# An Analysis of Regional Building Stocks for Material Flow Assessment

Dr. Suxia GONG*, suxia.gong@uliege.be, ORCID: 0000-0002-8468-8652
Ir. Amandine BRASSEUR, amandine.brasseur@uliege.be, ORCID: 0009-0009-4387-9805
Pr. Dr. Ir. Luc COURARD, Luc.Courard@uliege.be, ORCID: 0000-0001-6573-6631
Pr. Dr. Ir. Jacques TELLER, Jacques.Teller@uliege.be, ORCID:0000-0003-2498-1838
University of Liège
Department of Urban and Environmental Engineering
Allée de la Découverte 9, 4000 Liège, Belgium
*Corresponding Author

**Abstract:** This study develops a GIS-based framework to create a high-resolution building inventory for Wallonia, Belgium, addressing a critical data gap for regional material flow assessment. Key methodological innovations include using LiDAR to estimate building volume, a jointness analysis to supplement missing building typologies, and a spatial matching technique to identify demolished structures, collectively overcoming common data scarcity issues. The resulting inventory identified 1.43 million residential buildings. The detected trend in demolition activity aligns with official statistics, validating the methodology's ability to capture meaningful stock dynamics at a regional scale. This work demonstrates that a spatially explicit inventory is a foundational and transferable tool for quantifying material stocks and determining construction and demolition volume, providing a critical evidence base for regional circular economy strategies.

**Keywords:** Regional Building Inventory, Construction and Demolition Waste, GIS, Material Flow Assessment, Circular Economy

# 1 Introduction

For regional governments, the challenge of managing construction and demolition waste (CDW) is twofold: it is both an environmental imperative, as it accounts for almost 40% of all waste generated in the EU (Cristóbal García et al., 2024), and a missed economic opportunity to recover valuable secondary materials. Rather than merely being waste, however, building stocks are increasingly recognized as an important future anthropogenic reservoir of secondary raw materials (Kleemann et al., 2017). A thorough understanding of CDW generation is essential to unlock this potential, enabling these materials to be reclaimed and looped back into the economy (Lanau & Liu, 2020). Accurately estimating the quantity and composition of future CDW requires advanced methodologies, such as bottom-up material flow analysis. This approach involves categorising the building stock and applying the material intensity coefficient (MIC) to calculate the material stock, effectively multiplying the volume of buildings by their MICs (Augiseau & Barles, 2017; Kleemann et al., 2017).While this method is theoretically sound, it requires exhaustive data.

In practice, comprehensive data for demolished buildings or the older structures slated for demolition are often unavailable or incomplete. Such a data gap hinders effective waste management and resource recovery, underscoring the need for thorough assessments of existing buildings before demolition. To address this scarcity of building-level data in bottom-up analyses, a common approach is to enrich existing building data with insights from building typology archetypes (Dabrock et al., 2025). Here, the Geographic Information System (GIS) plays a pivotal role by enabling the integration, analysis, and spatial visualization of building stocks alongside their material inventories (Paz et al., 2020). The result is a geo-referenced building dataset linked to the material inventory, which is essential for robust large-scale material stock analysis. This GIS-based approach is especially powerful on a regional scale. Since building attribute data are predominantly sourced from national or regional stock datasets (Pei et al., 2022), the regional scale emerges as the optimal level for management. Operating at this scale streamlines data integration, ensures consistency, and directly supports the development of targeted and effective policy.

However, the quality and coverage of data are highly variable across different regions, necessitating localised case studies to develop and validate methodologies that can improve the reliability of estimates (Augiseau & Barles, 2017). This is critically important given significant regional disparities in construction practices, which directly influence material composition. Studies highlight stark contrasts, such as the use of high-density sandstone in Germany versus hollow bricks in Vienna (and Austria), and the prevalence of Ytong lightweight concrete in post-World War II Belgium (Lederer et al., 2021; Attia et al., 2021). These variations make generic material coefficients unreliable. The Wallonia region exemplifies these data challenges. Its cadastral records provide detailed parcel information but lack comprehensive building-level data, creating gaps in typological classification. To address this, our study developed a high-resolution, region-wide building inventory for Wallonia by fusing cadastral, land use, statistical, and property records within a GIS. The primary innovation of this case study is the creation of a validated spatial inventory specifically designed to calibrate and enhance the accuracy of bottom-up material stock and flow analyses, thereby contributing to more effective circular economy strategies.

