibration and removal of built-up land area other than buildings, such as transport infrastructure, we compared this GHSL BUFRAC data with the corresponding building polygons' total ground area in the twelve independent reference case study data sets. This comparison yielded a best match for GHSL BUFRAC cells with values of 35 and higher. We then summed only these cells in each NLC (implicitly assigning cells with $BUFRAC < 35$ a value of zero building land area), resulting in a NLC-scale $BUFRAC_{NLC}$ value of the land area covered by buildings.

$H_{NLC,h}$ captures the vertical dimension of floor area, i.e. above-ground building stories. Two independent sources (indexed h) of building height data are available and we therefore calculated two competing assessments of the average building height factor of each NLC, $H_{NLC,h}$, from each of these global building height datasets. The two sources are the World Settlement Footprint 3D (WSF3D) dataset ⁹⁹ which contains average building heights with a geometric resolution of 2.8 arcsec (~90m) for the year 2019; and the GHS-H dataset ¹⁰⁰ from the GHSL project, which contains the average building height at a resolution of 100m for the year 2018. Both of these datasets are rasters that describe the average height of buildings within each of their grid cells. These two data sources have unique idiosyncratic spatial resolutions, scope of coverage, units, and other characteristics that may not be related to actual building properties. For these reasons, they don't directly equate to "bottom-up" estimates obtained from individual building polygons data, such as the twelve calibration datasets. Averaging the values of the grid cells within each NLC, Most of the $H_{NLC,h}$ values range between 0 – 7.6 with a median value of 3.02 for the WSF3D, and 0 – 4.02 (median of 2.5) for the GHSL, with few higher-valued outliers. $H_{NLC,h}$ therefore represent the relative differences in average heights between NLCs.

The factor α_h rescales and converts the product of $BUFRAC_{NLC}$ and $H_{NLC,h}$ into units of m² of floor area. These α_h factors inherently include the rescaling and conversion from relative heights to average number of floors, and correcting for the idiosyncratic characteristics of each data source. We calculated a α_h factor for the products obtained with each building heights dataset h using OLS regression against the twelve calibration datasets with the intercept set to zero. The regressions yielded values of $\alpha_{WSF} = 22.053$ and $\alpha_{GHS_H} = 15.536$. From the two assessments of $H_{NLC,h}$ and α_h , we preferred the GFA_{NLC} results with $h = WSF3D$ because they proved to replicate the four validation datasets' $GFA_{NLC,reference}$ values more accurately, both for the entire datasets' coverage (Table 2) and per dataset (Figure 1). However, the WSF dataset's spatial coverage covers 98.4% of all NLCs, so the remaining 1.6% of NLCs – mostly remote settlements with few buildings spread across the world – use the GFA_{NLC} with $h = GHS_H$. The sum total gross floor area of the world is estimated to be 1.127 trillion (10¹²) square meters.

Table 2: Goodness of fit statistics of the gross floor area calibration and validation regressions. RMSE = Root Mean Square Error, MAPE = Mean Absolute Percentage Error.

	Regression models to estimate α_h (N = 3063 NLCs in 12 calibration locations datasets)		Validation of α_h (N = 326 NLCs in four validation locations datasets)	
Dataset h	WSF3D ⁹⁹	GHS-H ¹⁰⁰	WSF3D ⁹⁹	GHS-H ¹⁰⁰
Estimated value α_h	22.053	15.536		
RMSE	750,988.945	1,827,748.153	1,020,181.172	1,524,706.730

