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RESEARCH

Enhanced material stock accounting by predicting building structures with morphological indicators

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Abstract

Material stocks (MS) represent the amount and composition of construction resources embodied in the built environment, and are critical to understanding long-term resource use, waste generation, and circular economy strategies. The reliability of building MS modelling depends largely on the appropriateness of archetype classification, with building structure being a key descriptor as it reflects the core materials used. Yet, structural information is often missing from building inventories, particularly in Europe. In contrast, building features such as shape (e.g., GIS polygons), age, and height can be derived from increasingly widely available data. This study develops and tests a model that predicts building structures based on building features—particularly morphological features, using Gothenburg as a case study. A dataset of 331 multi-family residential buildings was compiled, combining building features with manually identified structural types. Multinomial logistic regression was applied to examine the relationship between building features and building structures. The results show that morphological indicators and building age significantly influence structural prediction, with building height and age exerting the greatest impact. The model demonstrated strong predictive performance, with an accuracy of 83%. Based on the predicted building structures, we estimated the MS of multi-family buildings in Gothenburg, amounting to a total of 17.2 megatons, with an uncertainty from structure classification amounting to 5.8 megatons. This study supports the enrichment of building inventory with structural information, thus supporting a more robust accounting of MS.

Keywords Material stock · Residential building · Prediction model · Morphological indicators · Building structure · Industrial ecology

Abbreviations

CMF	Concrete multi-family building
FA	Footprint area
FSI	Floor space index
GFA	Gross floor area
GSI	Ground space index
MF	Multi-family
MI	Material intensity
MMF	Masonry multi-family building
MNLR	Multinomial logistic regression
MS	Material stock(s)
PA ratio	Perimeter-area ratio
PP ratio	Points-perimeter ratio
SF	Single-family
WBMF	Wooden-brick multi-family building
WSF	Wooden single-family building

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1 Introduction

1.1 Background

Against the backdrop of climate change mitigation and sustainable resource use, the construction material embodied in buildings has become a growing focus of research and policy. These material stocks (MS) function as potential "urban mines," offering considerable opportunities for material recovery and reuse. A systematic assessment of existing MS is critical to inform better management and reuse of building materials (Lederer et al., 2020) and reduce environmental impact such as embodied carbon emissions (Liang et al., 2024; Peng et al., 2021).

The characterization of MS is particularly relevant in the context of the European Union Renovation Wave driven by the urgent need to increase the energy performance of the EU building stock (European Commission, 2020). As buildings undergo large-scale renewal, a clearer understanding of the building MS, including location and quantity, is required to inform circularity strategies—a cornerstone of the Renovation Wave. In the region of Gothenburg, almost half of apartment buildings were built during the 1960s and 1970s as part of the public housing initiative 'Million Homes Program' (BPIE, 2018). These buildings are in urgent need of renovation and high investments are being made to drive this process (Business Region Göteborg, 2016).

Although Gothenburg's residential MS has been estimated previously (Gontia et al., 2019), the results remain too coarse and uncertain to support circular renovation strategies. This limitation can be traced to a key building information that is missing from the city's building inventory, namely building structural information. To frame, this issue more precisely, we succinctly summarize below the existing MS estimation approaches and the central role of archetype descriptors.

1.2 Material stock estimation and archetype descriptors

In general, MS can be accounted using two methods: the top-down (Müller, 2006) and bottom-up approaches (Tanikawa & Hashimoto, 2010). The top-down approach quantifies MS by calculating inflows and subtracting outflows from inventory over time, which relies on highly aggregated statistical data (Liang et al., 2023). Compared to the top-down approach, bottom-up MS accounting offers advantages in terms of spatial representation and object-level specificity (Lanau et al., 2019; Schiller et al., 2017). In the bottom-up approach, building MS are estimated by using the inventory of buildings in a case area and applying material intensity coefficients (MIs—the material mass per dimension unit of building) to all buildings. Since building inventories are often extensive and varied, buildings are categorized into archetypes (Tanikawa et al., 2015) to homogenize the inventory, and MIs are developed for each archetype to convert the physical size of buildings into material quantities. MIs can vary significantly across archetypes and classifying buildings into archetypes that reflect their materiality is crucial.

In MS and MI literature, various archetype descriptors have been used to categorize buildings. Common descriptors include building use (Müller, 2006), building age (Yang et al., 2020), and building structure (Hu et al., 2010). MS studies with large geographic scope also use building location (Marinova et al., 2020). In the literature, other descriptors include height-to-width and number of rooms (Drewniok et al., 2023) and building's relative height (e.g., low-rise, mid-rise, high-rise) (Haberl et al., 2021). However, the choice of archetype descriptors is often severely constrained by the limited information available in building inventories, and the substantial variation of MIs across different descriptors can directly propagate into MS estimation results (Zhang et al., 2022). Therefore, identifying reliable archetype descriptors and establishing methods for their consistent acquisition is essential to strengthen the robustness of MS studies.

1.3 The importance and absence of structural information

To better understand the importance of various archetype descriptors, Zhang et al. (2022) applied a random forest model to assess the importance of four building attributes (building structure, construction year, use type, and region) on MIs and identified building structure as the most influential attribute. Since a building's structure significantly impacts its material composition, developing building archetypes based on their structural information can enhance the reliability of MS accounting. However, this strategy requires building inventories to include the structural information of each building, which is not always the case.

In Europe, building inventories primarily does not include structural information (Heeren & Fishman, 2019; Zhang et al., 2022). Instead, they include building descriptors such as their use (e.g., residential) and construction year, which are then used—for lack of a better alternative—to develop building archetypes (Haberl et al., 2021; Kleemann et al., 2016; Peled & Fishman, 2021). However, these categories do not systematically capture the building's structure and dominant materials. To mitigate the lack of structural information in building inventories, a few researchers have used a building's number of stories as a proxy for its structure. For example, in their study of Japanese buildings, Tanikawa et al. (2015) assigned a reinforced concrete structure to all buildings with four or more stories, while three-story buildings were steel frame, and those with two stories or less were timber. Similarly, in their study of Chinese building MS, Hu et al. (2010) and Guo et al. (2019) assumed buildings of 1–6 stories to have a masonry–concrete structure, and those of seven stories and higher to have a steel–concrete structure. While such assumptions mitigated the lack of structural information, the lack of statistical evidence behind these assumptions make MS results remain uncertain.

1.4 Aim and objectives

Building on these insights, the aim of this study is to develop a predictive model that captures the relationship between building features and building structures, enabling the prediction of structural types for buildings across an entire city. To achieve this aim, we formulate several research objectives: (1) To understand the typical structures that can be found in residential buildings in Gothenburg. (2) To determine which building features (including morphological features) contribute to the prediction of building structure, and in what way. (3) To develop the building structure prediction model and apply the resulting structural information in MS accounting.

2 Literature review

2.1 Predicting building characteristics

Recently, much research has been done around predicting and recognizing various building characteristics. Computer vision and machine learning have been used to identify building surface characteristics. For example, Sezen et al. (2022) collected 1,000 building images and applied machine learning methods for window and door detection. Raghu et al. (2023) developed a fine-tuned image classification model for building facade material detection using GIS and street view imagery. But because it relies on surface-level features, computer vision cannot identify building's structures. Indeed, building structures can seldom be identified from their external appearance. Besides this, machine learning–based approaches typically require large, well-labeled image datasets, which are not always available for structure-related classification at the city scale.

Additionally, some studies have used building features extracted from LiDAR data to classify non-surface building features, such as building use and building age. For instance, Lu et al. (2014) examined 1,510 buildings using LiDAR, incorporating features related to shape, spatial, and land use, to classify buildings into residential and non-residential buildings through machine learning. Tooke et al. (2014) extracted 16 morphological features—such as height, volume, slope, and area—from LiDAR data for 3,282 residential buildings and used a random forest regression algorithm to predict building age based on these features. Despite the significance of the efforts, these attempts didn't extend to the structural aspects of buildings.

