# From Orthophotos to Building Footprints over a decade: Model Inference-Based Approach for Urban Densification Analysis in Iași, Romania

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## Abstract

Urban densification in post-socialist cities involves fine-scale spatial transformations that are difficult to quantify in data-scarce environments. This study proposes FLAIR-HUB2BF, a model inference-based workflow for automated building footprint extraction and multi-temporal change analysis, applied to the city of Iași, Romania. The methodology extends the SUBDENSE conceptual framework by integrating the FLAIR-HUB deep learning model for semantic segmentation of very high resolution aerial orthophotos from 2011 and 2024, followed by binary mask extraction, instance segmentation, and Douglas–Peucker polygon generalization. The approach demonstrates good spatial transferability of the FLAIRHUB model which was trained on France to generate buildings (for 2024) and less good temporal transferability (for 2011) due to the quality of orthopothos in 2011.
To support rigorous evaluation, the first open benchmark building footprint datasets for Romania in 2024 were produced through manual photo-interpretation correction across four morphologically distinct urban neighborhoods of Iași, and assessed against ISO 19157 spatial data quality standards, achieving commission and omission rates of 1.95% and 2.39% respectively. Quantitative evaluation using complementary GMA (Geometric Matching of areas) and MCA (Multi-Criteria Algorithm) data matching algorithms confirms moderate-to-high spatial accuracy for 2024, with MCA surface agreement rates reaching 91%. The proposed workflow establishes a transferable, reproducible, and open methodology for building-level urban monitoring applicable to other Romanian and European cities facing similar data constraints.

## 1. Introduction

During the past decades, Romanian cities have undergone accelerated changes in land-use, particularly through the transformation of natural and agricultural areas into residential, commercial, and industrial uses. In major urban centers, this expansion has frequently occurred at the expense of green spaces and has been accompanied by the development of the transport infrastructure. These processes are further exacerbated by insufficient legal protection of green areas and the inconsistent enforcement of urban planning regulations The city of Iași has experienced rapid urban expansion in recent years, driven by residential development and population migration from the urban center to the peri-urban area such as Miroslava, Valea Lupului, Breazu, Barnova cities. This phenomenon poses challenges for urban planning, infrastructure management, and spatial data-based decision-making. Traditional analyses, based on administrative boundaries, do not always reflect the actual changes in city structure and population density, thus requiring functional and geospatial data-based approaches for an accurate assessment of urban densification (Broitman and Koomen, 2015), (Bucher et al., 2025). Previous research demonstrates that the state of urban densification in Iași city is characterized by the most important densification occurring in the city center, notably through massive projects like the Palas urban complex, alongside the conversion and densification of former industrial sites such as the old municipal swimming pool or the former Textila Factory into commercial, real estate areas, and new high-rise, high-density neighborhoods, often involving building on interstitial spaces between dwellings within the urban core (Ursu et al., 2016, Foșalău et al., 2025). Previous studies primarily adopted a methodology centered on remote sensing and Geographic Information Systems (GIS) techniques. For example, Ursu et al. (2016) investigate changes in built-up areas for the years 2006, 2009, and 2012 at the building scale, the building footprints for the three snapshots being manually digitized through photo-interpretation from orthophotos, and not openly available. In contrast, Foșalău et al., (2025) propose an approach for mapping urban changes in the same area of interest at the gridded built-up area scale by applying spatio-temporal analysis from 1987 to 2023, time-series clustering, and multivariate clustering (Foșalău et al., 2025).

Recent research has investigated if buildings and their changes can support densification studies that are transferable across cities and countries; Buildings change data has the potential to support densification studies as it can be observed from data, with national coverage and regularly updated, it relates to dwellings, and it has the needed granularity to grasp local contrasts in densification benefits (Bucher et al., 2025). Producing Building Changes data can be challenging as it requires gathering building data with required completeness on the spatiotemporal scope of interest and computing changes in each building footprint over time.
(Bucher et al., 2025) proposed a Git-based collaborative dashboard, the Subdense dashboard, to share knowledge (*e.g.*, densification concepts) and resources (*e.g.*, data, algorithms) among various types of experts (*e.g.*, GIS researchers, urban plan-

ners, and stakeholders) to produce BuildingChange data useful for comparable analyses of densification situations across different countries. To construct building footprint change data (*i.e.*, change at the scale of building between two dates), open-source data matching approaches are employed (Guardiola et al., 2024). Post-processing rules are then applied, specific to each Building data product, to differentiate BuildingChanges that can be explained by changes in the data survey procedure and not in reality. It uses quotes of the product documentation shared on the git, *e.g.*, in French BDTopo, a building footprint was only mapped if its area exceeded $20m^2$ until 2018, whereas no such threshold was applied afterwards. The Subsense dashboard was prototyped in three countries, Germany, France, and the United Kingdom (UK), and designed as an open solution that could be extended to new countries.