# 2 Methodology

## 2.1 Research Framework

The methodological framework for analysing regional residential building stocks and constructing the material inventory using GIS techniques is presented in Figure 1. The method begins by characterising the building stock in three steps: differentiating residential from non-residential buildings, calculating building height, and identifying building types. It then focuses on dynamic changes by detecting demolished buildings and verifying these demolitions. Finally, the material inventory is constructed by determining material indicators and deriving the final stock composition.

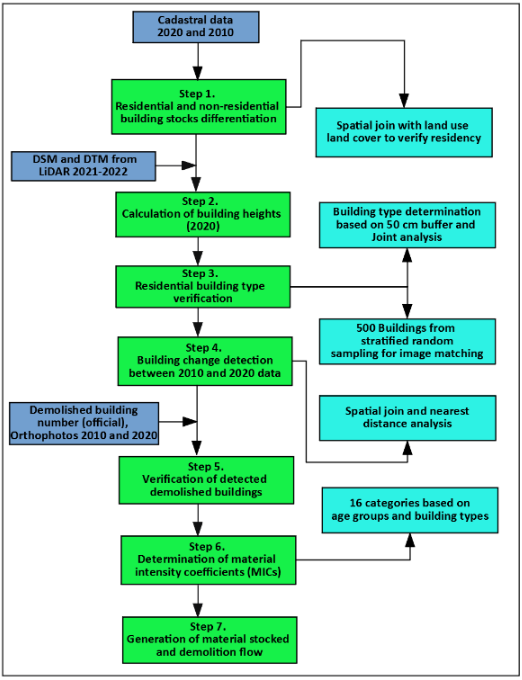


Figure 1: Framework for constructing a comprehensive building inventory using GIS techniques.

## 2.2 Data

The datasets utilised in this study are summarized in Table 1, which details their dates of creation and last update, sources, data types, geographical coverage, and spatial resolution. Further details are provided below.

- Cadastral data from 2020 and 2010: The cadastral data are confidential and obtained through data conventions with the SCIP (Structure de Coordination de l'Information Patrimoniale). The data comprises parcel and building shapefiles that are linked through a spatial join approach. The parcel includes a nature code to clarify its utilization. In addition, the construction year, building type, last modification date, and number of floors are recorded for buildings on the parcel.
- Raster Data: Building height, required for volume calculation, was derived from a 1-metre resolution LiDAR-derived (Light Detection and

Ranging) Digital Surface Model (DSM) and Digital Terrain Model (DTM) from 2021 to 2022. LiDAR data serve as a primary source for estimating relative height due to their high-quality geometry (Laupheimer, 2024). This feature was derived by calculating the difference between the DSM and DTM. We selected this direct measurement method over inferring height from floor counts to ensure greater accuracy across the diverse building stock.

- Land Use Data: To enhance the reliability of the cadastral building use classifications, this dataset was applied for cross-validation. Its primary functions were to: (1) verify and correct the designated use of each building, and (2) identify ancillary structures (e.g., garages, sheds) misclassified as primary residences, allowing for their removal from the final residential building count.
- Official Demolition and Building Stock Statistics: The Belgian statistics office (Statbel) provided two key datasets. The first is a record of all buildings demolished annually in Wallonia from 1996 to 2023, which is not disaggregated by building use. The second, the "cadastral statistics of building stocks", provides the official count of residential buildings and serves as a benchmark for validating our own identified number of residential buildings.