2.2 Morphological features and building structures

Morphological features include both urban morphology and building morphology. Building morphological features capture geometric aspects such as height, floor area, and shape complexity, which often imply structural constraints and influence building structural choices (Guo et al., 2019; Hu et al., 2010). For instance, a large floor area requires stronger foundations and support systems to ensure stability, and a high shape complexity usually means a stronger structural design requirement (Pei & Stouffs, 2025; Zhou & Chang, 2021).

Building morphological features have been increasingly applied in MS research. Recent study shows that building morphological indicators can be used to refine traditional building archetypes to reduce uncertainty in MS estimation (Dai et al., 2025). In terms of classification, Zhou and Chang (2021) applied machine learning to predict building structures in Beijing based on morphological and point-of-interest features, achieving 90.6% accuracy. Pei et al. (2026) developed a framework using various machine learning classifiers to categorize structural types based on geometric and functional features in Singapore. However, several limitations hinder the direct application of their frameworks to our research objectives. First, the definition and labeling of building structures remain relatively constrained in terms of both data sources and structural classification scope. Second, the use of machine learning restrains the interpretability of results, which contrasts with our goal of gaining insight into how various factors influence building structure. Third, only building morphological features were considered in their study, without accounting for broader urban morphological context.

Urban morphological features can be operationalized through two main sets of density measures: building density and network density. These density indicators can reflect the functional and morphological zoning (Živković, 2020), which in turn shapes prevailing building structures. However, to our knowledge, no studies in structure prediction have integrated urban morphological features that allow the consideration of buildings as part of a wider urban fabric, rather than simple standalone artefacts.

Building density can be measured with the floor space index (FSI) and ground space index (GSI), respectively. FSI is used to describe the total amount of built floor space in an area (gross floor area, GFA) and GSI describes the division between built and non-built land in an area, from which, a distinction can be made between different building types (Berghauser Pont & Haupt, 2023). Network density is commonly used to measure the importance or connectivity of nodes within a spatial network, reflecting a building's position and role in the urban space or transportation network.

In an urban context, buildings are not isolated entities; their structure and form are often influenced by the surrounding built environment, following Tobler's First Law of Geography (Tobler, 1970). Urban morphological features reveal these interrelationships between buildings and their surroundings, highlighting the statistical associations between local spatial conditions and structural characteristics. Since these interdependencies provide valuable information on structural variation, urban morphological features are incorporated in this study as supplementary predictors of building structure.

3 Material and methods

3.1 Case city and scope of study

Case city As Sweden's second-largest city, Gothenburg has about 609,000 inhabitants, and its population is projected to grow by 16% by 2050 (Stad, 2024). This growth translates into sustained demand for housing, while much of the city's housing stock now requires substantial renovation. In parallel, Gothenburg has adopted ambitious climate and housing goals (Stad, 2015, 2021). Such a combination of rising housing demand, aging building stock, and circularity goals makes Gothenburg a very relevant case for residential MS modeling.

Data availability In Gothenburg, high-quality building archives and spatial inventory data are provided by local authorities. Their use in this study is described in detail in Sect. 3.2. The MI database was constructed using a bottom-up approach based on 34 representative multi-family (MF) building archetypes built in Sweden between 1880 and 2010. The MI values were derived from (1) detailed architectural documentation and (2) material density information for construction components. Importantly, the structural classification scheme adopted in the present study is consistent with that used in MI database (Gontia et al., 2018), ensuring a direct correspondence between building structural types and their associated MI values. In this study, the original MI values were further restructured using the BUD-MI data template to improve material resolution and to ensure consistency with the building-level MS accounting framework (Lanau et al., 2026), without altering the underlying MI assumptions. Additional details on the MI data are provided in Table S3 and S4 in Supplementary Information SI1.

Scope of study In this study, we distinguish residential buildings into single-family (SF) and MF buildings but restrict both the prediction model and the MS accounting to MF buildings. SF building structures are highly homogeneous in Sweden, with approximately 90% of SF buildings were built with a wooden structure in Sweden (Stehn, 2018). Such statistics were confirmed by our archival analysis of building samples in Gothenburg (see Sect. 4.1, and Supplementary Information SI2), which brought us to focus our efforts on better understanding the structures of MF buildings. For MF buildings, the model produces probabilistic predictions of structural types, enabling Monte Carlo simulations to assess how this uncertainty propagates into the MS estimates.

3.2 Methodological framework

The methodological framework of this study is illustrated in Fig. 1. First, we collected data on residential buildings in Gothenburg (Sect. 3.2.1) and extracted building features that may influence structural types. Second, we randomly selected building samples and obtained their structural information from the municipal building archives (Sect. 3.2.2). Multinomial logistic regression (MNLR) was then employed to analyze the relationship between building features and structural types (Sect. 3.2.3), and to develop a predictive model for estimating the structural composition of Gothenburg's residential buildings (Sects. 3.2.4–3.2.5). The predicted structural results were expressed in probabilistic terms and combined with a Monte Carlo approach to calculate the MS of MF buildings in Gothenburg (Sect. 3.2.6).

3.2.1 Development of the residential building database

The residential building database was collected from various sources. The building footprint, building use, building addresses, and property ID (for locating building archive documents), were extracted from the data provided by Lantmäteriet for the year 2024 (Lantmäteriet, 2024). Data on building height, age, GFA and building density type was collected from Berghauser Pont et al. (2019), who statistically clustered the building typologies based on density indicators. This database also includes two density indicators: GSI and network density. GSI, which represents the ratio of building footprint area (FA) to the total area within a defined spatial unit, is derived following Berghauser Pont et al. (2019). Network density, which refer to the total length of street within a specific accessible distance, is calculated using street network data (Stavroulaki et al., 2020) which we retrieved from the Swedish national database.

3.2.2 Building sample selection and characterization

We collected a sample of 400 residential buildings in Gothenburg, manually extracting their structural information from historical archives. This sample size was determined by balancing the requirement for statistical representativeness with the intensive labor required for archival documentation analysis. To capture the diversity of building structures, the population was initially stratified along two dimensions: construction period and density type. Buildings were divided into pre- and post-1950 categories to reflect the widespread adoption of concrete construction in Sweden since the 1950s (Rosenberg, 2018). Density type data was retrieved from the work of Berghauser Pont et al. (2019), who categorize residential buildings in Gothenburg across "spacious low-rise", "compact low-rise", "spacious mid-rise", and "compact