A key limitation of this approach arises when building footprint data are not openly available, when cadastral datasets are incomplete or outdated, and when the generation of temporal footprint snapshots is not feasible. In the same time, much effort has been made to classify Land Cover (LC) (Garioud et al., 2025, Garioud et al., 2023) or building footprints from imagery (Rastogi et al., 2022).

The current research work goes beyond existing approaches by demonstrating that building-level densification patterns can be derived in data-scarce environments starting from orthophotos, without relying on complete cadastral datasets, which are not always open or may lack completeness and up-to-date information. We build our approach on the FLAIR-HUB model (Garioud et al., 2025), developed by the French National Institute of Geographical and Forest Information (IGN), that combines very high-resolution aerial imagery with multi-temporal satellite data, providing the capability to semantically segment land and infrastructure elements, including buildings, roads, paved areas, and green spaces. This approach enables precise assessment of built-up areas and infrastructure, offering essential information for the design, management, and monitoring of urban development and construction projects.
Thus, the goal of this current work is to propose and evaluate an approach for generating building footprints from orthophotos by applying an existing AI model in an inference setting. Particular emphasis is placed on assessing the transferability of the model by comparing the results with ground truth data in four different urban neighborhoods in the Municipality of Iasi, Romania and for two time periods : 2011 and 2024.

The contributions of this work are:

1. to enhance the methodology proposed in (Bucher et al., 2025) by extending the existing pipeline to generate building footprints from orthophoto;
2. to produce ground truth building footprints datasets;
3. to describe the processes, datasets, and results, and publishing them as open data to address the lack of open-source building footprints in Romania.

The paper is structured as follows: Section 2 presents the data and study area. Section 3 describes the proposed methodology. Section 4 reports and discusses the results. Finally, Section 5 concludes the paper and outlines future research directions.

## 2. Study area and data sources

### *2.1 Study Area*

The municipality of Iași, located in northeastern Romania (see Figure 1, spans an area of 94 km² and had an estimated population of approximately 610,000 in 2023. As the second-largest city in Romania, it presents a highly heterogeneous urban environment, combining a dense historic core, extensive residential neighborhoods from the communist period, transforming industrial areas, and rapidly growing peri-urban zones. Population distribution varies significantly across the city, reflecting both long-standing urban structures and recent migratory movements from surrounding rural areas. These demographic patterns, together with ongoing urban expansion, create a complex spatial structure that is particularly suitable for studying urban densification processes.

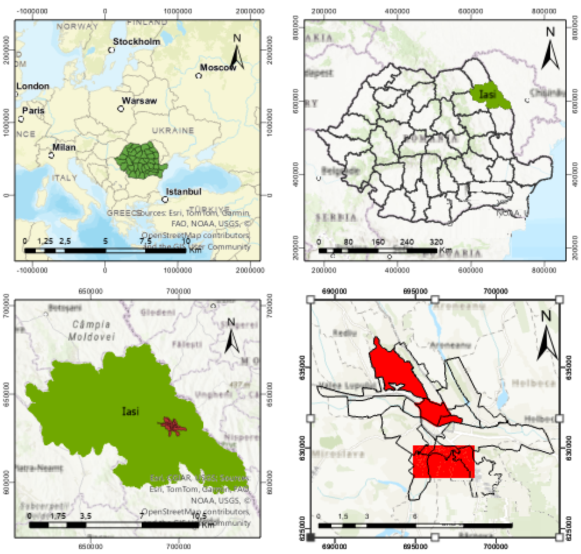



Figure 1. Location of the study area (Municipality of Iași, Romania) with marked locations of the validation areas in red.

Consequently, Iași offers a representative case study for evaluating urban densification and urban growth, and the interaction between built-up areas and demographic trends, providing valuable insights for spatial planning and urban management in medium-to-large cities in Eastern Europe.

### *2.2 Existing building footprint data*

As we mentioned earlier, we chose to use the methodology proposed in (Bucher et al., 2025) to study the densification in the city of Iasi, Romania. The choice of this approach is justified by its open-source nature, its capacity to engage with multiple users, its ability to generate and explain open data and results through the dashboard, and its demonstrated efficiency in generating comparable densification data across countries and study areas. The implementation of this methodology faces several challenges that collectively constrain the ability to perform a densification study for our study area or to extend the analysis to a national scale for Romania.
The first challenge concerns access to current, historical, and reliable building footprint data in Romania, particularly regarding completeness, spatial accuracy, and acutality. Indeed, to perform densification analysis at the building scale, we need two snapshots at two periods, T1 and T2, containing building footprints. The most recent dataset of building footprints available from the National Agency for Cadastre and Land Registration (ANCPI) for the study area represents buildings from

This contribution has been peer-reviewed.
 