Table 1: Data sources

| Data | Date | Last update | Institution | Data type | Geographical coverage | Resolution |
|---|---|---|---|---|---|---|
| Cadastral data 2020 | 2021 | - | SCIP | 2D Shapefile | Regional | Building level |
| Cadastral data 2010 | 2011 | - | SCIP | 2D Shapefile | Regional | Building level |
| DSM and DTM | 2021-2022 | 2024 | SPW | Raster | Regional | 1 m |
| Land use data | 2023 | 2023 | SPW | 3D Shapefile | Regional | Building level |
| Official demolition statistics | 1996-2023 | 2024 | Statbel | Excel file | National | - |
| Cadastral statistics | 1995-2024 | 2024 | Statbel | Excel file | National | - |
| Orthophotos 2010 | 2011 | - | SPW | Orthorectified and mosaicked imagery | Regional | 0.25 m |
| Orthophotos 2020 | 2021 | 2025 | SPW | Orthorectified and mosaicked imagery | Regional | 0.25 m |

- Building Construction Periods: The typological construction periods were retrieved from reports about different cost-optimal levels of the minimum energy performance requirements conducted in 2013, 2018, and 2023 by the Public Service of Wallonia (SPW) for the European Commission, supplemented by the international Tabula study.

### 2.3 Procedural Workflow

- First, building stocks were derived from the 2010 and 2020 cadastral datasets, comprising approximately 2.2 million and 2.3 million buildings, respectively. Initial classifications of building use (residential/non-residential) and type (individual/collective) were based on cadastral codes. To ensure accuracy, land use data were integrated to correct misclassifications and remove ancillary structures (e.g., garages, sheds) misidentified as primary residences. The final, validated distribution of residential building density per municipality is shown in Figure 2. The density was calculated by dividing the buildings' counts by the municipality's area.

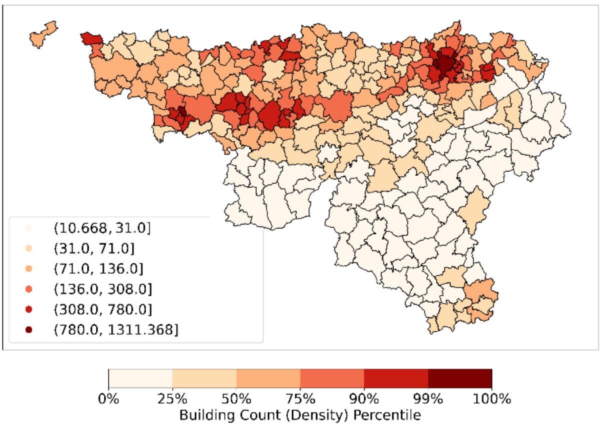


Figure 2: Distribution of residential buildings in the cadastral 2020.

- Second, we subtracted the DTM from the DSM to create a raster file that represents the height of above-ground elements with a resolution of one meter. This raster was then converted to a point layer, where each point represented a pixel centroid and stored the corresponding height value.

This point layer was spatially joined to the building footprint polygons. The final height for each building was defined as the third quantile ($75^{th}$ percentile) of the height values of all the points located within its footprint, a method chosen to provide a stable estimate that is resistant to both low and high outliers.

- Third, to address the 16.92% of buildings (cadastral 2020) with missing values in building types (i.e., terraced, semi-detached, and detached), we proposed a "jointness analysis" for in QGIS. For each building, a buffer of 50 cm was created around its footprint, facilitating the assessment of spatial relationships and the influence areas surrounding the buildings. The degree of connectivity, termed 'jointness', was then quantified for each building using the following formula:

$$Jointness\ (\%) = \frac{Area\ of\ Buffer\ Overlap\ with\ Neighbouring\ Buildings}{Total\ Buffer\ Area} * 100$$

  This metric yields a value ranging from 0% for a fully detached building to 100% for a building completely surrounded by others, with intermediate values indicating semi-detached or row-house configurations. The accuracy of this classification was validated through a manual verification study. A stratified random sample of 502 residential buildings was selected based on location, building type, and construction period. Each building in the sample was visually classified by comparing its spatial configuration against high-resolution reference imagery, including Google Open Street Map and Web Map Service available in the Wallonia database "Wallonmap[1]" namely Orthophotos 2020. The results of this manual verification were used to calibrate jointness thresholds and confirm the reliability of the typological classification.
- Fourth, the building stock dynamics were analysed by detecting changes between the 2010 and 2020 cadastral data, as illustrated in Figure 1. A building presented in the 2010 dataset but absent in 2020 was classified as demolished. Conversely, a building appearing in 2020 but not in 2010 was identified as newly constructed.