MAPE	33.637	48.471	67.904	43.284
R ²	0.969	0.816	0.944	0.876

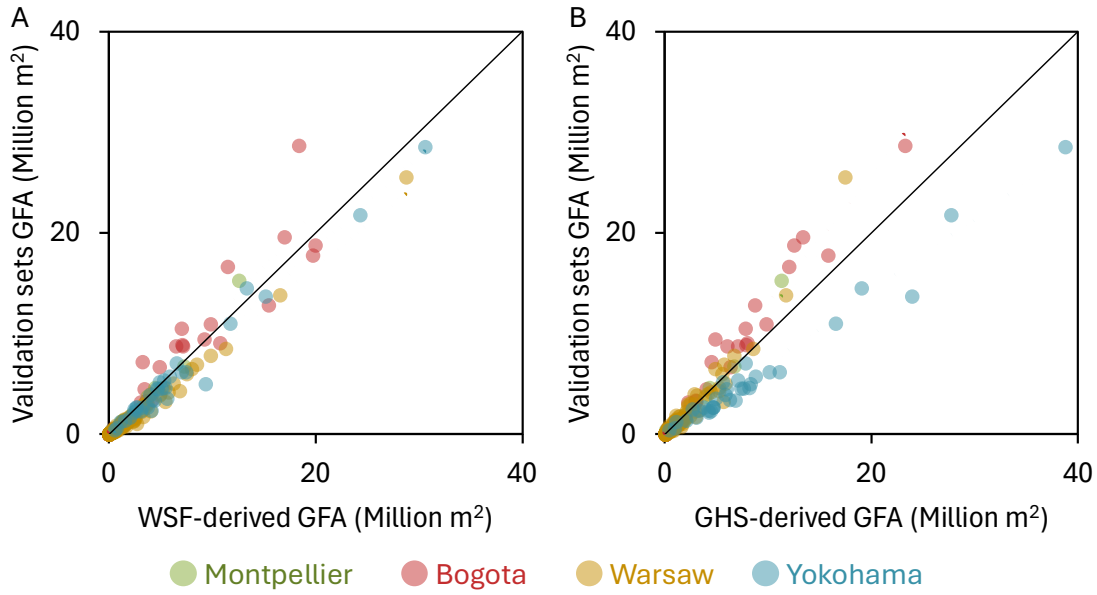


Figure 1: comparison of the two Gross Floor Area (GFA) estimations to the four validation locations datasets. Each scatterpoint is an NLC. The WSF-derived estimates (panel A) perform better than the GHS-derived estimates (panel B), as evident by the individual locations' regression lines slopes and the overall scatterpoints' closeness to the 1:1 diagonal.

Differentiation of gross floor area by function and structure types

We differentiate 15 function-structure combinations of buildings: three building function classes f – non-residential (NR), residential multi-family (RM), and residential single-family (RS) – each differentiated into five structural construction types s : reinforced concrete structures (C), masonry structures (M), steel frame structures (S), timber construction (T), and unspecified construction (U) that represents informal, indigenous, and other construction styles.

The total gross floor area of each NLC is split into the 15 function-structure combinations using NLC-specific ratios (equation 4):

$$GFA_{NLC,f,s} = GFA_{NLC} \times function_ratio_{NLC,f} \times structure_ratio_{ADM,f,s} \quad (4)$$

The $function_ratio_{NLC,f=NR,RM,RS}$ for each NLC were created by first obtaining non-residential, residential, and non-built areas ratios from the GHS-MSZ¹⁰¹ land use raster data, summed and normalized to the land area of each NLC. Then we further split the residential fraction into single and multi-family fractions by classifying the GHS-MSZ dataset's discrete building height categories to single and multifamily uses. We treated

residential raster grid cells of the lower two categories (below 3 meters and between 3-6 meters) as entirely representing single-family buildings. We divided each of the remaining three categories (residential buildings between 6-15m, 15-30m and above 30m) into single and multi-family residential use fractions by comparing them to a random global sample of 66,467 buildings from OpenStreetMap ⁹⁷ that include function information (either ‘house’ or ‘detached’ values), to obtain a representative single- to multifamily usage distribution for each height category (Table 3). These were then summed and normalized to the total residential area of each NLC.

Table 3: Classification of single and multi-family residential buildings according to height categories.

	GHS-MSZ residential building height category		
	6m < height <= 15m	15m < height <= 30m	height > 30m
Single-family share	59.8%	8.9%	0.5%
Multi-family share	40.2%	91.1%	99.5%

The $structure_ratio_{ADM,f,s}$ for both residential and non-residential construction are based on ratios from the Global Exposure Model (GEM) ¹⁰². The GEM has a rich building taxonomy classification system ¹⁰³ covering all countries of the world except the United States and Canada, for which it uses the HAZUS ¹⁰⁴ building classifications. We mapped these detailed building classification taxonomies to the five construction structural types of MaterialCities (Table 4). GEM includes statistics of building types in the 1st administrative levels of each country (e.g. the states of the USA and of India, Japanese prefectures, Swiss cantons). We use the GIS (Geographic Information System) spatial overlay tool to match the GEM fractions of structure type per function type (i.e. $structure_ratio_{ADM,f,s}$) to the corresponding NLCs. We do not use GEM’s fraction of function types in the overall building stock (i.e. $function_ratio_f$) because the 1st level administrative levels are far less spatially resolved than the resolution obtained with the raster sources detailed in the previous section. We combined GEM’s commercial and industrial functions to MaterialCities’ nonresidential function, and differentiated GEM’s residential function to MaterialCities’ single- and multifamily functions using GEM’s statistics on numbers of floors, dwellings, and occupancy per construction type. The GEM single-floor building type categories are classified as single family in MaterialCities, and the GEM categories of 2-4 floors and over 4 floors buildings are classified as multifamily. For building types that either have a range of 1-4 floors or unspecified number of floors we used the number of dwellings statistics: more than 3 dwellings per building are multifamily, less than 1.5 dwellings are single family, and the values between 1.5 and 3 are converted to single- to multifamily ratios, e.g. a location with 2.25 dwellings per building (the midpoint between 1.5 and 3) corresponds to an equal split between single- and multifamily types; 2.7 corresponds to 80% multifamily, etc. In case the number of dwellings data was not available in GEM, it was estimated from the GEM occupancy statistics and occupants per dwelling statistics from the United Nations ¹⁰⁵. If

occupancy statistics were not available either, then the single family function type of each structure type was assumed to represent smaller buildings of less than 120m².