2019 but covers constructions from 2009 to 2018, without specifying the exact year of construction, reducing the possibility to generate accurate snapshots (Table 1). Although this dataset demonstrates very good spatial accuracy, it suffers from low completeness, limiting its suitability for comprehensive densification analyses (see Figure 2). OpenStreetMap (OSM), the most widely known open-source crowdsourced platform, could be another alternative solution. Nevertheless, OSM data in Romania also presents data quality issues: building footprints in our study area are sparse and exhibit low spatial accuracy with random geometric deviations. One solution could be to combine ANCPI and OSM data, as proposed in (Van Damme and Olteanu-Raimond, 2022), by integrating authoritative spatial data with crowdsourced data to enhance completeness. However, despite the license incompatibility, this is not feasible in our case, without introducing inconsistencies in accuracy, and completeness still remains an issue in areas where buildings are missing from both datasets. Moreover, this also complicates the generation of building footprint snapshots over time given the lack of construction year for each building.

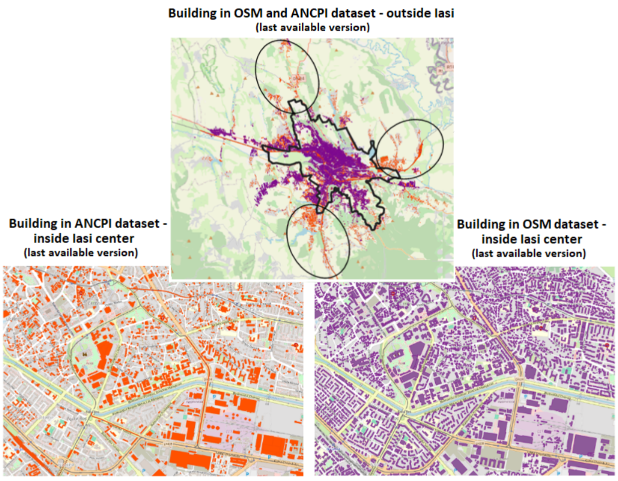



Figure 2. Examples of building footprints in OSM and ANCPI datasets (the last current available data).

### *2.3 Orthophoto Data*

The second challenge concerns the quality of historical orthophotos. To envisage an approach that generates building footprints from aerial images from existing models, such as (Garioud et al., 2025), there is need to have image resolution at a minimum that was used for training (e.g., 20 cm). In our case, this applies to 2024, the most recent orthophoto available to us, but it does not hold for the 2011 orthophoto, which has 50 cm resolution. In addition, the development of deep learning algorithms for historical orthophotos depends on the availability of accurate ground-truth data. Details regarding the two available orthophoto datasets used in this investigation, are described in Table 2.

Figure 3 illustrates the orthophoto comparison at three representative locations in the study area. The top and middle pairs show peri-urban zones (Valea Lupului / Miroslava) where, between 2011 and 2024, largely undeveloped or agricultural land was converted into dense residential developments, exemplifying the greenfield expansion pattern that dominates the peri-urban fringe of Iași. The bottom pair shows a central industrial zone where large-scale functional transformation is underway, with former industrial structures being replaced or converted to commercial and mixed-use developments. The resolution difference between the 2011 orthophoto (0.50 m, RGB) and the 2024 true orthophoto (0.2 m, RGB+NIR) is clearly visible and directly influences the performance of deep learning-based building detection. It is worth noting that, unlike conventional orthophotos in which building rooftops are displaced radially from their true ground position due to relief displacement, the 2024 orthophoto constitutes a true orthophoto, generated through differential rectification using a high-resolution Digital Surface Model (DSM). As a result, each pixel is projected to its correct planimetric position, including above-ground objects such as buildings. While this ensures superior geometric fidelity, it also introduces a systematic geometric discrepancy relative to the training domain of the FLAIR-HUB model, which was developed on standard orthophotos at 0.20 m resolution. This difference may affect the spatial accuracy of predicted class boundaries, particularly along building edges, and constitutes an additional source of domain shift beyond that induced by geographic and resolution differences.

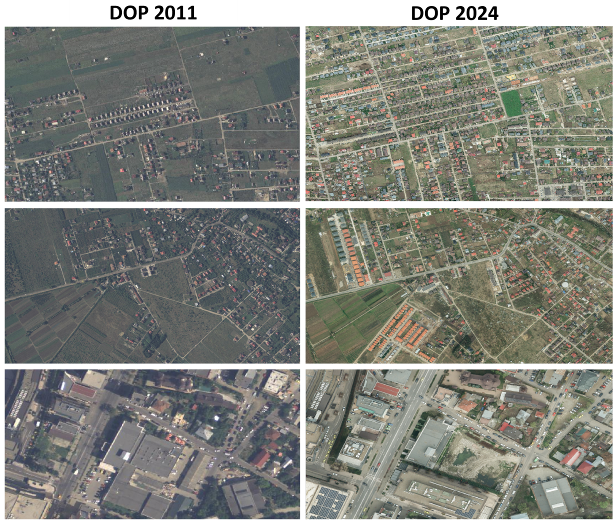



Figure 3. Multi-temporal orthophoto comparison illustrating urban expansion and densification processes in Iași between 2011 (left) and 2024 (right)

Finally, although in Romania recent national initiatives promote the use of open-source geospatial data, implementation remains limited, and access to comprehensive, high-quality datasets continues to be restricted (OECD, 2023).