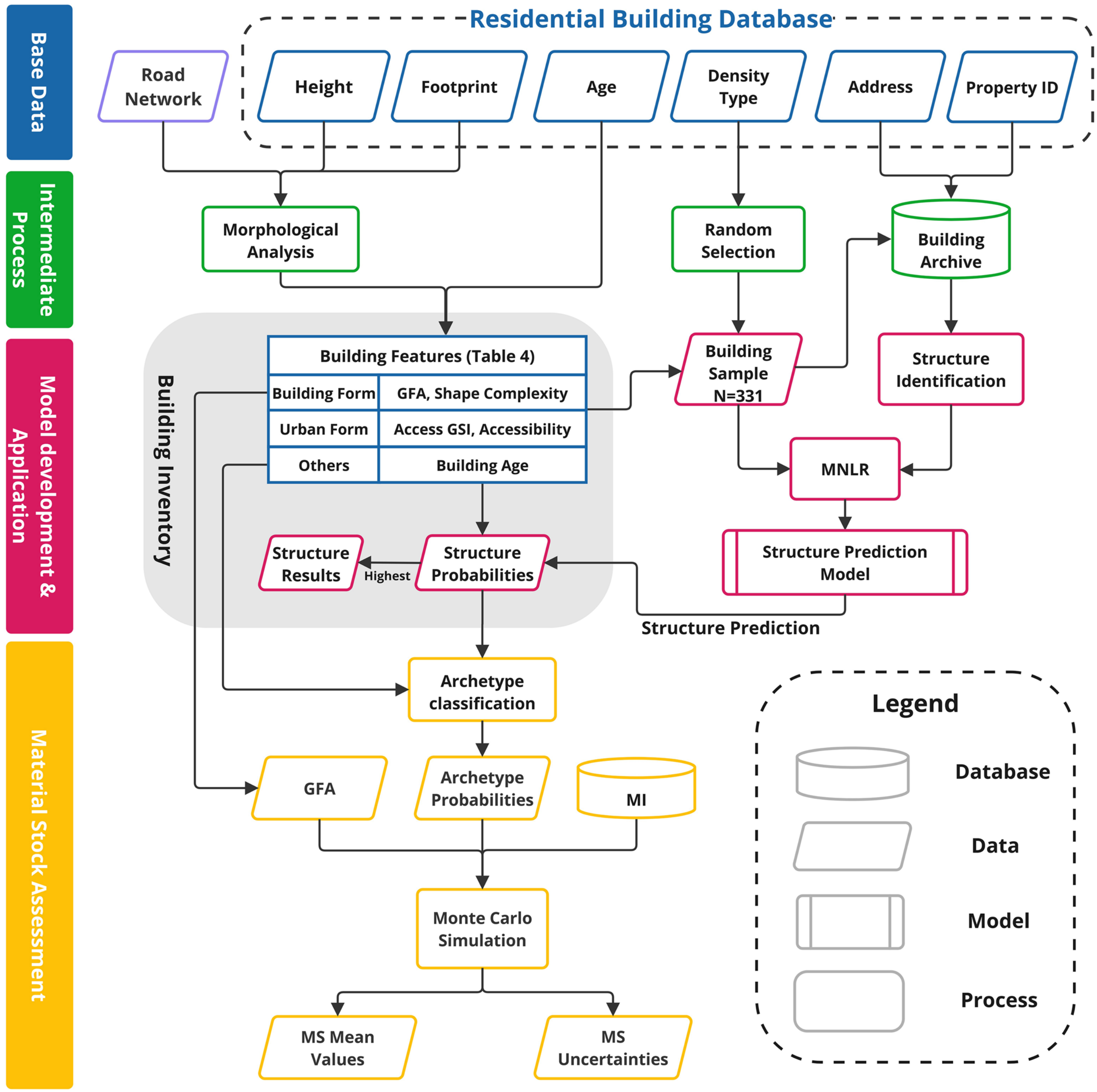

Fig. 1 Overview of the methodology adopted to predict building structures and assess the material stock of residential buildings in Gothenburg. Abbreviations: GFA, Gross Floor Area; GSI, Ground Space Index; MI, Material Intensity; MNLR, Multinomial Logistic Regression; MS, Material Stock

mid-rise" (Fig. 2a). Combining these two building classifications yielded eight distinct strata.

Given the highly imbalanced distribution of buildings across these temporal and morphological categories in Gothenburg, and the practical constraint on total sample size, proportional stratified random sampling would have resulted in an insufficient representation of minority classes. We therefore employed a stratified random sampling with equal allocation, which consisted in randomly selecting 50 buildings from each of the eight strata, resulting in a total sample of 400 buildings. Of these 400 samples, 69 were SF buildings that were used to confirm the assumption that the majority of the SF buildings are wooden in Sweden (see Sect. 4.1). The remaining 331 samples, all MF buildings, were then used to train the model, with cross-validation applied to ensure its validity and predictive accuracy. Figure 2b presents the distribution of building samples across different density types.

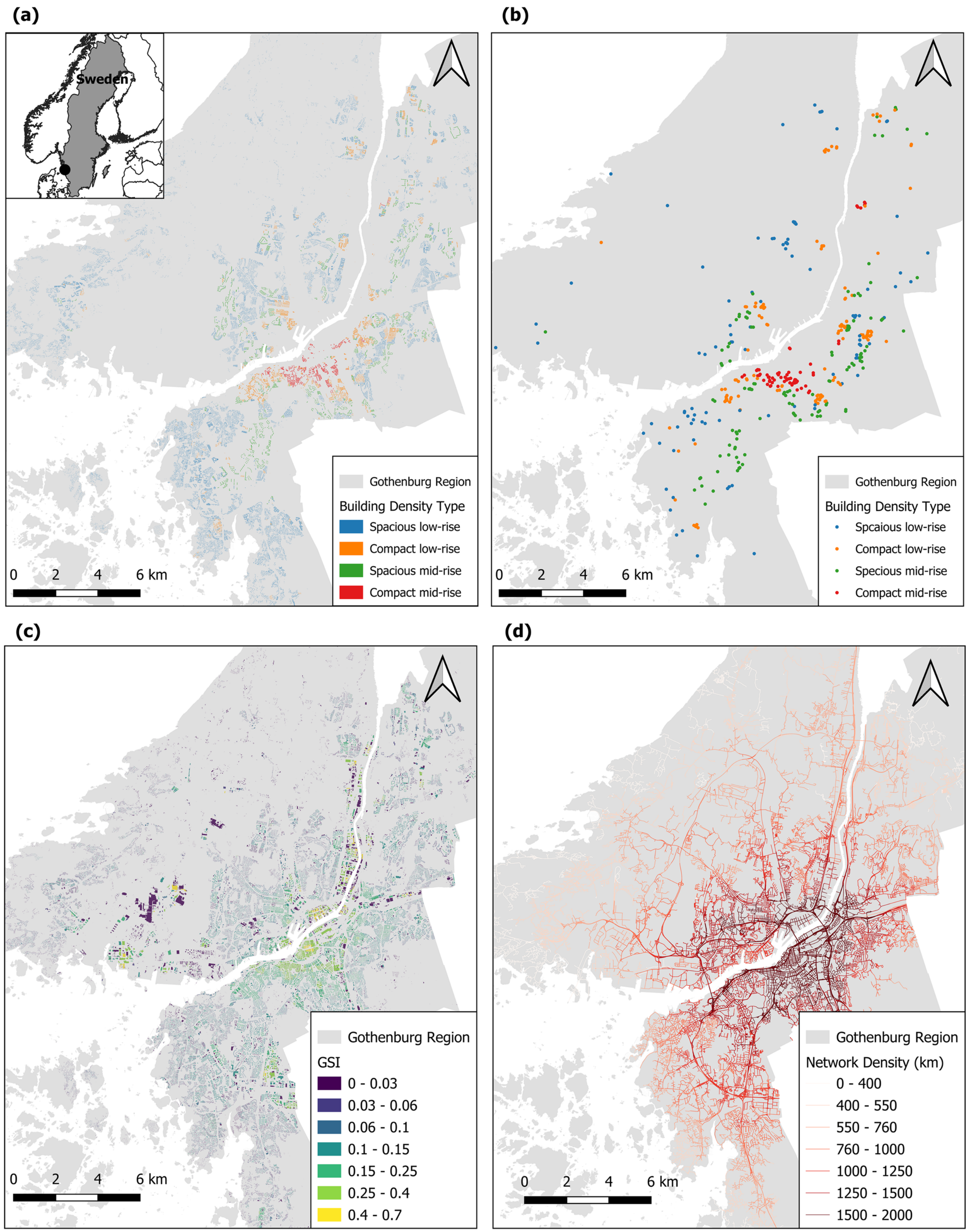

Fig. 2 **a** Study scope, i.e., residential buildings in Gothenburg, categorized by building density types (as defined by Berghauser Pont et al. (2019)), **b** distribution of building sample, **c** Illustration of GSI within a 500-m network distance, and **d** network density, measured by the total network length within 10 km network distance

For each building, we retrieved their building plans from the municipality's building archives and manually identified their structure. We categorized the residential buildings in Gothenburg into 5 structural types: Wooden Single-family Building (WSF); Wooden Multi-family Building (WMF); Wooden-Brick Multi-family Building (WBMF); Masonry Multi-family Building (MMF); Concrete Multi-family Building (CMF) (see detail classification in Table S1, Supplementary Information SI1). These structures are based on the description of typical Swedish residential buildings by Björk et al., (2009) and Björk et al., (2021), which Gontia et al. (2018) also used to develop the Swedish residential MIs that we adapt in this work. We note here that we changed the original "Brick Multi-Family" category into "Masonry Multi-Family". This change was made because in modern housing, the use of concrete masonry to replace brick is quite common. However, the production process of light concrete in the concrete masonry differs significantly from ordinary concrete. Therefore, it is challenging to classify these results directly to concrete structures.