Table 4: mapping of the GEM and HAZUS building taxonomies to the five structural construction types of MaterialCities. Refer to ^{102–104} for descriptions of the building taxonomy codes.

MaterialCities structural construction types	GEM taxonomy codes for all countries except the USA and Canada	HAZUS taxonomy codes for the USA and Canada
reinforced concrete structures	CR, CR+CIP, CR+PC, MIX(CR-W), MIX(MUR+CR), SRC	C1, C2, C3, PC
masonry structures	M+CB, MCF, MCF+CB, MCF+CBH, MCF+CL, MCF+CLBLH, MCF+CLBRS, MCF+S, MIX(MR+W), MIX(M-ST), MIX(MUR+STDRE+W), MIX(MUR+STRUB+W), MIX(MUR+W), MIX(M-W), MIX(W-M), MR, MR+CB, MR+CL, MUR, MUR+ADO, MUR+ADO+MOC, MUR+CB, MUR+CBH, MUR+CBS, MUR+CL, MUR+CLBLH, MUR+CLBRH, MUR+CLBRS, MUR+MO, MUR+ST, MUR+ST+MOC, MUR+ST+MOL, MUR+ST+MOM, MUR+STRUB	RM1, RM2, URM
steel frame structures	S, S+SL, S+SO, S+SR, SR	S1, S2, S3, S4
timber construction	EWV, MIX(W+EU), W, W+WBB, W+WHE, W+WLI, W+WO, W+WS, W+WWD	W1, W2, MH
unspecified construction	E+ETO, ER+ETR, EU, EU+ETR, MATO, ME, ME+MEO, UNK	

The resulting splits of the global floor area to the 15 structure-function combinations are presented in Table 5.

Table 5: ratios of the 1.127x10¹² m² of global gross floor area to the 15 structure-function combinations. The values in this table are rounded and may not sum to exactly 100%.

	Reinforced concrete structure	Masonry structure	Timber structure	Steel-frame structure	Unspecified or other structure
Residential single-family	16.5%	28.8%	17.3%	0.7%	3.8%
Residential Multifamily	13.7%	8.5%	2.8%	0.4%	0.05%
Nonresidential	3.1%	2.0%	0.6%	1.4%	0.3%

Material intensities

The material intensities $MI_{R,f,s,m,p}$ are sourced from RASMI ⁶⁶, a comprehensive dataset of representative building material intensity coefficients (MIs) of eight construction

materials s used in 12 building function-structure combinations in 32 global regions R . For each region-function-structure-material combination, RASMI describes a range of MI values that embody the variabilities inherent in building construction and uncertainties related to estimation and measurement of MIs. These ranges are quantified as non-parametric percentile values from the MI data in the literature and synthetic data derived by similarity of construction styles across regions. We use the 5th, 25th, 50th (median), 75th, and 95th percentiles variant values, indexed p , to likewise capture the variability and uncertainty of the material stocks, so that every region-function-structure-material combination has five variant estimations of material stocks, labeled $p05$, $p25$, $p50$, $p75$, and $p95$.

Each NLC is matched to one of the 32 global regions R by its location. The RASMI building function f and structure s types are identical to those of MaterialCities. The current version of RASMI doesn't include MIs describing the unspecified structure type due to the insufficient information in the literature on the wide diversity and informality of these building types. This leads to 12 function-structure quantified combinations of material stock estimates in the data version described here. The floor areas of the three GFAs of nonresidential, multi-, and single-family residential functions of unspecified construction styles (ca. 4.1% of total GFA, cf. Table 5) are not converted to material stocks, but for forward compatibility they appear as *NaN* (not a number) in dedicated columns in the material stocks data records, to be filled in future versions when appropriate MI data becomes available.

Aggregation of material stocks to administrative boundaries

MaterialCities is also available as spatial data in multiple levels of political and administrative boundaries for additional ease of use and analysis. These cover higher-resolution 2nd level and 1st level subnational administrative divisions of countries (ADM2 and ADM1, respectively), individual countries and territories (so called 0th level administrative divisions – ADM0), and the 32 global regions and 5 global macro-regions of the Shared Socioeconomic Pathways ¹⁰⁶ (SSP32 and SSP5, respectively).