## 3. Proposed approach

The proposed approach is illustrated in Figure 4 and is composed by four main steps: description, footprint generation, ground truth generation, and evaluation. The first step is to use the Subdense Dashboard (Bucher et al., 2025) to document and describe the data sources, their imperfections, the context-specific concepts relevant to Romania, and the working hypotheses guiding the analysis. We create a metadata file on the dashboard to share knowledge, data, and maps to study densification for the Study Area of Iasi, Romania.

The second step consists of generating building footprints at a given date from orthophoto. We named this processing step FLAIR-HUB2BF, where BF stands for building footprint. To achive this goal, we propose four sub-steps: i) apply the existing FLAIR-HUB model (Garioud et al., 2025) to infer land

| Dataset | Buildings | Spatial Accuracy | Completeness | Period | Licence |
|---|---|---|---|---|---|
| ANCPI | 34,708 | High (< 0.5 m) | Low | 2009–2018 | Restrictive |
| OSM | 33,661 | Low (strong variation) | Moderate | Continuous | ODbL |
| Our approach | 17,141 | High (0.5 m) | Full coverage | 2011 | Open source |
| Our approach | 34,454 | High (0.2 m) | Full coverage | 2024 | Open source |

Table 1. Summary of existing building datasets and those generated by our approach.

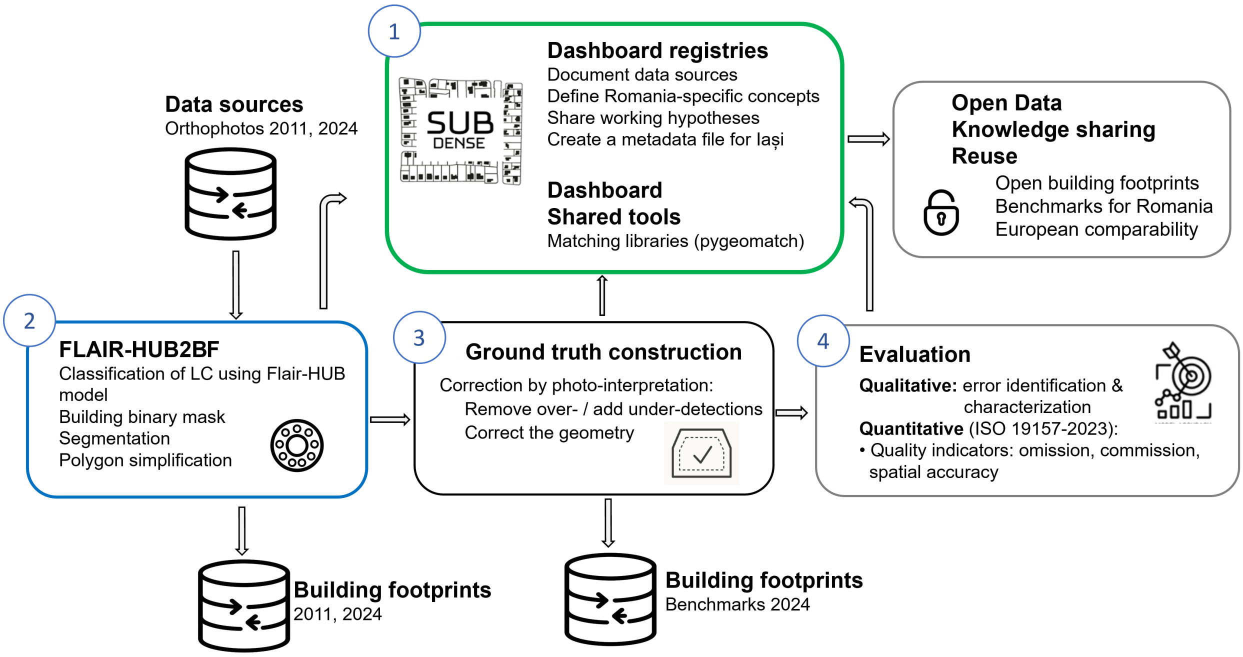



Figure 4. Proposed Approach.