3.2.3 Identification of building features

We identified several building features that may impact (or be impacted by) the building structure (Table 1) as potential predictors for the structure prediction model. These features serve to describe the structural characteristics of buildings, with an initial identification of ten potential distinguishing features, categorized into three groups: building morphological features, urban morphological features, and other features.

Regarding building morphological features, we first consider building height, as it often indicates structural constraints. Besides, we also include area indicators (e.g., FAs, GFAs), and shape-related indicators to reflect the ground complexity of a building's footprint. Such shape-related indicators include perimeter-area ratio (PA ratio), compactness and number of points-perimeter ratio (PP ratio).

We quantify the urban morphological features using density indicators such as GSI, FSI, and network density. FSI and GSI are calculated following Berghauser Pont et al. (2019) within a defined catchment area to capture the overall characteristics of the neighborhood. For this paper, a radius of 500 m walking-distance radius is adopted, reflecting a commonly accepted walking distance (Gehl, 2013). Because there is a strong correlation between FSI and GSI (Supplementary Information SI1, Table S2) and to avoid collinearity, we use GSI as the building density variable in the model. The spatial distribution of buildings and their corresponding GSI values in Gothenburg is illustrated in Fig. 2c. Network density represents the total street length within defined catchment areas. Here, total street length was calculated within a 10 km network-distance radius to characterize each location's connectivity to the wider urban system. The spatial distribution of network density across Gothenburg is presented in Fig. 2d. Network density values were assigned to individual buildings by linking nearby street segments, providing a proxy for building-level connectivity. These density indicators computed within defined spatial thresholds, capture information about the built environment at neighborhood and city scale, enriching the indicators used for building structure prediction.

Apart from morphological features, we also include building age as it can significantly impact structural characteristics due to the evolution of construction methods based

Table 1 Potential predictors of building structures and their definitions

Feature category	Feature name	Definition
Building morphological features	Building height	Distance from lowest ground level to building roof
	Footprint area (FA)	Area of building outline
	Gross floor area (GFA)	Total floor area of building
	Perimeter-area ratio (PA ratio)	Ratio of perimeter to FA. Measures the complexity of a footprint shape
	Compactness	Ratio of FA to area of its minimum bounding rectangle. Measures how closely a building's shape resembles a perfect rectangle (See Fig. S1 in Supplementary Information SI1)
	Points-perimeter ratio (PP ratio)	Ratio of total number of vertices to footprint perimeter (see Fig. S1 in Supplementary Information SI1)
Urban morphological features	Ground space index (GSI)	Ratio of building footprint to land area, here calculated within a 500-m network distance from each building (see Fig. 2c)
	Floor space index (FSI)	Ratio of GFA to land area, here calculated within a 500-m network distance from each building
	Network density	Total network length within 10 km network distance from a road segment (see Fig. 2d)
Other features	Building age	Age of building

on material and technology availability, architectural styles, and building regulations across different time periods.

3.2.4 Development of prediction model

For the development of the predictive model, we first conducted a correlation analysis of the potential predictors listed in Table 1 to avoid multicollinearity. Subsequently, an MNLR model was applied to examine the impact of selected predictors on the building structure (see equations in Sect. 3, Supplementary Information SI1). Both the correlation analysis and MNLR were performed using statistical software *jamovi* (version 2.6).

MNLR is a statistical method designed to estimate the probability of multi-class outcomes based on a set of independent variables (Smit et al., 2023). It has been widely applied to the classification of building characteristics (Middel, 2009; Xu et al., 2014). MNLR derives the probability of each category indirectly through comparisons. The reference level refers to the category of the dependent variable that is designated as the baseline. During model development, we separately selected each category as the reference to examine how the independent variables influence the likelihood of belonging to a specific category relative to that baseline. This approach of switching the reference category allows us to better understand the impact of variables on classification outcomes (see result in Fig. 3).

In MNLR results, the significance of features varies depending on the chosen reference level, making it insufficient to determine variable inclusion solely based on p-values. To address this problem, we explored different feature combinations and identified the best predictive model using accuracy as the selection criterion (see the optimal model in Sect. 4.2). The final model was then established and applied to predict the structural types of residential buildings in Gothenburg.

3.2.5 Result verification and performance comparison

Given the limited sample size, cross-validation was applied to make more efficient use of the data and improve the stability of model evaluation. A four-fold cross-validation was employed, where the data was divided into four equally sized subsets. In each iteration, three folds were used for training and the remaining fold for validation. This process was repeated four times so that each sample was used for both training and validation once.

To further assess the influence of individual predictors on building structure predictions, we applied the MNLR model with different sets of input variables and compared their predictive performance. A Leave-One-Variable-Out approach (LOVO) was adopted (Farber & Rashdan, 2025), whereby each feature was sequentially excluded from the model to evaluate its marginal contribution. This procedure helped

	Age	Height	FA	GFA	PA ratio	PP ratio	Compactness	GSI	Network density
MMF-CMF	0.08	-0.02	0.00	-3.41e−4	5.62	4.56	-1.06	-26.08	0.54
WBMF - CMF	0.18	-0.25	0.01	0.00	2.44	-0.68	-4.44	-17.14	0.83
WMF - CMF	0.13	-0.63	0.01	0.00	10.96	10.80	-1.31	-41.64	0.26
CMF - MMF	-0.08	0.02	-6.80e−4	0.00	-5.76	-4.58	1.04	26.10	-0.54
WBMF - MMF	0.10	-0.23	0.00	-9.81e−4	-3.19	-5.27	-3.36	8.99	0.29
WMF - MMF	0.05	-0.60	0.01	0.00	5.38	6.24	-0.22	-15.49	-0.27
CMF - WBMF	-0.18	0.25	-0.01	0.00	-2.07	0.25	4.38	17.08	-0.83
MMF - WBMF	-0.10	0.23	0.00	0.00	3.65	4.83	3.35	-8.98	-0.29
WMF - WBMF	-0.06	-0.37	0.00	0.00	9.20	11.02	3.13	-24.66	-0.56
CMF - WMF	-0.13	0.63	-0.01	0.00	-11.11	-11.10	1.20	41.56	-0.26
MMF - WMF	-0.05	0.61	-0.01	0.00	-5.27	-6.60	0.15	15.57	0.27
WBMF - WMF	0.06	0.38	0.00	0.00	-8.71	-11.81	-3.21	24.55	0.57

Fig. 3 Results of the multinomial logistic regression. Note: Coefficients in orange are positively significant at the level of 0.05, those in blue are negatively significant at the level of 0.05. Uncolored coefficients are not significant

identify which features contribute most effectively to accurate classification across structural types.

3.2.6 Material stock accounting and uncertainty quantification

The prediction model was applied to the building inventory, effectively resulting in the probability for each building to belong to each structure type. The structure type with the highest probability was assigned as its final classification (we address later in this section the uncertainties introduced by such choice). With the building inventory now containing structural information, buildings were assigned to their archetype based on their age and structure.

Equation 1 below was then used to calculate the MS of MF buildings in Gothenburg (Tanikawa & Hashimoto, 2010):

$$MS = \sum_i MS_i = \sum_i INV_i \times MI_i \quad (1)$$

where i represents the building archetype (following a structure-age archetype classification), INV_i is the inventory of buildings belonging to archetype i (in m^2.GFA), MI_i is the material intensity of building archetype i (in kg/m^2.GFA), and MS_i is the material stock of buildings belonging to archetype i (in kg).

