An ML-supported Pipeline for the Mapping of Urban Densification Potentials

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Keywords: Infill site, Vertical extension, Machine learning, QGIS.

Abstract

Using densification potentials for urban development is one of the current challenges in urban planning. An important prerequisite is an up-to-date GIS data basis, which contains potential densification sites. Existing data is often based on manual acquisition, which is time-consuming and costly. Therefore, the value of such data depends on the effort of creating and updating it, which can be improved by automatic data collection. We developed an ML-supported pipeline containing a deep learning model and 3D point cloud processing. This pipeline addresses two important densification potentials: infill sites and vertical extension. Integrating the automated processing into QGIS as a plugin provides users an easy-to-use tool to generate a data basis for densification potentials for their decision-making process. We evaluate the effectiveness of our approach using real-world data from two different cities. The results show its usability in practice and the possibility of transferring it to different locations.

1. Motivation

Determining the potential for urban densification addresses several issues in the context of urban development. First, increasing housing demands are considered while preventing land consumption in the margin of a city (Dettweiler, 2025). Thus, urban densification enables ecological and sustainable growth of a city (Schiller et al., 2021). Second, identifying densification potential supports the decision-making process for the various stakeholders involved in urban development (Schiller et al., 2021). These include the city planning office as well as private landowners (Dettweiler, 2025). In addition to legal and technical aspects to realize densification (Deng et al., 2022, Dettweiler, 2025, Gillott et al., 2022, Reinhard and Wiemers, 2023), addressing and involving these landowners plays a major role in the activation of built-up potential (Dettweiler, 2025, ProRaum Consult, 2025).

Two types of densification potentials are mainly discussed in the literature: infill sites (Eichhorn, 2023, Schiller et al., 2021) and vertical extensions (Gillott et al., 2022, Reinhard and Wiemers, 2023). Figure 1 illustrates both concepts. Infill sites are used to build new buildings in open spaces and offer densification in the short to medium term due to their attractive locations and legal status (ProRaum Consult, 2025). Vertical extensions of existing buildings are another opportunity for creating new living spaces by constructing additional storeys with fewer resources—financially as well as in terms of materials—compared to new buildings (Reinhard and Wiemers, 2023, Tichelmann and Günther, 2019).

Even though the necessity of such densification types is apparent, data at the municipality level is required to address densification. Mapping of possible densification sites allows for a better prioritization between different sites and helps with urban planning. However, such data does not yet exist for all municipalities, requires manual effort, is not updated regularly, and uses different definitions across cities (Schiller et al., 2021, ProRaum Consult, 2025). To improve the data basis, the automation of the densification potential mapping is essential (Schiller et al., 2021).

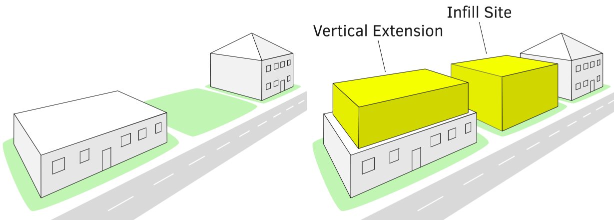

Figure 1. Sketch of the two considered methods of urban densification. Left: current situation, right: yellow cubes indicate potentials for densification.

We address this requirement with our automated ML-supported processing pipeline. We use basic commonly available geodata as an input. The processing finds potential infill sites and vertical extensions, which it outputs as polygon objects. These can be used for further GIS-based processing and visualization.

This leads to our contributions, which are as follows:

- automatic mapping of potential infill sites,
- automatic mapping of candidate buildings for vertical extensions,
- integrating the processing into QGIS as a plugin, and
- evaluation using two different cities (cities of Münster and Neuss, Germany).

Our mapping process for potential infill sites is based on a custom-trained machine learning model. It segments orthophotos into covered and open spaces where new buildings could be placed. The results are aggregated on the level of individual parcels, because this is the level of information that city planners commonly work on and which allows the densification data to be related to respective landowners.

The suitability of a building for vertical extension depends on many factors including structural capabilities, roof geometry (flat or gable roof), or maximum building heights, as defined in the urban development plan (Sanei et al., 2026). We focus on the last aspect, because it is possible using the available data and allows municipalities to quickly identify candidate buildings as a first planning step before bringing in additional stakeholders for more detailed assessments. The processing pipeline uses 3D information from point clouds acquired by airborne laser scanning to identify buildings that are small enough to fit another storey without exceeding the maximum building height in their region.