| Year | Camera sensor | GSD [m] | Bands | Type | Prec. XY | CRS EPSG |
|---|---|---|---|---|---|---|
| 2011 | Leica ADS80 | 0.50 | RGB | Standard | <1 m | 3844 |
| 2024 | UltraCam Eagle M3 | 0.084 | RGB+ NIR | True ortho | <1 m | 3844 |

Table 2. Summary of existing orthophotos in the study area.

cover (LC) classification at the pixel level; ii) binarization of the resulting LC classification to obtain a binary mask containing only building pixels; iii) segment the binary mask to generate vector polygons. This is achieved by a home-made python algorithm (Study Area of Iasi, Romania.) which enables the delineation of building footprints; iv) Finally, a post-processing step is applied to remove noise and generalize building by using Douglas-Peucker (Douglas and Peucker, 1973). This final step is only required for very high spatial resolution data (i.e., finer than 50 cm).
The third step consists of constructing the ground truth data required for evaluation. In the absence of reference datasets, we propose an approach to generate such ground truth. Starting from the building footprints produced by the FLAIR-HUB inference combined with the segmentation step, we manually corrected the generated outputs through photo-interpretation. Over-detections were removed, while under-detections were manually added. This process ensures the creation of exhaustive datasets with high geometric accuracy, consistent with the orthophotos, which will be published in open source (see Study Area of Iasi, Romania).
Finally, the last step involves evaluating the generated building footprints. Two types of assessment are conducted: a qualitative evaluation, aimed at identifying and characterizing errors, and a quantitative evaluation based on ISO data quality standards (ISO, 2013). To perform the latter, two data matching algorithms GMA (Geometric Matching of areas) (Harvey et al., 1998) and MCA (Multi-Criteria Algorithm) (Olteanu-Raimond et al., 2015) are first applied to establish homologous features, meaning that n buildings in the ground truth are associated with a corresponding m buildings in the dataset under evaluation, where n and m can be 0,1, or many. It is important to note that both datasets represent real-world entities at the same temporal reference, so the 0 to 1 link cardinality means commission, 1 to 0, means omission, n:m, means matching pairs. The GMA and MCA data matching algorithm are available in open source pygeomatch library), and are used for their complementarity, the first define n:m links, whereas the second defines only 1:1 links. Based on the matching results, quality indicators derived from ISO standards (ISO, 2013) are computed, including omission, commission, and spatial accuracy.

## 4. Results

In this section, we present the results through both qualitative and quantitative evaluations. The quantitative analysis is conducted only on buildings generated for 2024, as the results for 2011 were found to be insufficiently reliable.

### 4.1 Building Footprint generation from orthophotos

The pipeline described previously was applied for both orthophoto from 2024, and 2011. For 2024, the initial ortophotos

(0.084m) has been transformed into 0.2 resolution in order to have the same resolution as the FLAIR-HUB trained model. In total 34,454 buildings and 17.141 buildings for respectively 2024 and 2011 are mapped. The FLAIR-HUB model inference was applied by using the same parameters proposed by (Garioud et al., 2025), resulting in a classified raster file with 15 classes (Figure 5 (b)). For the post-processing step, buildings with an area smaller than $10\,\mathrm{m}^2$ were removed from the dataset. This filtering step was implemented to exclude small structures such as garden sheds and garages. The geometries were then smoothed using the Douglas–Peucker algorithm with a tolerance of 8. Figure 5 illustrates a typical example of LC classification and buildings segmentation.

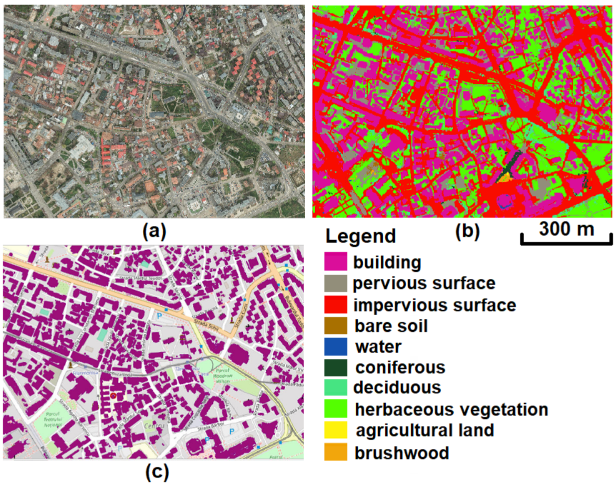



Figure 5. Mapping Building footprints: (a) Orthophoto from 2024 (at 0.084 m resolution); (b) FLAIR-HUB model inference on the orthophoto from 2024; (c) Building footprint polygons.

Figure 6 shows a typical example of each step of the pipeline: LC classification, binarization, segmentation, and Douglas–Peucker generalization.

### 4.2 Qualitative evaluation of building footprints

A qualitative validation was conducted through visual comparison between the extracted building footprints, multi-temporal orthophoto imagery (2011 and 2024), and available reference datasets. This assessment aimed to identify systematic errors, evaluate spatial consistency, and analyze the influence of input data characteristics on segmentation performance.