With MS results being highly sensitive to structural information, assigning a building to the structure type with the highest probability inevitably introduces uncertainty into MS modeling. To better understand the extent of the uncertainty introduced by the selection of the single-most-probable result, we conducted a Monte Carlo analysis. Input parameters were the probabilities of each building belonging to each structure type (i.e., results from Sect. 4.3), and 10,000 simulations were run.

4 Results

4.1 Sample & model predictors

From the archive documents we found that over 93% (64 out of 69) of SF building samples are in wooden structures (Supplementary Information SI2), which is consistent with estimates in the literature that over 90% of SF buildings were built with a wooden structure in Sweden (Stehn, 2018). Given the high structural homogeneity within SF buildings, developing an MNLR for structure prediction becomes irrelevant, and we exclude them from our scope. In contrast, MF buildings are much less homogenous in structure, making them the focus of this study. After excluding the SF building samples, the remaining 331 MF buildings were used for model development, with the following distribution: 111 CMFs (33%), 78 MMFs (24%), 73 WBMFs (22%), and 69 WMFs (21%) (see Fig. S2 in Supplementary Information SI1).

For all potential predictors, we first conducted a correlation analysis (see Table S2 in Supplementary Information SI1). The strongest correlations were observed between FA, GFA, and compactness, as well as between GSI and FSI. To mitigate multicollinearity in the model, adjustments to the input features were therefore required.

Figure 3 presents the MNLR coefficients across building structure categories. Statistically significant predictors ($p < 0.001$) are highlighted, with positive effects shown in orange and negative effects in blue. The effects of these predictors on building structure can be interpreted as follows. Building age shows a negative effect on the likelihood of classification as CMF or MMF, compared to WBMF, suggesting that older buildings are more likely to be WBMF. Similar, building height increases the probability of classification as CMF or MMF relative to WMF, indicating that taller buildings are less likely to be WMF. Building ground complexity was measured using three different indicators, each capturing a distinct aspect of footprint irregularity and influenced by building scale, which makes an overall evaluation difficult. Nevertheless, a clear pattern emerges: more irregular footprints reduce the likelihood of classification as CMF. Density indicators show that CMF buildings are associated with higher GSI but lower network density, reflecting their prevalence in newer, less connected suburban neighborhoods. In contrast, WBMF and MMF were constructed earlier and are concentrated in central areas of the city with the highest connectivity.

The high p-values (above the conventional 0.05 threshold) of GFA and FA suggest that these predictors do not significantly influence building structure classification and were therefore excluded from further model development. This result was unexpected, as GFA is often among the first aspects considered when discussing building morphology. A possible explanation is that Gothenburg's MF building stock is generally low-rise, reducing variation in floor area across structural types.

The generally low rise of buildings in Gothenburg also helps explain why building height is found to be statistically insignificant in many cases (Fig. 3). The average height of all MF buildings in Gothenburg is only 14.1 m, with CMF buildings being the tallest on average at just 15.2 m. Nevertheless, as shown in Fig. 4b, building height still has a substantial effect on the model's predictive accuracy for structural classification. Therefore, when applying this model to other regions, particularly those with greater variations in number of floors, building height is expected to be an important predictive variable.

4.2 Prediction model

The optimal model for predicting MF building structures in Gothenburg includes "Building age", "Building height", "PA ratio", "Compactness", "GSI", and "Network density", with an 83% of overall prediction accuracy. Figure 4a presents the row-normalized confusion matrix of this model, where each cell value represents the percentage of instances classified into a specific category relative to the total number of actual samples in that class. The model achieved the highest recognition rate for CMF (88.2%), likely due to its distinct morphological features. In contrast, WBMF showed the lowest recall at 78.1%, with 13.7% of its instances being misclassified as MMF. This reduced accuracy may be attributed to substantial overlap in building height and age between WBMF and MMF categories. This pattern is consistent with the findings in Sect. 4.3, which show that MMF represents the most likely alternative classification for WBMF.

As can be seen in Fig. 4b, the model achieves its best performance when all predictors are included. The only exception is for WBMF, for which the model's prediction accuracy remains unchanged when PA ratio is excluded. The model's performance dropped significantly when building height and building age are excluded, highlighting their importance in structural classification. Specifically, removing building height from the model led to a 22% decline in overall prediction accuracy. WMF was the most affected by the height exclusion, with the model's accuracy dropping by 43% in predicting the structure. Similarly, building age had a significant impact on overall prediction accuracy. Its exclusion resulted in a 20% decline of the model's accuracy, with the most pronounced effect being observed in MMF and CMF for which the accuracy dropped of 31% and 24%, respectively. These findings suggest that building height is particularly important for predicting wooden structure buildings which are strongly restricted by height, while building age plays a crucial role in classifying structures associated with specific historical periods, such as MMF, CMF and WBMF.

4.3 Structures of residential buildings in Gothenburg

The results of the MNLR provide the probability of buildings belonging to different structural types. These results are then used to assign each building a structure based on the highest probability. However, in some cases, the highest and second-highest probabilities may be very close, making it challenging to assign a structure in absolute terms.

We exemplify such ambiguities in Fig. 5a, in which structures within the same building block were primarily categorized as MMF and WBMF. For building 1, the highest probable structural outcome is MMF (55.6%), followed extremely closely by WBMF (41%). In contrast, building 2 sees WBMF as its highest probability (54%), followed even more closely by MMF (43.4%). For such close results, the assignment of one structure over another becomes rather arbitrary. Meanwhile, building 3 exhibits yet another pattern of results, with a 60.4% probability to be MMF—against 35.8% to be WBMF. In this case, the question becomes

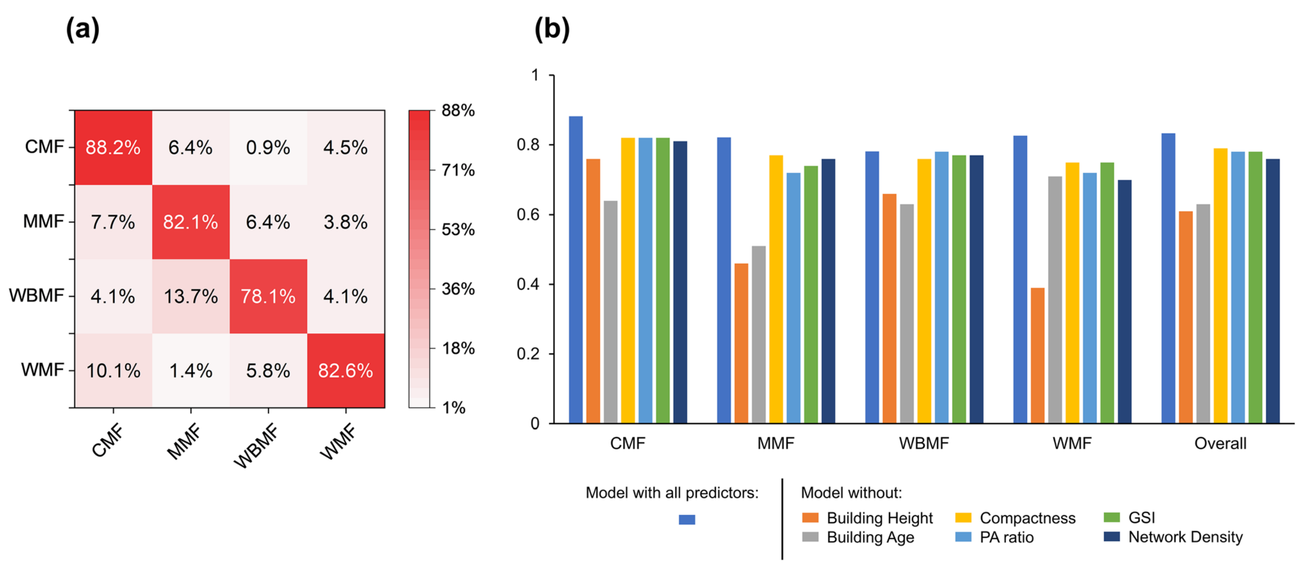

Fig. 4 **a** Row-normalized Confusion Matrix for Residential Building Structure Prediction Model (Reference Level: CMF), **b** results of leave-one-variable-out approach. Abbreviations: CMF, Concrete Multi-Family; GSI, ground space index; MMF, Masonry Multi-family Building; WBMF, Wooden Brick Multi-Family Building; PA ratio, Perimeter-Area Ratio; WMF, Wooden Multi-Family Building. The sample data used to derive these results are provided in Supplementary Information SI2