The results of our mapping process can be easily updated using orthophotos and point clouds without the need for pre-knowledge about densification attributes. In addition, the mapping process can be directly used in municipal practice due to its implementation as a QGIS plugin. The code of the developed QGIS plugin is available at `github.com/igd-geo/building-potential-analysis`.

2. State of the Art

Analysis of urban densification potential is often related to interviews and questionnaires (Schiller et al., 2021, ProRaum Consult, 2025). Although these interviews and questionnaires draw on knowledge of the city derived from local expertise, objectivity is compromised and the diversity between various municipalities is increased. In addition, collecting data about potential densification sites via interviews is time-consuming (Schiller et al., 2021). In contrast, GIS-based approaches enable a higher degree of automation and objectivity in the context of urban densification (Schiller et al., 2021). However, comparing different approaches is difficult, because they consider different aspects of densification. Eichhorn analyzes the changes in density in the past (Eichhorn, 2023), and Mohajeri et al. include simulations for the future into the density calculation (Mohajeri et al., 2023). While studies often focus on infilling (Dettweiler, 2025, Schiller et al., 2021), investigating the potential of vertical growth is conducted as a separate topic (Gillott et al., 2022, Koziatek et al., 2016, Reinhard and Wiemers, 2023, Tichelmann and Günther, 2019). Another disadvantage for the comparability of the existing methods is the use of different data sources, which are not equally available everywhere. Eichhorn includes census data (Eichhorn, 2023), while Mohajeri et al. use vector data about buildings, streets and gardens (Mohajeri et al., 2023). One of the more commonly used data sources is a land-use or land-cover map (Chotirosniramit et al., 2025, Ehrhardt et al., 2023, Schiller et al., 2021). Such maps might not be up-to-date and typically contain only general urban class categories such as water or buildings.

From a machine learning perspective, the various data sources not only lead to different models but, in combination with the various densification aspects, also to different classes. Mohajeri et al. differentiate between density zones using Random Forest (Mohajeri et al., 2023). Ehrhardt et al. identify infill sites at the parcel-level with a decision tree (Ehrhardt et al., 2023). Deng et al. consider several densification types but using a density-driven GIS workflow (Deng et al., 2022). Using

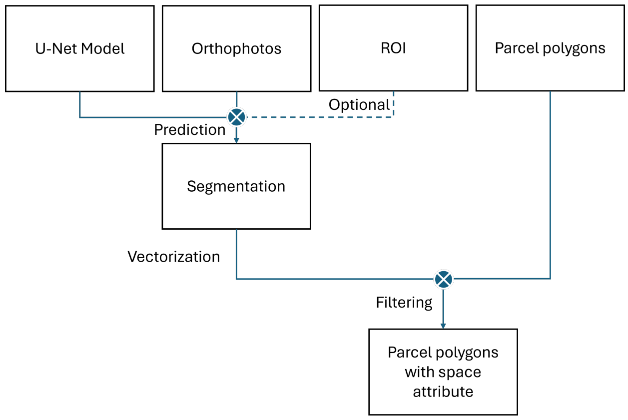

Figure 2. Components for the detection of potential infill sites.

deep learning models to analyze geodata for densification potential mapping is still rare. Even though Chotirosniramit et al. use a Swin Transformer, orthophotos as input are not sufficient for them (Chotirosniramit et al., 2025). Instead, they combine existing land-cover maps with specific parcel attributes including the number of storeys, which are not available for all municipalities and require knowledge about which attributes are relevant. Furthermore, missing code availability complicates the comparison of the mentioned models.

3. Proposed Pipeline

We developed a pipeline to map possible infill sites and vertical extensions using available basic geodata, focusing on a high degree of automation. The processing is implemented as a QGIS plugin, which consists of two tools: one for infill sites and the other for vertical extension. The results are GIS-compatible maps which can be used for further GIS-based refinements and analyses as well as for visualizations.

3.1 Infill Site Potential

The main goal of the infill site pipeline tool is the identification of parcels that show potential for new buildings. Figure 2 presents the components of our infill sites mapping tool, where the U-Net model is the core of the tool. This U-Net model predicts binary segmentation masks from orthophotos. These resulting segmentation masks highlight open spaces, which correspond to potential infill sites. Details about the U-Net model training are described in Section 3.3.

We apply additional post-processing steps to the mask predictions for refinement. The first step of this post-processing reduces misleading detections by removing infill sites that are very small. For this, we use a morphological opening operation with a squared filter size of 20 on the mask level. As a second step, the predictions are vectorized to generate polygons representing open spaces by identifying connected regions based on a neighborhood of eight.