The application of the pipeline (FLAIR-HUB2BF) to the 2024 true orthophoto (0.2 m) yielded well-delineated building polygons, particularly for detached and semi-detached residential structures in peri-urban zones. Visual quality inspection identified six systematic error types (Table 3), the most frequent being vegetation/building confusion, affecting primarily isolated trees in residential gardens, and building fusion due to morphological closing in densely built areas.

Direct application of FLAIR-HUB to the 2011 orthophoto ($0.50\,\mathrm{m}$, RGB) yielded significantly noisier segmentation outputs, showing that the FLAIR-HUB model did not transfer well to the 2011 orthophotos. This result can be attributed to the lower resolution of the existing orthophoto ($0.50\,\mathrm{m}$ instead of $0.2\,\mathrm{m}$ used to train the FLAIR-HUB model), as well as the very

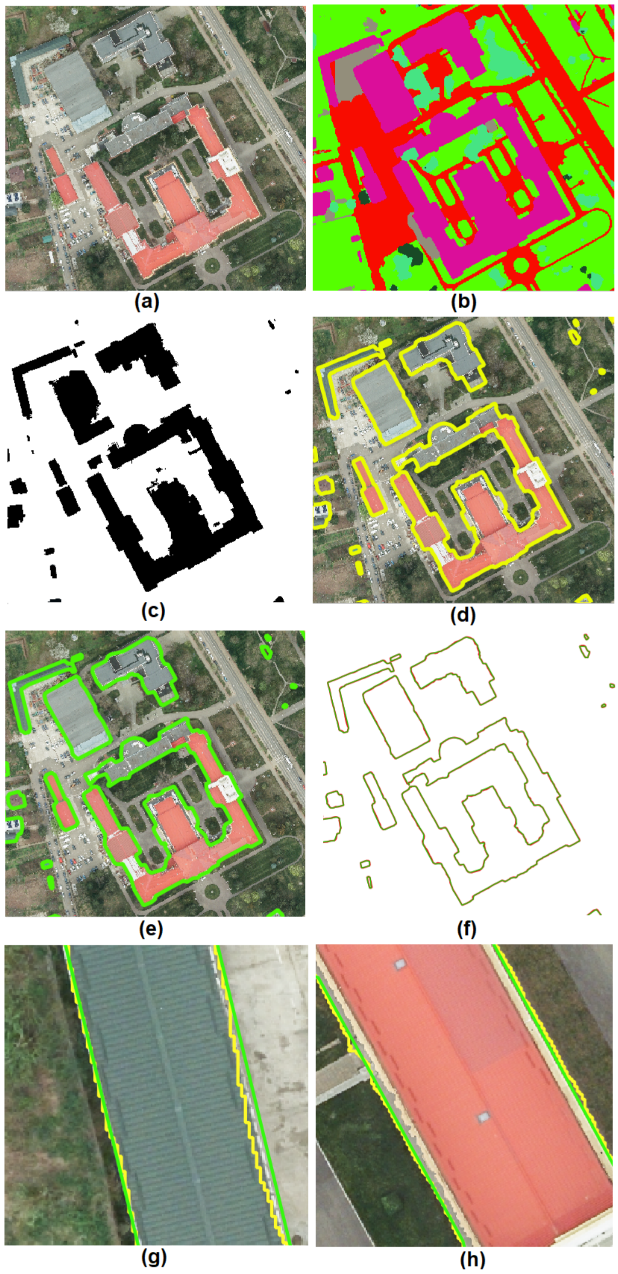



Figure 6. Mapping Building footprints pipeline: (a) Orthophoto from 2024 (at 0.2 m resolution); (b) FLAIR-HUB model inference on the orthophoto from 2024; (c) Binarization; (d) Building footprint polygons derivation; (e) Douglas-Peucker generalization; (f) Building footprint polygons before (red) and after Douglas-Peucker generalisation (green); (g) and (h) Detail-view comparisons before (yellow) and after (green) Douglas-Peucker generalization.

degraded quality of the 2011 orthophoto due to compression artifacts. Table 4 illustrated the systematic error types.

The results indicate a clear improvement in building extraction quality when using the 2024 true orthophoto, which benefits from higher spatial resolution and improved geometric accuracy. In this case, building footprints are well delineated, with consistent boundaries and reduced noise. In contrast, the 2011 orthophoto introduces several limitations, including lower spatial resolution and geometric distortions caused by facade ef-

| Error type | Category | Example | Description |
|---|---|---|---|
| Vegetation / tree canopy | Commission (False Positive) |  | Dense tree canopies with sharp edges produce building-like spectral signatures. Most frequent error type. Predominantly affects residential gardens with mature vegetation in peri-urban zones. |
| Empty swimming pool | Commission (False Positive) |  | Light-colored concrete base of empty pools presents high reflectance similar to flat rooftops, classified as a building by FLAIR-HUB. |
| Synthetic sports pitch | Commission(False Positive) |  | Artificial turf with uniform color and regular geometry is detected as a large flat-roofed building. |

Table 3. Systematic error types in the 2024 FLAIR-HUB2BF results.