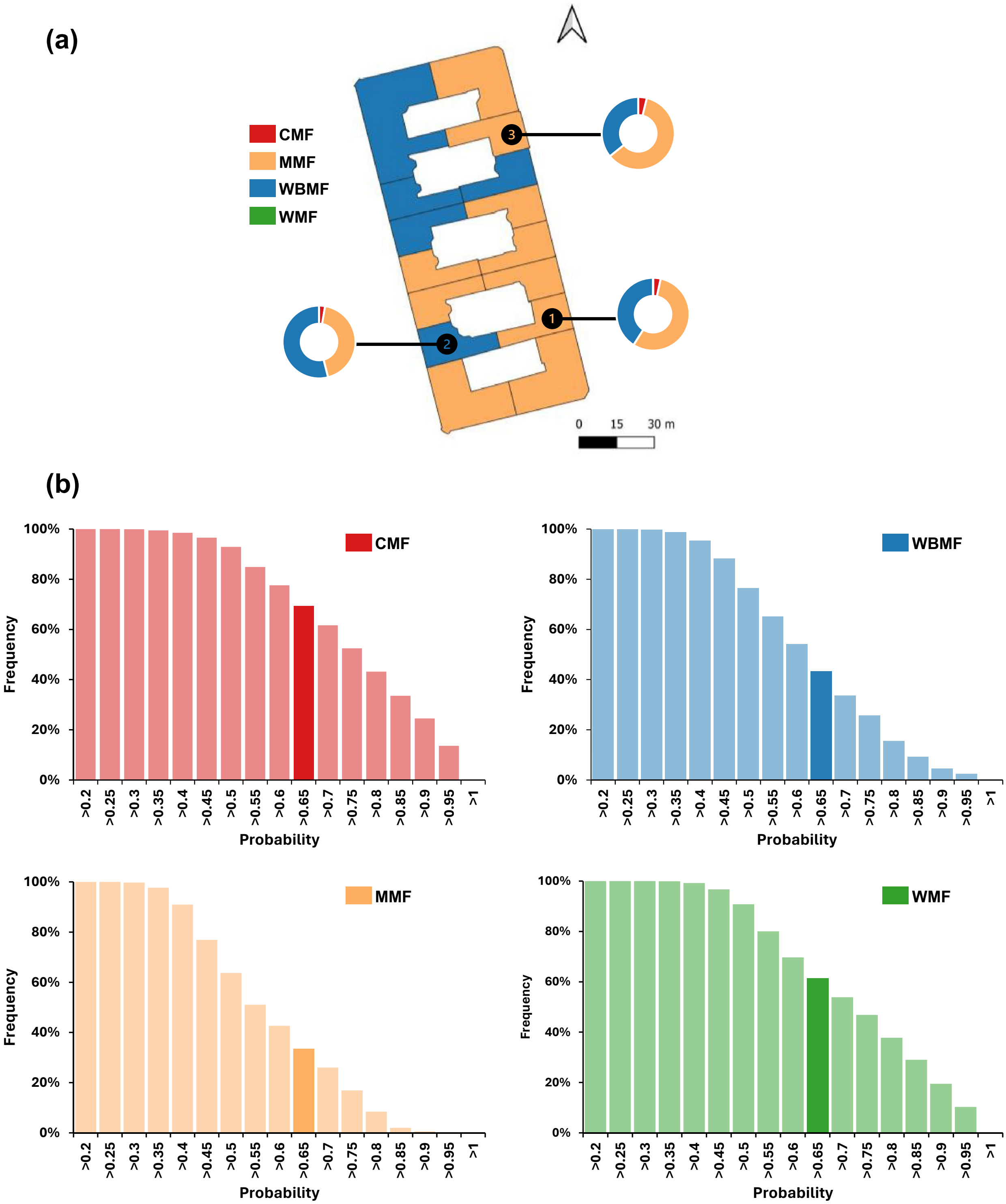

Fig. 5 **a** Example of results for three buildings in the same block, showing their probability to be of each structure, **b** Complementary cumulative probability distributions of predicted building structures in Gothenburg. For the underlying data, see the Data Availability Statement

whether a specific probability threshold (e.g., 65%) is strong enough to robustly assign a structure.

Such robustness threshold is explored in Fig. 5b, which displays a complementary cumulative distribution function of the results. In other words, it shows the proportion of predictions higher than a specific value. In the following content, we use a robustness threshold of 65% to explore results. We find that the proportion of robust predictions is relatively lower for MMF and WBMF (34% and 43%, respectively), compared to a higher number of robust predictions for CMF and WMF (69.3% and 61.4%, respectively).

For MMF, the most probable alternative classification is CMF. Indeed, non-robust MMF predictions are classified as CMF with an average probability of 21.5%. Similarly, for non-robust WBMF predictions, the most likely alternative classification is MMF with an average probability of 31.1%. These findings suggest that the model's predictive performance for MMF requires improvement. Future refinements may involve incorporating additional variables to enhance the model's ability to distinguish MMF from CMF and WBMF more effectively.

Although the predicted probability for a specific structural type may be relatively low for some individual buildings, this reflects classification uncertainty rather than model misperformance, and the overall classification accuracy of the model remains high at 83%. To increase the reliability of the MS estimation, this classification uncertainty is explicitly propagated into the final MS calculations (Sect. 4.4), allowing the resulting MS estimates to reflect uncertainty arising from structural classification.

Figure 6 presents the spatial distribution of prediction outcomes and robust results. SF buildings (WSF), 34% of the total residential GFA, are greyed out. Within MF buildings, CMF is the largest category with 3,075 units, followed by MMF (1,776), WBMF (1,271), and WMF (1,308). CMF accounts for 39% of the total residential GFA. Notably, although the number of WMF buildings is comparable to WBMF and MMF, its GFA share is only 4%, far below the 14% and 9% observed for MMF and WBMF, respectively (see Table S5 in Supplementary Information SI1). This discrepancy is mainly attributable to the relatively lower building heights associated with wooden structures.