We identify the desired parcels by intersecting the open space polygons with available parcel geometries, which are a common unit in the context of planning (Koziatek et al., 2016). Finally, we determine the open space area per parcel and store this as an attribute to parcel objects.

In the post-processing it is also possible to filter out parcels with open space areas smaller than a user-defined threshold and

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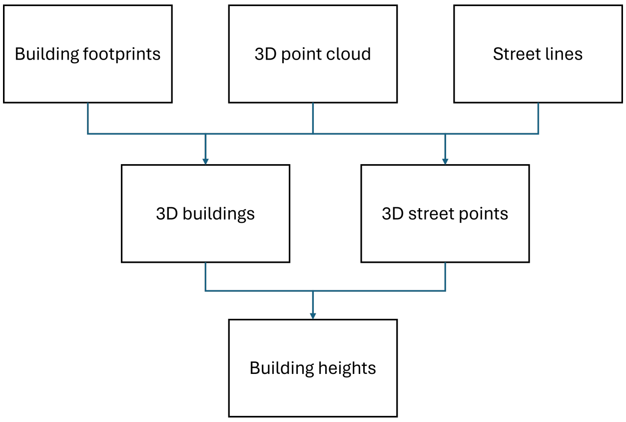

Figure 3. Components for calculating building heights for the detection of potential vertical extensions.

to shrink the segmented regions to consider building distances. To enable location-specific mapping, a user-defined Region of Interest (ROI) can be selected.

3.2 Vertical Extension Potential

The goal of the vertical extension potential analysis is to identify buildings that can be extended by additional storeys. A limiting factor here is the maximum building height defined by the urban development plan. The task of finding eligible buildings is therefore split into two subtasks:

1. Determining the current height of a building.
2. Determining the possible maximum building height for a building.

The difference in meters between the current and maximum height of a building is what we call the extension potential. A building is suitable for extension if the extension potential leaves room for at least one additional storey. The workflow extracts all height information from a point cloud acquired by airborne laser scanning. It also uses 2D building footprint polygons and street center lines.

Current Building Height Estimation. Figure 3 presents the process of the three input sources for the estimation of the building heights. The roof heights are identified by intersecting the point cloud with the building footprints. The point cloud is prone to outliers, such as cranes or tree tops hovering over the roofs, or points from other walls that are inside the footprint polygon. To reduce the impact of these outliers, the points that fall into a building footprint are tiled into a $1\,\mathrm{m} \times 1\,\mathrm{m}$ grid. For each tile, the median of the z-coordinates of all points in the tile and its direct neighbours is calculated. The highest median is used as the absolute building height.

The roof height as derived from the point cloud z-coordinates is only an absolute value and is not useful on its own. To obtain meaningful building heights, it must be related to the absolute height of the ground. The ground height is estimated using the street center lines, because they indicate locations with almost no buildings or other structures above ground level. The height of the point cloud is sampled at regular intervals along the street lines. A 2D B-Spline is optimized to fit the collected samples. This creates a ground height model that we can use to infer the ground height at the center point of each building, essentially interpolating the heights of all surrounding samples. The building height is then the difference between the absolute roof and ground heights. Figure 4 illustrates the street point sampling and the fit of a B-spline to these points.

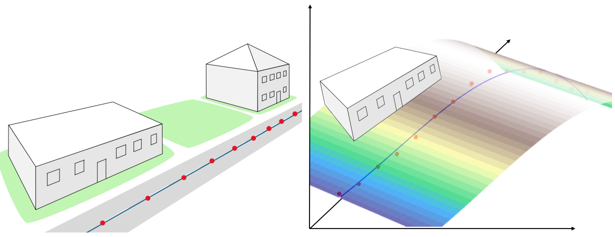

Figure 4. Sketch of the B-Spline fitting. Left: Sampling of street-level points, right: B-Spline fitting based on sampled street points.

Maximum Building Height Estimation. Urban development plans are typically not available in a machine-readable format. This includes the official maximum building heights. Therefore, we estimate the maximum building height based on a neighborhood analysis. We assume that the maximum building height is constant within some reasonably sized area (e.g. within one urban district). Based on this, the height of the largest building in this area can be thought of as a lower bound for the official maximum building height. The maximum allowed height for a building is therefore estimated from the highest building observed within a user-defined radius. The use of a percentile ensures outliers such as church towers are excluded.

From the current and maximum building heights, we can then compute the extension potential, as described above. Additional filtering removes buildings with a vertical extension potential of less than one additional storey. In addition to a vertical extension map, 3D Tiles are generated based on the results, where volumetric boxes represent the densification potential.