[1] Catalogue des données | Géoportail de la Wallonie

- Fifth, to validate the demolition rates derived from our geospatial change detection, official annual demolition statistics for Wallonia (1996-2023) were obtained from the Belgian statistics office. These statistics provide a regional benchmark, encompassing all types of demolished buildings reported in Wallonia without distinguishing between residential and non-residential structures. The geospatially-derived demolition rate, once validated against this official benchmark, can be applied to the total material volume of a given building category to project a preliminary estimate of its CDW output.
- Sixth, residential buildings were classified into a typology of 16 categories based on construction periods (≤1945, 1946-1970, 1971-1995, ≥1996) and building types (collective, individual terraced, individual semi-detached, and individual detached). The construction periods selected for this study were retrieved from reports about different cost-optimal levels of the minimum energy performance requirements conducted in 2013, 2018, and 2023 by the SPW for the European Commission, as well as from the Tabula study, which includes data from Belgium, Germany, and other countries. Given the significant regional variation in construction characteristics, Wallonia-specific MICs were developed. For each of the 16 categories, it is critical to define the corresponding MICs, expressed as mass per building volume (e.g., $kg/m^3$), to calculate the total amount of materials stocked in each structure type. This is the focus of ongoing work, which involves identifying representative reference buildings for each category and quantifying the material mass for components of those buildings.

# 3 Results

## 3.1 Building Type

To assess the quality of cadastral data, we compared its building type classification against the results from our jointness analysis and a manual survey (see Table 2). Following the removal of ancillary structures with the help of land use data, the surveyed sample size reduced from 502 to 486 buildings. For the cadastral data, 1,426,028 residential buildings were identified, of which 1.89% had missing building type information. Using the jointness metric, buildings were classified as follows: detached (0% to 0.1%

jointness), semi-detached (>0.1% to 25% jointness), and terraced (>25% to 100% jointness). The threshold for the detached category was set as a range (0% to 0.1%) rather than a unique value of 0% to account for the complexity of building shapes and minor spatial inaccuracies within QGIS calculation, which could cause a slight intersection within the 50 cm buffer for truly detached structures. The validation against survey data revealed an accuracy of 69.55% for the cadastral data classification, compared to 59.88% for the jointness-based classification. As detailed in Table 2, the cadastral data demonstrated a superior match with the surveyed building types across all classes. Additionally, the jointness analysis yielded a significantly lower proportion of semi-detached buildings than expected from other sources, indicating a need for more precise boundary definitions between semi-detached and terraced structures in the geometric model.

Table 2: Building types of residential buildings in the 2020 data in Wallonia

| Residential | Cadastre | Jointness analysis | Survey | Cadastre-Survey Accuracy | Jointness-Survey Accuracy |
|---|---|---|---|---|---|
| Terraced | 31.65% | 47.78% | 37.04% | 0.840 | 0.720 |
| Semi-detached | 28.10% | 21.75% | 29.42% | 0.595 | 0.593 |
| Detached | 38.36% | 30.47% | 33.54% | 0.701 | 0.776 |
| Other | 1.89% | 0% | 0% | | |

### 3.2 Building Change Detection

Building change was detected through a spatial joint analysis between 2010 and 2020 cadastral datasets. Buildings present in the 2010 data but absent in the 2020 data were classified as demolished, yielding a preliminary count of 43,696 demolished structures. Conversely, buildings appearing only in the 2020 data were classified as newly constructed, resulting in 161,032 new buildings. Figure 3 shows the spatial distribution of detected demolished and new buildings. The map depicts building change density, calculated as the number of buildings per square kilometre within each municipality in Wallonia. To validate the demolition detection accuracy, a visual check was carried out on a random sample of 500 detected demolished buildings. The presence of the building in 2010 and its absence in 2020 were verified using Orthophotos 2009/2010 and 2020 (aerial photographs). This verification revealed four distinct outcomes: buildings that were actually demolished (52.5%); buildings that were not demolished but were detected as such because of an error in the spatial superposition of the two cadastral data sets (29.9%); buildings that were not demolished but were detected as such because of a shortcoming in the 2020 cadastre (5.8%); the final group includes buildings that cannot be verified because they are missing from Orthophotos or because they were demolished before 2010 (11.8%). A significant portion of the false positives identified during validation was attributed to spatial misalignment between the 2010 and 2020 cadastral layers. To correct this, we re-evaluated false-positive demolitions by cross-referencing their parcel codes and applying a 10-metre distance threshold between the centroids of superpositions. This refinement successfully reclassified 6,379 buildings, reducing the preliminary demolition count from 43,696 to a more reliable estimate of 37,317 buildings.