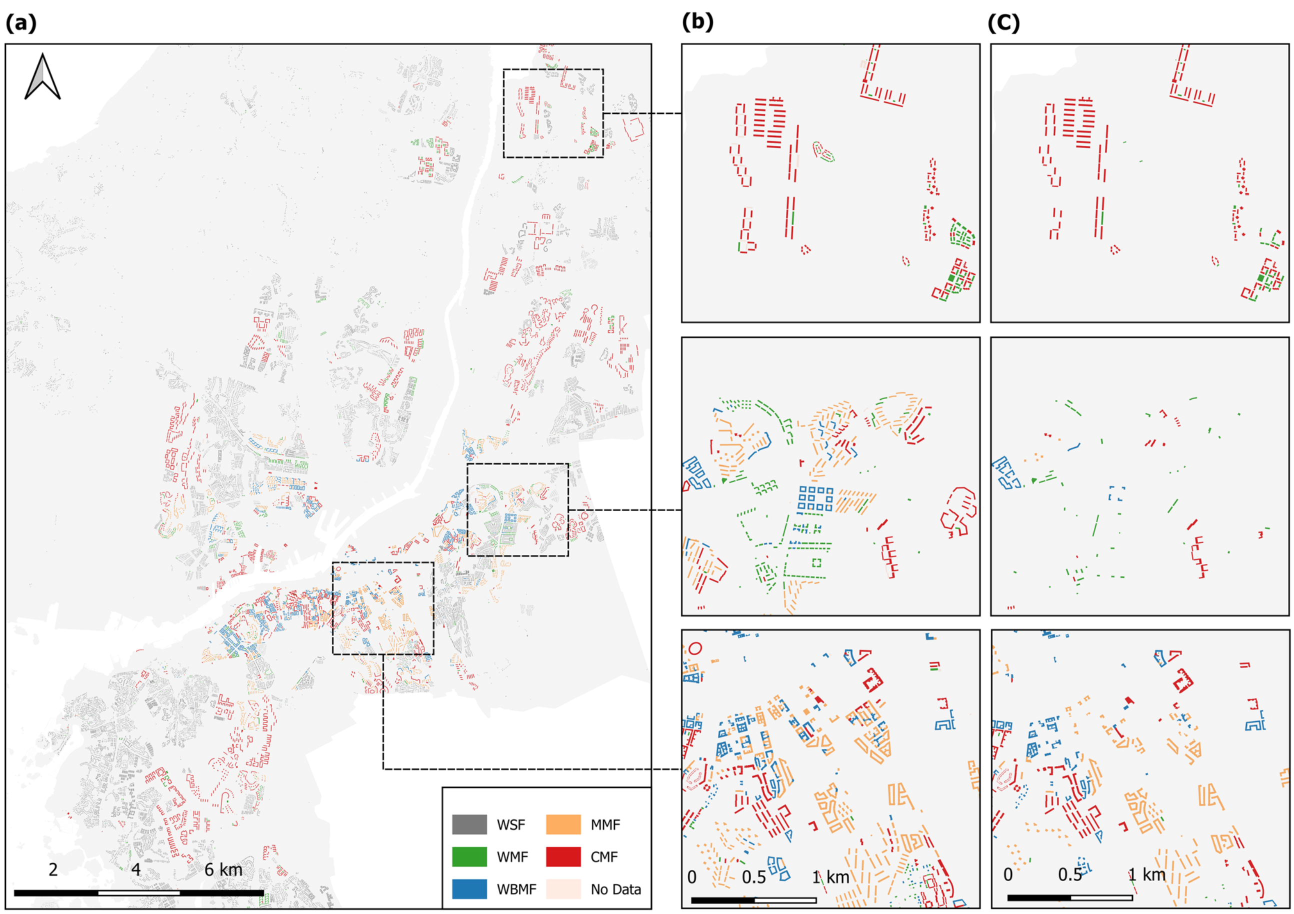

Fig. 6 Predicted building structures in Gothenburg. **a** Model outputs showing the building structures across the entire city, **b** zoomed-in panels of selected areas illustrating the predicted building structures, **c** robust result with prediction probability above 65%

From the spatial distribution of the predicted results, the building structure has obvious spatial distribution characteristics. MMF and WBMF buildings are mostly distributed in the central area of the city, while many WMF and CMF buildings are distributed in the edge area of the city. Robust prediction results are more frequently observed in areas where building structures are relatively homogeneous, such as newly developed residential districts in the northern part of the city, which are dominated by CMF. In addition, a relatively high concentration of robust outcomes is also found in the city center, where the building stock tends to be denser and more systematically planned. These patterns suggest that structural uniformity and coherent urban planning contribute to greater stability in the prediction results.

4.4 Multi-family residential material stock of Gothenburg

Both building structure prediction and MS estimation are performed at the individual building level, enabling object-specific analysis where required. The results below are subsequently aggregated and presented at the city scale, providing a macroscopic perspective that facilitates comparison and supports strategic urban-level interpretation.

The results indicate that in MF buildings, the MS is 17.2 ± 5.8 megatons (Mt) in 2024. The material composition of MS is shown in Fig. 7. Concrete constitutes the largest share of MS, accounting for 64.3% (11.1 ± 1.9 Mt) of the total mass, followed by brick (13.1%), sand and aggregates (5.1%), and wood (4.1%). These materials together form the structural backbone of the buildings, reflecting the prevalent use of reinforced concrete and masonry in construction. In contrast, materials such as glass (0.37%), tiling and roof tiles (0.72%), and stone (1.33%) contribute minimally to the total MS. Steel and cast iron (2.76%), insulation (3.09%), and mortar and plaster (3.88%) also play a notable role, particularly in structural reinforcement and thermal efficiency. An analysis of the coefficient of variation (CV), which measures the relative variability of MS, reveals that brick (80%) and stone (73%) exhibit the highest variability, suggesting greater fluctuations in their usage across different buildings. Concrete (17%), on the other hand, has the lowest variability, indicating its consistent and dominant presence in the MS of MF buildings.

5 Discussion and conclusion

5.1 Summary of results

In this article, we used MNLR to predict the structure of the MF buildings in Gothenburg, based on building ages and morphological indicators. We then used the model results to estimate MS of the MF buildings. This work led to four key results. The first result is the significance of building age and morphological indicators in building structure prediction. Older buildings are more likely to have wooden-brick structures, lower-rise buildings tend to be associated with wooden structures, simpler footprint shapes are linked to concrete structures, and masonry and wooden-brick buildings generally exhibit higher network density.

A second result is that the optimal model for predicting MF building structures in Gothenburg includes “Building age”, “Building height”, “PA ratio”, “Compactness”, “GSI”, and “Network density”, with an 83% prediction accuracy overall. Among these features, building age and building height emerged as the most critical factors for accurately predicting building structure. An additional result is how the robustness of the model predictions varies across structural types. Predictions for CMF and WMF are more reliable, whereas those for MMF and WBMF show lower robustness, with their most likely alternative classifications being CMF and MMF, respectively.

A final result is the MS quantification in MF buildings in Gothenburg, amounting to 17.2 ± 5.8 megatons and dominated by concrete and other non-metallic minerals like clay brick and sand. Previous estimates of MS in Gothenburg MF buildings lacked structural information, requiring proportional or averaged redistribution of MIs and resulting in variations of about 30% (Gontia, 2019). Our study addresses this limitation by developing an MNLR model to predict building structures, thereby refining MS accounting and providing a more robust estimate compared to the earlier figure of 23 ± 6.9 megatons (Gontia et al., 2019).

5.2 Limitations

To our knowledge, this article is the first comprehensive attempt to predict building structures by integrating both building and urban morphological features. The MNLR model developed in this study has proven to be a feasible approach for identifying the structure of MF buildings. A limitation pertains to the sample size which, as is often the case for bottom-up studies, was limited by the time- and labor- intensiveness of data collection. Nevertheless, our sample of 331 buildings was sufficient to showcase the relevance of morphological attributes as predictors of building structures.