3.3 Implementation

The infill sites and vertical extension are integrated into a single QGIS plugin. In terms of structure, the plugin consists of two separate processing tools that can be executed independently. This plugin needs to manage different dependencies such as Rust code and Python packages used for deep learning. In detail, Rust was chosen for the vertical extension calculations to process the point clouds efficiently. In contrast, the infill sites are determined using Python and Pytorch. Also, the plugin itself is based on the QGIS Python API. Depending on the available computing resources, the QGIS plugin uses CUDA for accelerated model predictions. Moreover, the size of the orthophoto tiles used for prediction can be changed from 512×512 pixels to 2080×2080 pixels depending on the computing resources. As input for the model, 4-channel images are expected, i.e. RGB plus near-infrared.

We trained a U-Net model (Ronneberger et al., 2015) with ResNet101-Encoder (He et al., 2015). The weight initialization of the model is based on the ISPRS Potsdam dataset (ISPRS Potsdam, 2015). For the actual training we used ALKIS data (Amtliches Liegenschaftskatasterinformationssystem ALKIS North Rhine-Westphalia, 2025) to generate reference samples. More specifically, we excluded parcels of water surfaces, streets, and railroad areas as well as building footprints from the urban area. The remaining areas, e.g. vegetation areas, are considered open spaces. Further processing for training includes rasterization and cropping to the corresponding orthophoto samples. Due to the low specificity of the ALKIS-based reference and to avoid overfitting, we only used a small training set containing six orthophotos and one image for validation. The training configurations are cross-entropy loss, AdamW optimization, and a learning rate of 0.001. The model is trained with ten epochs and a batch size of four.

3.4 Data

We use basic geodata from two different locations for the evaluation of our pipeline, namely the cities of Münster and Neuss. Both are located in North Rhine-Westphalia, Germany.

Münster Data. We use laser scanning-based point clouds and orthophotos with a spatial resolution of 5 cm and RGB plus near-infrared channels. Both data sources were acquired in 2025. The data of Münster is not only used for evaluation, we use a subpart to train the described U-Net model. For the evaluation, we ensure that the training region is different from the evaluation region within the city of Münster. In addition to the point clouds and orthophotos, vector-based data is used such as street lines and building footprints. Compared to the orthophotos and point clouds, building footprints are updated every six months (Amtliches Liegenschaftskatasterinformationssystem ALKIS North Rhine-Westphalia, 2025). Furthermore, the city of Münster collected examples of infill sites manually. We expand this small reference set by greenfield and brownfield land-use classes from OpenStreetMap (OSM) (OpenStreetMap contributors, 2017) and use both for the evaluation of our identified infill site potential. Due to licensing restrictions, we cannot publish the point cloud, the orthophotos, or the manually collected reference data of the city of Münster.

Neuss Data. We test the transferability of the developed processing by using data of Neuss as a secondary location. In this case, the orthophotos have a spatial resolution of 10 cm. As spectral information, RGB and near-infrared channels are available. In contrast to the Münster data, there is a time gap between the point clouds from 2022 and the orthophotos from 2025. The data is available at the OpenNRW portal (Caffier et al., 2017, NRW, 2026). Additionally used geodata such as ALKIS (Amtliches Liegenschaftskatasterinformationssystem ALKIS North Rhine-Westphalia, 2025) and street lines for Neuss from OSM (OpenStreetMap contributors, 2017) are also open data.

4. Results and Discussion

As described in Section 3.4, we evaluate the developed mapping pipeline for two different locations. The first location, Münster, is considered as in-domain location as the used training samples for the infill site prediction are from this region. The second location, Neuss, is selected as out-of-domain location.

4.1 In-domain Location: Münster

Figure 5 shows the evaluation region used for the infill site potential tool from Section 3.1. It visualizes the determined open space attribute of each parcel. Parcels with an undeveloped portion of at least 42 % appear to be suitable for densification. Open space values of more than 80 % indicate parcels with only very small building objects or no buildings at all.

Figure 5. Potential of infilling based on segmentation masks for the test region in Münster.