We use the GADM ¹⁰⁷ administrative divisions polygons dataset which consistently covers the entire world, after removing its polygons of inland water bodies and simplifying the polygon shapes to reduce geometric complexities that increase file sizes. We sum the material stocks of all NLCs of the $p50$ variant data within each administrative division polygon, keeping the differentiation of function, structure, and materials:

$$MS_{ADM,f,s,m,p=p50} = \sum_{NLC \in ADM} MS_{NLC,f,s,m,p=p50} \quad (5)$$

Where *ADM* is the various administrative division levels. The summation from the NLC level to the highest-resolution administrative level (ADM2 or ADM1, whichever is available per country) was done using the GIS spatial join tool to match the administrative level name to the NLC by location, then summing the values of all NLCs in that administrative area and joining these summed values to the polygon shapes of the administrative area. We then reiteratively summed to the bigger levels using the GIS dissolve tool.

For reference, we added human population estimates to each administrative area. The population source is WorldPop¹⁰⁸ gridded data at 30-arc-second resolution (approximately 1 km at the equator). We summed the grid cells whose centroids are within the administrative area polygons. Grid cells whose centroids are outside administrative boundaries, e.g. on a coastline, were assigned to the nearest overlapping administrative polygon and added as well.

Data Records

MaterialCities covers 1,790,264 NLCs of individual settlements, 47,874 2nd-level administrative regions, 3,667 1st-level administrative regions, 251 countries and territories, 32 global regions, and 5 global macro-regions. At the NLC resolution, each location has 600 material stocks estimates differentiated by material, function, structure, and estimate variant, and 15 gross floor area estimates differentiated by building function and structure.

The MaterialCities data at all spatial resolutions are available as a Zenodo data record ¹⁰⁹ in two file formats, GeoPackage (GPKG) files of polygon vector features layers for use in GIS software, and comma-separated value (CSV) files without the geospatial information of coordinates and polygon shapes. A web platform to easily filter and select only required data is also available.

The general structure of the data are wide-format tables. Each row represents a unique location, defined an id number and by location name. The columns detail the quantitative and descriptive attributes of the location, as exemplified in Table 6 for the material stock data. The titles of the columns that describe the main quantitative values of material stocks or of gross floor area follow the naming convention format *materialMSPP_FF_S* and *GFA_FF_S*, respectively, where:

- (in the case of material stocks) *material* is the name of a construction material (8 options): concrete, brick, wood, steel, glass, plastics, aluminum, copper.
- (in the case of material stocks) *MSPP* is the variant *p* of the range of material stocks estimations. For example, MS50 are the p50 material stocks estimations.
- *FF* is the function *f* of the floor area (3 options): NR non residential, RS residential single-family, RM residential multi-family.

- S is the structure type s of the floor area (5 options): C reinforced concrete construction, M masonry construction, S steel frame construction, T timber construction, U unspecified or other construction. As explained in the methods section, the GFA of the U columns are available, but the material stocks in the U columns cannot yet be quantified and are left empty as 'NaN' values for forward compatibility.

The material stocks datasets have 120 columns of material stocks by material, function, and structure, while the floor area datasets have 15 columns of gross floor area by function and structure. These quantitative columns of material stocks or of GFA are summable. The horizontal sum of one row across its columns is the total material or floor area in a location, whereas the vertical sum of rows of one column is the total material or floor area of that structure-function type in a greater region.

The native NLC-level data have 1,790,264 rows (polygons). The material stock data variants ($MS_{NLC,f,s,m,p}$) are provided in five pairs of GPKG / CSV files, with file names nlc_msPP where PP is the variant p . These variant material stock results are in separate files to emphasize that they are alternative estimations of the material stocks and are not summable, and to keep file sizes below 2GB. The gross floor area by each function-structure combination in square meters ($GFA_{NLC,f,s}$) are provided as a pair of GPKG / CSV files with the file name nlc_GFA .

Accompanying the NLC material stocks and floor area data files is the $nlc_ratios_regions_metadata$ GPKG / CSV pair, which have the same row structure and NLC IDs, and their columns contain $GFA_{NLC,f,s}$, the values of the parameters $BUFRAC_{NLC}$, $H_{NLC,h}$, $function_ratio_{NLC,f}$, and $structure_ratio_{ADM,f,s}$, and the full location names and various location code systems from GADM¹⁰⁷ for reference.

The aggregations of floor area and of the p50 variant material stocks to the five levels of administrative and political boundaries are also stored as both CSV and GeoPackage formats. The CSV files are named adm_gfa_REGION and adm_ms50_REGION , where $REGION$ is ADM2, ADM1, ADM0, SSP32, and SSP5. The geospatial data are stored in two adm_ms50 GeoPackage files that include all five aggregations as polygon vector feature layers. The Zenodo record also contains a codebook CSV file that lists the column descriptions and their units of measurements, summarizing the details described in this data descriptor.