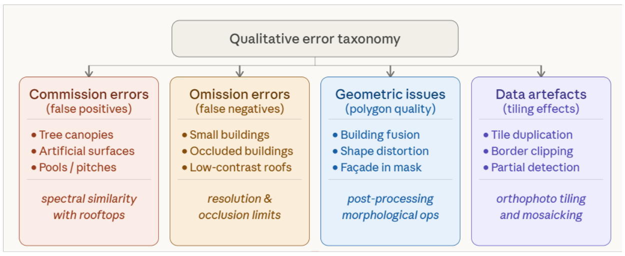



Figure 7. Qualitative error taxonomy

fects, which lead to less accurate building representation.

Several types of systematic errors were identified see Figure 7. False positives occur mainly in areas with vegetation cover and artificial surfaces, such as parking areas and empty swimming pools, which present spectral similarities to building roofs. False negatives are primarily associated with small buildings, partially occluded structures, and low-contrast surfaces, especially in the 2011 dataset.

Additional geometric inconsistencies are introduced during the polygonization stage, including the merging of adjacent buildings and the simplification of complex building shapes. Furthermore, tile boundary effects generate local artefacts, where buildings may be partially detected or duplicated along orthophoto seams.

These observations demonstrate that the quality of input data plays a critical role in deep learning-based building extraction and directly influences the reliability of subsequent change detection.

## 4.3 Ground truth data construction

Four ground truth data were manually mapped following the approach explained in Section 3.

The choice of the four areas are as follows.

**(1) Copou:** The Copou area of Iași stands out as a unique urban district, distinguished by its historical, architectural, and environmental qualities that set it apart from other neighborhoods. The built environment reflects a gradual and selective urban evolution, with historic buildings mainly constructed between the late 19th century and the interwar period (ca. 1870–1940).

**(2) City Center:** The City Center, the historic center of Iași, represents the city’s cultural, administrative, and touristic core, distinguished by its highly compact built environment and diverse architectural heritage. Unlike other districts, the historic center features high built-up density, limited green space, and predominantly mixed-use functions, combining cultural, administrative, and commercial activities with residential units. The low to medium rise scale of the buildings contrasts with taller blocks elsewhere in the city, while the compact street layout preserves the urban fabric and heritage.

**(3) Student Campus:** The Student Campus Tudor Vladimirescu area in Iași represents a planned residential and academic district, distinct from the historic and peri-urban neighborhoods of the city. The area comprises multi-story apartment blocks with 4–10 floors, designed to accommodate a dense student population. The architecture is largely functional and uniform, characteristic of the late communist period, with long rectangular buildings, repetitive façades, and limited ornamental features.

**(4) Mixed area:** The mixed ground truth area, represents three distinct types of urban fabric corresponding to the CUG area (west), the central industrial platform (central zone), and the Bucium neighborhood (east), each reflecting different stages of urban development in the city of Iași.

## 4.4 Quantitative evaluation of building footprints

For the GMA data matching, commission and omission errors of 1.95% and 2.39%, respectively, were found. This means that

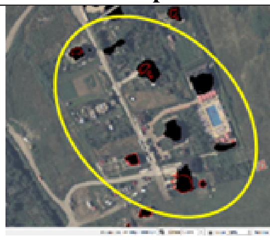
| Error type | Category | Example | Description |
|---|---|---|---|
| Small buildings / low contrast | Omission (False Negative) |  | Small outbuildings and low-contrast rooftops in the 2011 0.50 m RGB imagery fall below the effective detection threshold. Resolution limitation specific to the historical orthophoto. |
| Tile boundary artefact | Data artefact (tiling/mosaicking) |  | Buildings at the junction between orthophoto tiles are partially duplicated, clipped, or geometrically distorted due to mosaicking effects. |
| Facade/roof confusion | Geometric inconsistency |  | Standard (non-true) orthophotos include the visible façade in the building mask. Affects tall apartment blocks in 2011 imagery. Overestimates footprint area by 8–15%. |
| Building fusion | Geometric inconsistency |  | Morphological closing operation merges adjacent buildings separated by gaps narrower than the kernel radius. Prevalent in the historic city center dense fabric. |

Table 4. Systematic error types in the 2011 FLAIR-HUB2BF results.

the results are generally accurate, with a low rate of false positives and missed detections. See 3 for qualitative examples.