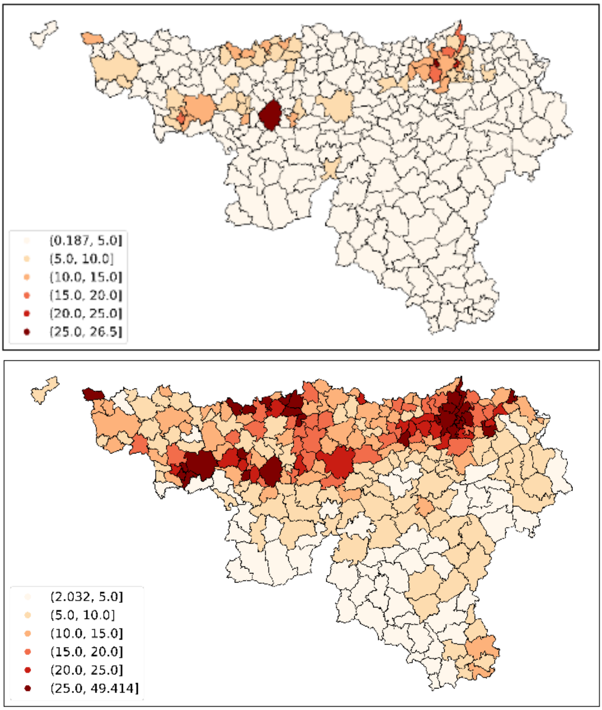


Figure 3: Building change density (number per km$^2$) of the detected demolished (upper) and new (lower) buildings.

Our geospatially-derived demolition count is higher than the official figure of 16,339 from the Belgian statistical office. This discrepancy can be attributed to key methodological differences. The official statistics exclusively record demolitions conducted with formal permission, whereas our method captures all physical changes evident in the cadastral data, potentially including unpermitted activities. Besides, inherent spatial inconsistencies between the cadastral datasets for different years contribute to a residual overestimation, despite their shared coordinate reference system. Notably, when translated into an annual demolition rate for the region, our estimate aligns more closely with the official statistics, as shown in Table 3. This suggests that while the absolute counts differ, the overall trend and intensity of demolition activity are comparable.

Table 3: Comparison of the detected demolition number and the official statistical demolition number

| | Detected number | Official number |
|---|---|---|
| Total number | 37,317 | 16,339 |
| Over 11 years | 1.67% | 1.02% |
| Yearly | 0.148% | 0.090% |

## 4 Discussion

This study develops a foundational, spatially explicit method for measuring material stocks in residential buildings, which is essential for supporting a circular economy in the construction industry. While material flow analysis tracks outputs, effective management requires accurate knowledge of existing stocks first. Our research fills this gap by creating a high-resolution, validated residential inventory for Wallonia, acting as a geolocated resource map for the region’s urban mine. The main strength of our approach is its solid, typology-based framework. By classifying the building stock into 16 distinct categories, it enables a representative sampling approach where characteristic material compositions are derived from analysed construction plans for each typology. This study advances the typological approach for material stock analysis by implementing and validating it at the regional scale, a significant step beyond its established application at the city scale (Kleemann et al., 2017; Lanua & Liu, 2020). Furthermore, it provides a critical enhancement over national-scale studies (e.g., Ortlepp et al., 2018) by delivering a fully transparent and replicable workflow from cadastral processing to validation. This work thus bridges a key methodological gap, offering a crucial model for generating the reliable, spatially explicit data necessary for effective regional circular economy planning.