Table 6: general structure of the “attribute table” (non-spatial information) of MaterialCities material stocks datasets, with two examples. Each row represents a location, and the columns represent its quantitative and descriptive attributes.

Attribute	Location_ID	SSP5	SSP32	ADM0_NAME	ADM1_NAME	ADM2_NAME	ADM2_area_sq_km	GFA	concreteMS50_NR_C	...	copperMS50_RS_U	NLC_count	GID_0	...	ENGTYPE_2	population
Sample data from the ADM2 dataset	0	ASIA	PAK	Afghanistan	Badakhshan	Baharak	3003.880436	269817.24	0	...	NaN	3	AFG		District	125386
	:															:
	47873	OECD	EU15	Åland	Mariehamn	Mariehamn	13.53814	1584844	1.16E+08	...	NaN	1	ALA		Municipality	11611.37
description	ID number of the location. The IDs are consistent within each level of resolution across the MaterialCities datasets	Codes of the 5 macro-regions and constituent 32 regions of the SSPs ¹⁰⁶		Full names of the countries and territories (ADM0) and their 1st- and 2nd-level administrative areas of the location, from GADM ¹⁰⁷ , corresponding to the aggregation level (e.g. the ADM0 dataset does not include ADM1_name and ADM2_name columns)			Total land area of the location, in km ²	Total gross floor area, in m ²	120 columns of material stocks, in kg, of each material-function-structure combination. Refer to the main text for description of the column titles' naming conventions			Number of NLCs composing this location, column not included in the NLC-level data	Additional descriptive attributes of the location, including codes (e.g. ISO), type of location, etc. sourced from GADM ¹⁰⁷ . Columns not included in the NLC-level data			Population in number of persons from WorldPop ¹⁰⁸ . Column not included in the NLC-level data

Data Overview

Figure 2 presents a sample of the MaterialCities material stocks data in its various levels of detail, at the native spatial resolution of NLCs. The example uses the eastern Mediterranean basin area because it covers 16 countries and territories belonging to 8 SSP global regions within a relatively small area. For example, one can map and access the material stock data of each of the eight individual construction materials composing the non-residential reinforced concrete structures of this area. It is possible to sum the materials and compare the total masses of non-residential reinforced concrete structures to the non-residential buildings of the other three structure types. This reveals differences in construction styles across countries. For example, countries like Cyprus and the Levantine countries (Syria, Lebanon, Israel, Jordan, and the Palestinian territories) do not have non-residential timber structures, but do use steel-frame structures. In comparison, Turkey uses less steel-frame structures and more timber structures. The material stocks of all non-residential structures can be summed and compared to the material stocks of multifamily and single family functions. Note that the design of Figure 2 should not suggest a hierarchical structure to the data. The MaterialCities data can be spliced and aggregated in any variation of function, structure, and materials, so that materials could also be summed first by function and then by structure types, and similarly for only one or several materials.