Three quality indicators, issues from the quality ISO norm (ISO, 2013): MeanAbsolute (Mean), RootMeanSquareError (RMSE), AgreementRate (similar), and AgreementRate (identical) are computed to evaluate the spatial accuracy of the building generated by the pipeline FLAIR-HUB2BF. To do so, two types of data matching are performed between the ground-truth buildings in 2024 and the buildings generated by FLAIR-HUB2BF, both representing buildings from the same date, 2024. The first algorithm, GMA, primarily relies on surface overlap to establish n:m links. This approach effectively captures the behavior of our FLAIR-HUB2BF pipeline when it perceives multiple terraced houses as a single building. In contrast, the second algorithm, MCA, combines radial distance ((Méneroux et al., 2023)) and surface distance to identify corresponding buildings, establishing only 1:1 links.

| **Data matching method** | **Mean** | **RMSE** | **AgrRate similar** | **AgrRate identical** |
|---|---|---|---|---|
| GMA (surface) | 0.36 | 0.51 | 0.54 | 0.36 |
| MCA (surface) | 0.1 | 0.15 | 0.91 | 0.6 |
| MCA (radial) | 1.1 | 2.4 | 0.6 | 0.07 |

Table 5. Spatial accuracy quality indicators.

Table 5 shows the quantitative metrics for each matching method computed for both surface distance (i.e., overlap between two homologous features) and radial distances (i.e., shape similarity between two homologous shapes). MeanAbsolute2D and RootMeanSquareError quantify the average geometric errors, with lower values indicating better accuracy. Agreement Rate measures the degree of similarity between shapes, or the extent to which two homologous building features overlap, with respect to a given threshold. This measure is reported for both "similar" (surface or radial distance is less than 0.3) and "identical" (i.e., surface or radial distance is in the order of 0).

The results obtained for GMA (surface) data matching show that the spatial accuracy is moderate in terms of mean and RMSE (0.36 and 0.51, respectively). The agreement rates indicate that there is good overlap between matched objects (AgrRate similar = 0.54; 54% generated buildings has an overlap with its homologous features greater than 0.3), but fewer complete overlaps are achieved (AgrRate identical = 0.36; 36% of buildings has a complete overlap with its homologue buildings in the ground truth). This aligns with the fact that the GMA allows multiple-to-multiple links.

The results show that for MCA, which matches 1:1 homologous buildings, the generated buildings have a spatial accuracy with low position errors and high agreement rates, whereas MCA with radial distance reflected in higher shape differences and lower identical agreement. Note that these results need to be confirmed after the validation of the data matching results.

## 5. Conclusion

This study presents a model inference-based workflow for generating building footprint data from multi-temporal orthophotos in a data-scarce context. Using Iași as a case study, the results demonstrate that building changes can be effectively derived from aerial imagery from orthophotos having at least 0.2m resolution. By combining deep learning-based semantic segmentation with polygonization and spatial matching techniques, the workflow provides a consistent and reproducible framework for multi-temporal urban analysis.

In addition, by improving the methodological framework proposed in (Bucher et al., 2025), this study demonstrates its applicability to other Romanian and European cities characterized by limited availability of long-term building footprint data, while opening new perspectives for the development of building-level digital twins and their temporal evolution. Furthermore, it enables the progressive development of benchmark datasets for Romania within an open data framework. Future work will focus on improving quantitative validation, integrating additional data sources, and extending the approach to other urban areas to support more comprehensive and scalable analyses of urban densification.

**Perspectives** The 2011 orthophotos, with a spatial resolution of 50 cm, produced less accurate results compared to the 2024 dataset (0.084 m). This difference in resolution has a big impact on the performance of the deep learning inference. To mitigate this limitation, our next step is to create ground truth data for the 2011 imagery and train a U-Net architecture to develop a model better suited for 50 cm resolution orthophotos. To do that, we will rely on collaborative, mapathon-based approaches by using the open source tool Annotator. The involvement of fourth-year students from the Department of Terrestrial Measurements and Cadastre, Faculty of Hydrotechnics, Geodesy and Environmental Engineering, “Gheorghe Asachi” Technical University of Iași, represents a structured and scalable strategy for improving the quality of building footprint extraction and change detection datasets. The same students will also be involved in validating the data matching links in order to obtain more accurate quantitative indicators.

Finally, once the building for 2011 generated, we will conduct the change detection changes between 2011 and 2024 to determine evolutions and determine densification indicators. The results will be presented to local stakeholders and end users to gather feedback and assess the relevance of the findings for urban densification analysis.

From a broader perspective, such approaches support the development of building-level digital twins and their temporal dynamics, while contributing to Sustainable Development Goals (SDGs), particularly those related to sustainable cities and communities. The integration of human in the loop validation within the Subdense dashboard also enhances reproducibility, stakeholder engagement, and the transferability of the methodology across different urban contexts.

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