An additional limitation pertains to MNLR itself. While MNLR is a robust approach for small to medium datasets, it assumes linear relationships between predictors and structural types. This limits its ability to capture more complex,

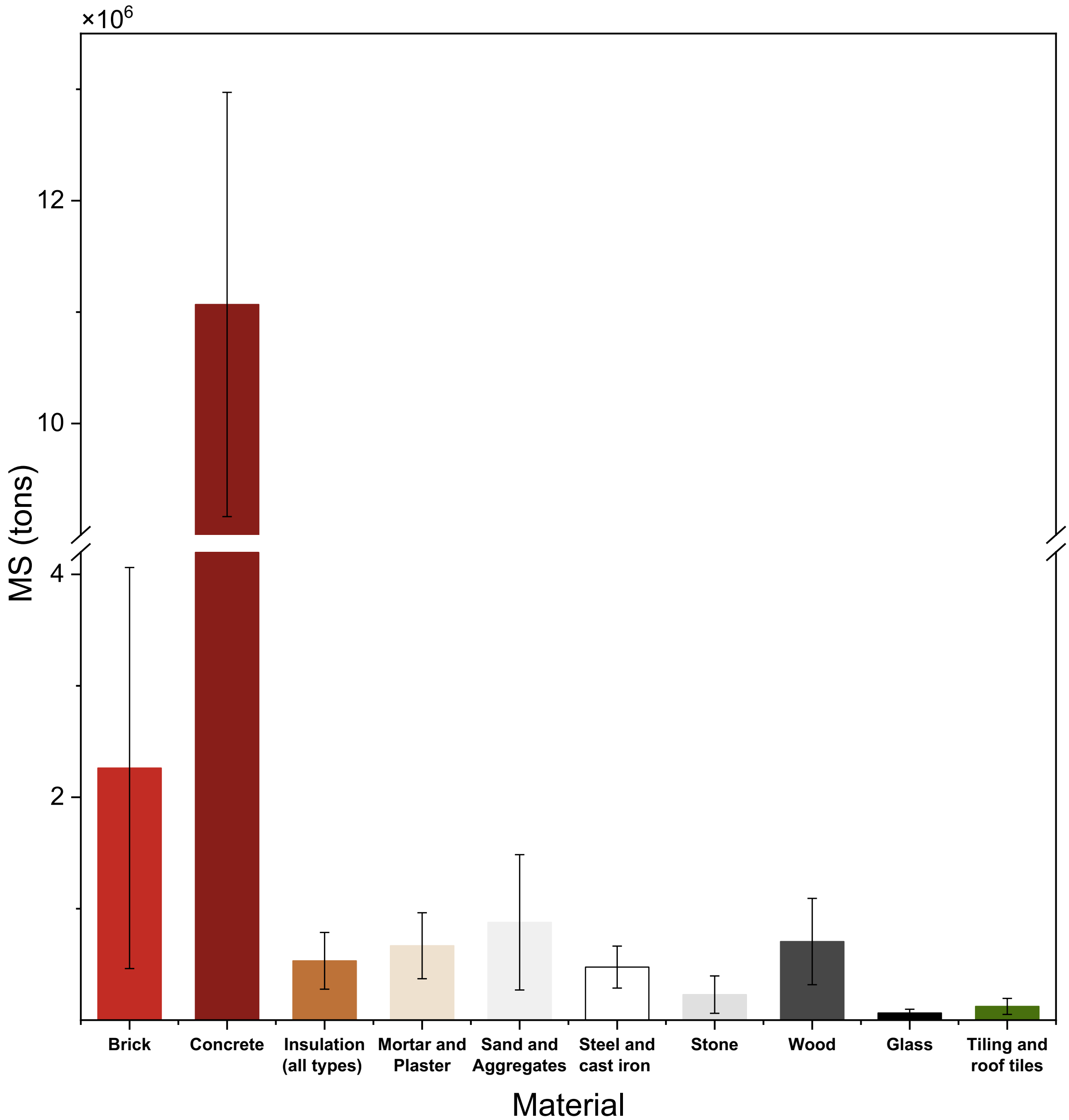

Fig. 7 Mean and standard deviation of MS results in Gothenburg. The standard deviation reflects the (in)accuracy of the structure prediction model. Note the broken axis for concrete. The aggregated MS values for this figure are available in Table S6 in Supplementary Information SI1

non-linear interactions among building features. In this regard, machine learning methods may be beneficial (see next section). Still, we here highlight the interpretability of results that MNLR offers, as well as the relatively low computational overhead that facilitates exploration of relevant features but also increases applicability and reproducibility of the method.

5.3 Transferability and future research

Transferability While the empirical findings of this study are specific to Gothenburg, the proposed methodological framework is transferable to other contexts with similar data availability. Regarding building inventory attribute, the availability of building height and age, which were identified as the most influential predictors of building structure, is particularly important. The building height is now available world widely from the work of Kamath et al. (2024). In contrast, building age data are frequently incomplete or missing, requiring approximation through proxy variables in data-scarce contexts (Heeren & Hellweg, 2018).

Furthermore, access to reliable structural data remains essential for calibrating and validating the predictive model. While this study relies on building archival records available in Gothenburg. In other contexts, alternative sources such as building surveys or on-site investigations could be used to obtain structural data. The strong influence played by building height and age means that the framework can be adapted to data-limited environments. A parsimonious model relying solely on building height and age can indeed yield first-order insights into dominant structural patterns. Still, beyond these core variables, road network data plays a nonnegligible supportive role in the model, as it is turned into secondary urban morphological indicators that further improve predictive accuracy of the model. Fortunately, road network data is widely available across the globe through spatial databases such as OpenStreetMap (OpenStreetMap contributors, 2024).

Additionally, this work focuses on structural systems that dominate the Swedish residential building stock. Whether the model would perform as well in contexts with different structural types cannot be assessed with certainty. Still, several lessons learned are worth highlighting to maximize the application of our model to other contexts. For example, it is crucial to identify major shifts in construction practices, such as the increased use of concrete in Sweden after the 1950s. It is also important to identify the typical construction types in the study area, including atypical construction styles such as the WBMF structure in Gothenburg.

Future research Future research should focus on collecting additional sample data to allow for the integration of additional explanatory variables and the classification of buildings into even finer structural types. A solution is to leverage large language models (LLM) to assist in the collection and interpretation of building archival information (Schmid et al., 2025). By applying LLM to automate or semi-automate this process, future studies could significantly expand the dataset and enhance both the accuracy and scalability of structural classification. With a substantially larger dataset, future research could replace MNLR with machine learning approaches—such as random forests, gradient boosting models, or neural networks—that are better suited to uncover non-linear relationships between building features and structural types.

5.4 Conclusive words

This study advances the automation of structural type identification by using morphological features. Because structural type plays a key role in building materiality (Gillott et al., 2025; Zhang et al., 2022), this advancement supports a more reliable estimation of building MS. Rather than providing a single deterministic estimate, this study embraces structural uncertainty by assigning each building probabilities of belonging to multiple plausible structural types, each linked to a distinct material composition. This reduces the risk of a false sense of precision arising from simplified structural assumptions. Additionally, the proposed framework allows the propagation of structural classification uncertainty directly into MS estimates. Doing so reduces the risk of systematic bias resulting from generalized structural misclassification and enables the aggregation of both expected values and uncertainty ranges.

For stakeholders involved in construction, deconstruction, and material reuse, such probabilistic outputs—at the building scale or aggregated to the city scale—are more actionable. Indeed, they enable risk-aware planning, scenario analysis, and flexible decision-making by distinguishing materials that are associated with specific structural types. By making uncertainty transparent rather than implicit, this approach better supports reuse strategies, logistics planning, and investment decisions under real-world conditions.

6 Summaries

Supplementary Information SI1: This supplementary information provides additional methodological details on model development, along with the supplementary results referenced in the main text.

Supplementary Information SI2: This supplementary information provides data on the building samples used for model development, including identified structural types and associated features used for model calibration and validation.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44498-026-00094-0.

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Author contributions Xin Bian: Writing—original draft, Conceptualization, Methodology, Data curation, Visualization, Validation. Meta Berghauser Pont: Writing—review & editing, Conceptualization, Supervision, Methodology. Jonathan Cohen: Writing—review & editing, Methodology, Software. Maud Lanau: Writing—review & editing, Conceptualization, Supervision, Methodology. All authors reviewed and approved the final manuscript.

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Data availability The building archive data supporting the findings of this study were obtained from the Gothenburg City Planning Administration. Access to these data requires permission and can be requested via https://goteborg.se. The network density data supporting the findings of this study is available at: https://researchdata.se/en/catalogue/dataset/snd1153-2. The data underlying Fig. 5 cannot be publicly shared due to data-sharing restrictions. However, the building data used to develop these result are available from Swedish Mapping, Cadastral, and Land Registration Authority (Lantmäteriet, 2024): https://www.lantmateriet.se/sv/geodata.

Declarations

Conflict of interest The authors declare no competing interests.

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