While this study offers valuable insights, certain considerations should be noted to inform future research. The methodology relies on certain assumptions of homogeneity, which, while necessary for large-scale analysis, introduce uncertainty, particularly for older building stocks (pre-mid-20th century) and renovated structures where material uniformity cannot be assumed (Augiseau & Barles, 2017). Future work should therefore cross-validate these results with alternative methodological approaches to quantify and reduce this inherent uncertainty. Furthermore, the classification of building types, a cornerstone of the typology, presents challenges. Despite its superior reliability (see Table 2), the cadastral data contained missing values that were supplemented using our jointness analysis. Future refinement of this jointness analysis should focus on developing more precise boundary definitions to better differentiate semi-detached from terraced buildings. The building height derived from LiDAR data provided a more realistic and physically plausible maximum (84 meters) than the estimate based on cadastral floor numbers (186 meters). While crucial for realistic volume estimation, the LiDAR-based heights require future validation against high-resolution orthophotos or stereo imagery. Finally, while this study's demolition detection relied on spatial matching, future work could develop a more robust, self-training system. Such a system would integrate geometric and semantic metrics with a deep learning algorithm, using its own high-confidence predictions to iteratively improve accuracy without manual intervention.

# 5 Conclusions

This study demonstrates the significant potential of a GIS-based data fusion approach to create a high-resolution, regional building inventory for material flow assessment. By systematically integrating cadastral, land use, and statistical data, we developed a validated spatial inventory for Wallonia that accurately classifies residential buildings and detects stock changes over time. The resulting map of demolitions and new constructions logically aligns with observed urban development patterns, showing heightened activity in core urban areas along the Meuse River and in municipalities with strong cross-border economic links. However, the process also underscored the persistent challenges of working with regional-scale data, including spatial inaccuracies, temporal inconsistencies, and a lack of detailed material attributes. Future work will directly build upon this foundational inventory by completing the ongoing development of region-specific material intensity coefficients. This crucial next step will enable the precise quantification of material stocks, thereby transforming this spatial inventory into a transferable tool for forecasting construction and demolition waste and strategically planning urban mining activities to advance the circular economy in the Wallonia region.

## Acknowledgements

The authors are grateful to the Government of Wallonia who financially supports the ReInvenTe project, part of the Walloon initiative for Circular Material (Win4C).

## References

Attia, S., Mustafa, A., Giry, N., Popineau, M., Cuchet, M., & Gulirmak, N. (2021). Developing two benchmark models for post-world war II residential buildings. Energy and Buildings, 244, 111052.

Augiseau, V., & Barles, S. (2017). Studying construction materials flows and stock: A review. Resources, Conservation and Recycling, 123, 153-164.

Cristóbal García, J., Caro, D., Foster, G., Pristerà, G., Gallo, F., & Tonini, D. (2024). Techno-economic and environmental assessment of construction and demolition waste management in the european union. Publications Office of the European Union: Luxembourg.

Dabrock, K., Ulken, J., Pflugradt, N., Weinand, J. M., & Stolten, D. (2025). Generating a nationwide residential building types dataset using machine learning. Building and Environment, 274,112782.

Lanau, M., & Liu, G. (2020). Developing an urban resource cadaster for circular economy: A case of Odense, Denmark. Environmental science & technology, 54(7), 4675-4685.

Laupheimer, D. (2024). Multi-modal data fusion and information transfer for geospatial semantics. gis.Science 2 (2024) 53-59.

Kleemann, F., Lehner, H., Szczypińska, A., Lederer, J., & Fellner, J. (2017). Using change detection data to assess amount and composition of demolition waste from buildings in Vienna. Resources, conservation and recycling, 123, 37-46.

Lederer, J., Fellner, J., Gassner, A., Gruhler, K., & Schiller, G. (2021). Determining the material intensities of buildings selected by random sampling: A case study from Vienna. Journal of Industrial Ecology, 25(4), 848-863.

Ortlepp, R., Gruhler, K., & Schiller, G. (2018). Materials in Germany's domestic building stock: calculation model and uncertainties. Building Research & Information, 46(2), 164-178.

Paz, D., Lafayette, K., & Sobral, M. (2020). Management of construction and demolition waste using gis tools. In Advances in construction and demolition waste recycling (pp.121–156). Elsevier.

Pei, W., Biljecki, F., & Stouffs, R. (2022, October). Dataset for urban scale building stock modelling: Identification and review of potential data collection approaches. In 17th 3D GeoInfo Conference (Vol. 10, pp. 225-232). Copernicus.