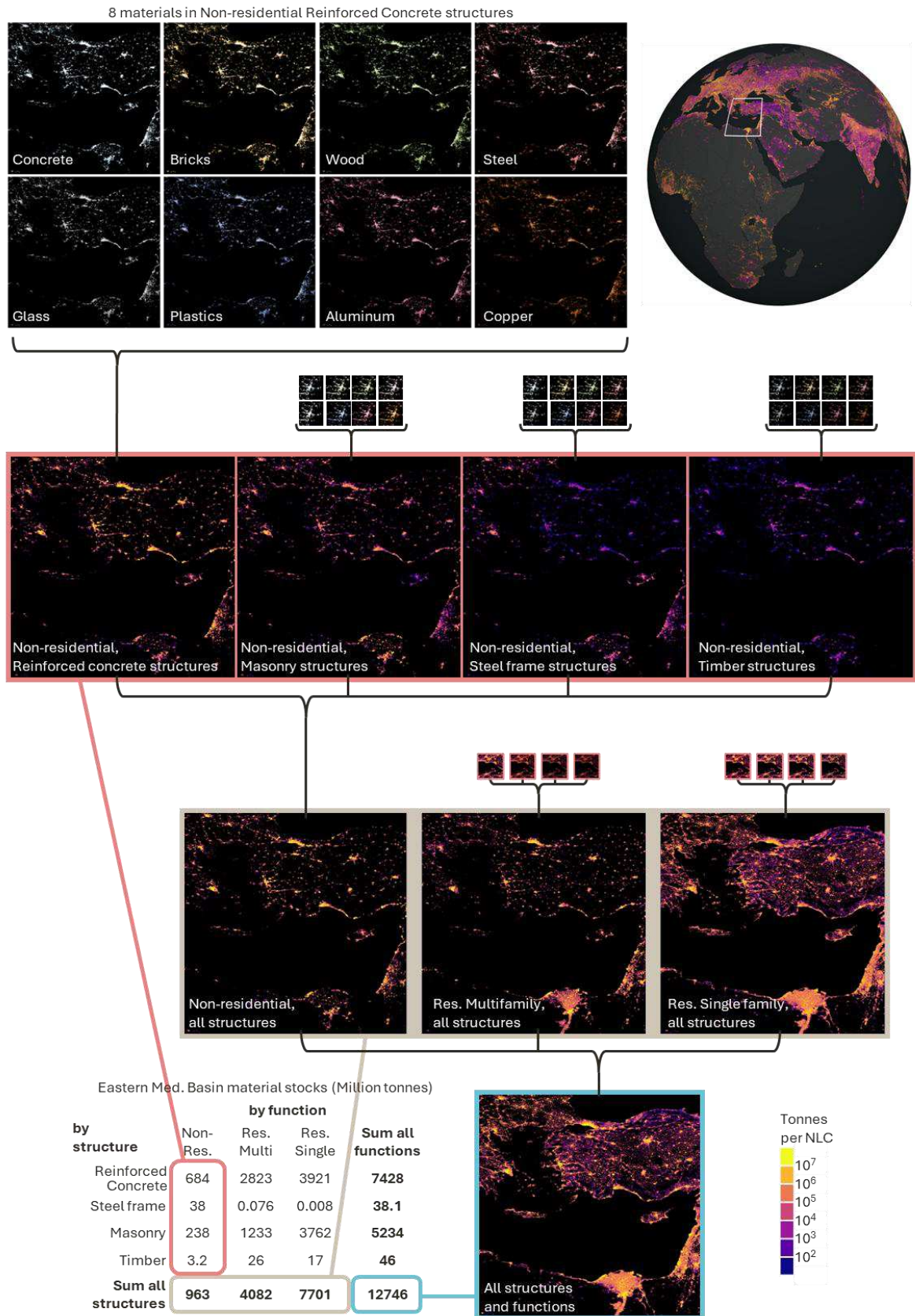


Figure 2: sample of the MaterialCities material stocks data (p50 variant), spliced and aggregated in various combinations of materials, structure types, and functions, using the eastern Mediterranean basin as an example. Note the logarithmic scale of the legend.

Technical Validation

We compared our MaterialCities material stocks data with findings from 30 previous studies^{9,21–23,27–35,40,44,48–51,54,55,110–118} that cover a variety of spatial scales and geographic regions, from city-level analyses to global assessments (Figure 3). Reflecting the diversity and ad-hoc nature of the building material stocks literature, each of the compared studies encompasses different building materials as well as construction typologies and functions of residential buildings, non-residential buildings, or a combination of both, culminating in 122 data points of various material-typology-scope combinations. Comparison with the high-resolution global-scope material stock estimates of Haberl et al.⁴⁶ and Foong et al.⁶³, is not done because they share substantial underlying data sources with MaterialCities and are therefore not independent of each other, whereas Sun et al.⁶² cover materials regardless of end-use, not only in buildings. Since the boundaries that we use may differ from the compared studies – which don't always precisely spatially define their geographical scope – we standardized the evaluation by comparing material stock density (the total material stock of the location divided by its land area, comparable with population density).

Figure 3 shows that the range of MaterialCities building material stocks data, represented by the p25, p50, and p75 variants, are in line with previous estimates despite their studies' varied data sources, methods, scope, resolution, and coverage of building types and materials. There are no patterns of over- or under-estimations that would have indicated systemic accuracy issues. 69 of the 122 compared estimates are within our p25-p75 range. Those that are out of this range are for the most part in the same orders of magnitude. Such discrepancies are common for material stock estimates¹¹⁹. Due to the highly varied aspects and lack of harmonization of previous estimates, discrepancies cannot be attributed to either MaterialCities or the compared studies. This is also evidenced in the few locations that have more than one previous independent assessment, such as Beijing's total materials whose previous assessments straddle the low- and high-end variants of MaterialCities. While these observations serve as a reminder that the accuracy and precision of material stock estimates can only be truly assessed by ground-truthing, the characteristics of MaterialCities' global coverage using a single methodological approach and ranges of values rather than point estimates allow it to serve as a baseline comparison and reasonability check for studies of individual locations.

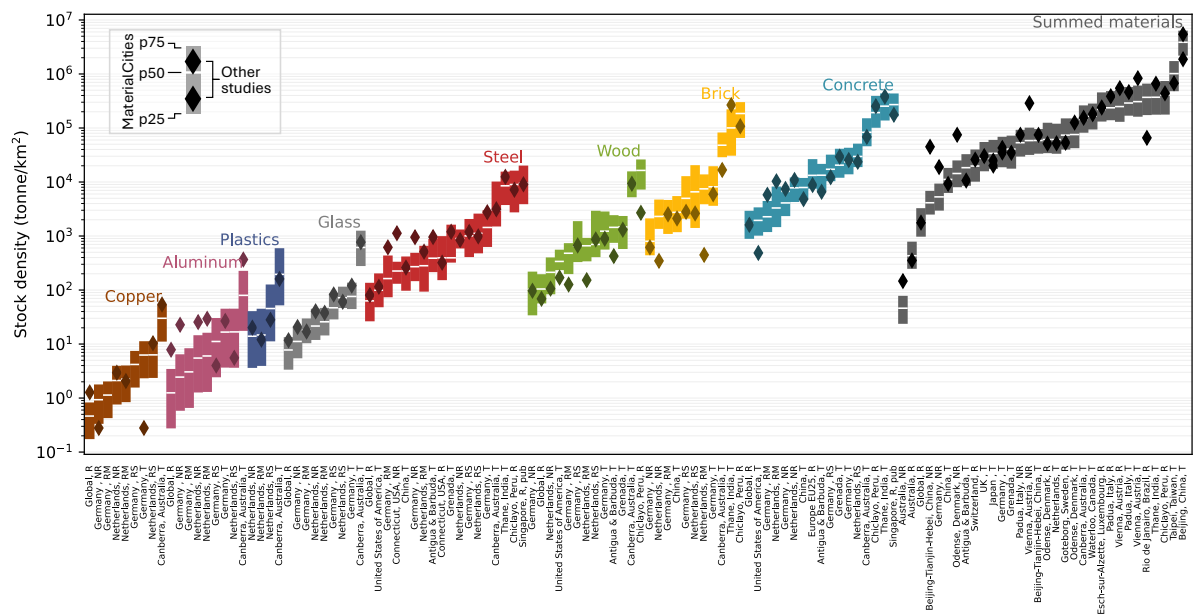


Figure 3 comparison of the MaterialCities building material stock ranges (using the p25, p50, and p75 variant estimates visualized as bars) to previous assessments^{9,21–23,27–35,40,44,48–51,54,55,110–118} (visualized as diamonds). ‘Summed materials’ are studies that didn’t provide values for separate materials, only sums or totals, and we summed the equivalent materials of MaterialCities for this comparison.

Usage Notes

Choosing a spatial resolution

The MaterialCities material stock and floor area data are available at multiple levels of spatial resolutions. The NLC resolution is highest and utilizes data-driven territorial boundaries, whereas the other resolutions utilize formal administrative boundaries. Singhvi et al.¹²⁰ describe characteristic advantages and disadvantages of territorial versus administrative delineations for research on material stocks in the built environment. Furthermore, the choice of which level to use should be done in consideration of the inherent effects of aggregation from the data’s native spatial units (NLCs) to administrative levels, which are often bigger in area than the NLCs. This aggregation to administrative boundaries therefore lowers spatial accuracy due to describing where the material stocks are in a less exact way, and lowers spatial precision due to summing and spreading the values homogenously over the space of the entire administrative area (Figure 4).

We therefore recommend using the NLC-level data to maintain spatial accuracy and precision – especially critical for research questions related to where the material stocks are – and to minimize spatial analysis issues like the modifiable areal unit problem and the scale problem that arise from aggregation and from the arbitrariness often associated with political boundary definitions. For within-city resolutions higher than the NLCs, other datasets are available^{46,63} with tradeoffs in other details as described in the background section.

The administrative levels data are recommended in two types of circumstances. First, they are more appropriate for research objectives that require aligning, linking, and attribution to commonly accepted location definitions, such as transboundary comparisons, combinations with socioeconomic statistics that were compiled by location, or decision-making at a certain administrative or political level. Second, the smaller number of spatial objects at the various administrative levels lead to substantially smaller file sizes and associated computer memory and processing power requirements, leading to ease of use.

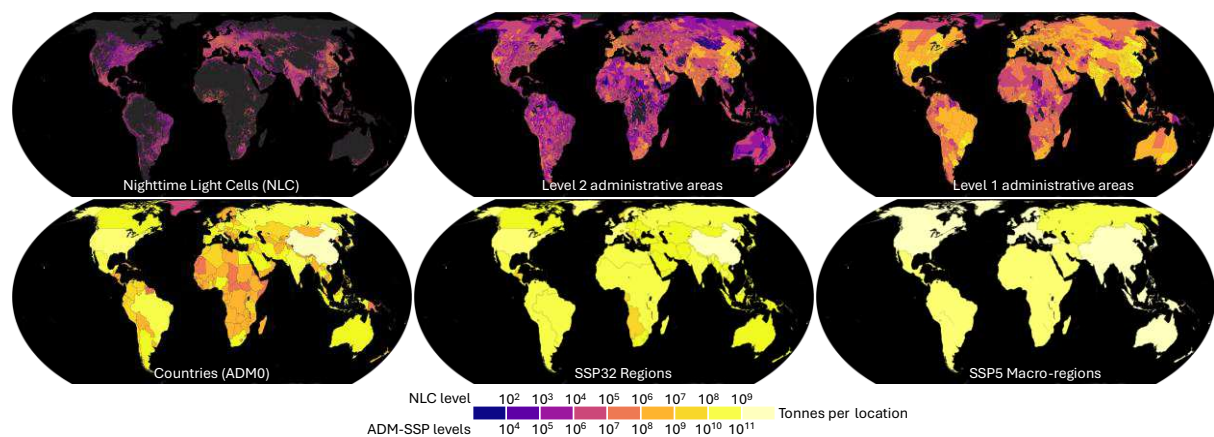


Figure 4: the global MaterialCities data is available in six spatial resolutions: the native spatial units of Nighttime Light Cells (NLCs), two levels of subnational administrative boundaries (ADM2 and ADM1), individual countries and territories (ADM0), and the 32 global regions and 5 macro-regions of the Shared Socioeconomic Pathways ¹⁰⁶. All panels display the sum of all materials in all building functions and structure types, using the p50 variant as an example.

Communicating variabilities and uncertainties using the variants

The MaterialCities data's five variants are meant to be used in tandem. While the p50 variant dataset can be used on its own as the primary point estimate “bottom line” representation of the material stocks of a given location, we recommend also including the pair of the p25 and p75 variants in analyses and for communicating the inherent variabilities and uncertainties of building material stocks, as exemplified in Figure 3. The p05 and p95 pair of variants can be added for further coverage, though these variants may be prone to outliers of material intensities and are less representative. Note that the five variant datasets are not formally descriptive statistics of the building stock because they were not created directly from observations or samples of the stock. It is recommended to refer to the RASMI data descriptor ⁶⁶, the source of the percentiles of material intensity values, for further discussion of the creation, recommended use, and interpretation of these values. In the MaterialCities database, the aggregated administrative levels data are provided based on the p50 values, and users can easily repeat the aggregation methodology with GIS software with the other NLC-resolution variants, as needed for any use.

Data Availability

MaterialCities are available as a Zenodo data record ¹⁰⁹. During the review process, its preview version can be accessed at <https://zenodo.org/records/18327825?preview=1&token=eyJhbGciOiJIUzUxMiJ9.eyJpZCJ6IjE6ImI4MmMwYTlhLTdlMDYtNDgyNS05NzlyLWQyZmE2N2YwNWNkNCIsImRhdGEiOnt9LjYyZW5kb20iOiIxMGQxZjhmZWUzYWNIWZGI3N2ZmNWE2NzYzNjUwMjl5ZiJ9.3YFVtSfjxOJBMmw8Js3Xa5rfNuTI9JAQGA8rSugFF1WoFUY2utHWQTcv4H1ToVDvXauU3mMUQOvvdKpNBFVZiw>.

A web platform to facilitate the access and use of MaterialCities can be visited at <https://b75f04e0-1770-4a9b-bc7e-b60c4d276887.plotly.app/> (demo version). The source code of the platform is also available within the Zenodo record with the full dataset, allowing users to run the platform locally. The platform allows users to filter the MaterialCities by construction material, structure technology and function. Users can then explore the data at the different spatial resolutions and under different variants. The platform generates a table with the user query and offers the opportunity to generate an interactive map (level 0 only for demo) to visualize the query outputs. Each user query output can be download in multiple formats (csv, gpkg, or parquet), allowing for simple access to relevant data for all practitioners.

Code Availability

The MaterialCities data were created stepwise using Geographic Information System (GIS) tools and database edits, as described in the methods section. The source code of the interactive web platform is available within the Zenodo repository with the full dataset, allowing users to run the platform locally.

Author Contributions

Conceptualization: TF, YP, NY, HT. Methodology: YP, TF, HT. Data Curation: YP, TF, JvO, AM. Software: YP, TF, JvO, NN. Validation: JvO, TF, UCM, PB, NN, TW, AM, NY, HT. Formal analysis: TF, YP, JvO, PB, UCM, NN, TW, AM, NY, SS, HT. Writing - Original Draft: TF, YP, JvO, PB. Writing - Review & Editing: UCM, NN, TW, AM, NY, SS, HT. Visualization: TF, YP, JvO, UCM, NN, TW. Project administration: TF. Funding acquisition: TF, TW, AM, HT. Artificial Intelligence (e.g. large language models) were not used in any kind of way in the writing of this manuscript.

Competing Interests

The authors declare no competing interests.

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