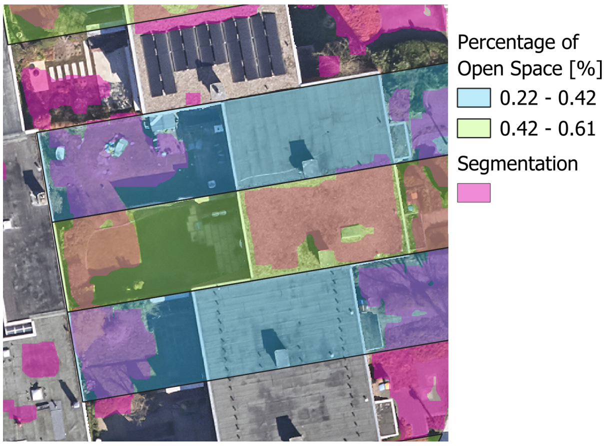

Figure 6. Example of misclassified open space.

Compared to manually collected infill sites, our processing highlights additional parcels as potential for densification. These additional parcels include green spaces, which should be preserved as such for the urban climate, parcels with inadequate shape for new buildings, and parcels where at least a horizontal extension of the existing building is conceivable.

Horizontal extension potentials are not considered in the OSM greenfield or brownfield land-use classes but they are an additional aspect of densification. Using the reference data for the user-defined ROI in Figure 5, a precision value of 23 % and a recall value of 43 % are achieved using an IoU threshold of 0.52. This IoU threshold is based on a receiver operating characteristic analysis. However, such quantification has low informative value as the quality of the reference is low and the distribution of infill sites in a city is inhomogeneous.

The incompleteness, imprecision on parcel-level, distribution, and timeliness of the reference collection are only some of the effects contributing to the low reference quality and thus to low accuracy values. Furthermore, the reference infill sites are collected more restrictively, i.e. they exclude parks, playgrounds, etc. In addition to the impact of the reference quality, the model predictions contain errors that result in misleading area calculations for some parcels. Consequently, a high number of false positive and several false negative detections can be observed. An example of such misclassification is presented in Figure 6, where roof greening prevents correct building recognition.

However, the modular characteristic of our pipeline allows further optimized trained models to be used, which can be based

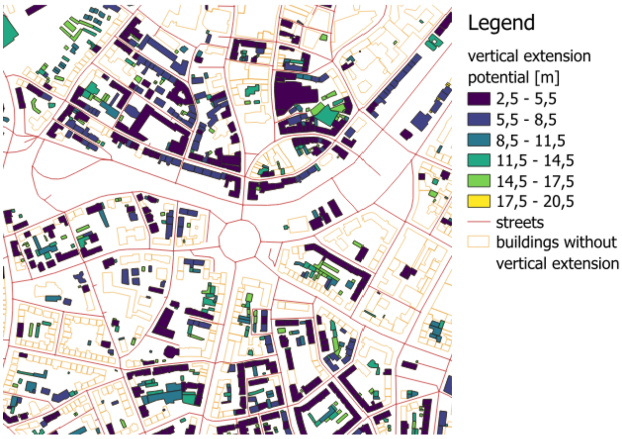

Figure 7. Potential of vertical extension based on 3D point clouds.

on specialized training data for infill sites compared to our indirect information extraction from ALKIS.

Figure 7 presents the determined vertical extension potential. The 3D visualization in Figure 8 offers a better impression of the effect of this type of densification. The grey blocks show the detected current size of the buildings. The red blocks on top visualize the extension potential up to the maximum building height where there is space for at least one more storey.

The method successfully identified buildings with extension potential. However, it currently only detects a single height for each building. Complex buildings with multiple parts of different heights cannot be adequately represented. To correctly analyze these, the building parts must be modeled as individual building footprints in the input data. Adaptations of the input footprints are also necessary if specific building types should be excluded such as garages. Furthermore, the building height extraction does not consider different roof types. Buildings with gable roofs will systematically appear higher than flat roof buildings. As flat roof buildings are better suited for vertical extension than buildings with pitched roofs, this would be useful information for the urban planner.

In the case of vertical extension potential, no reference values of actual vertical extensions exist. Height errors are based on the point cloud accuracy and the quality of the determined street points as ground height information. Without any additional external information, the determined building heights cannot be verified in our case.

Both types of identified densification potentials are based on basic geodata. This means that planning-related and legal aspects such as fire protection are not considered. However, additional information about recreational areas, contaminated sites, or areas with specific uses (playground, cemetery, etc.) can be applied in further GIS processing to refine the results.

4.2 Out-of-domain Location: Neuss

As the trained model uses areas from the region of Münster, we test the transferability of our pipeline with a second location: the city of Neuss, Germany. The transfer to a new location includes a shift in spatial resolution (orthophotos) and time (point clouds).

Figure 9 shows the results of the infill site potentials for samples in the city of Neuss. Although the spatial resolution is different,

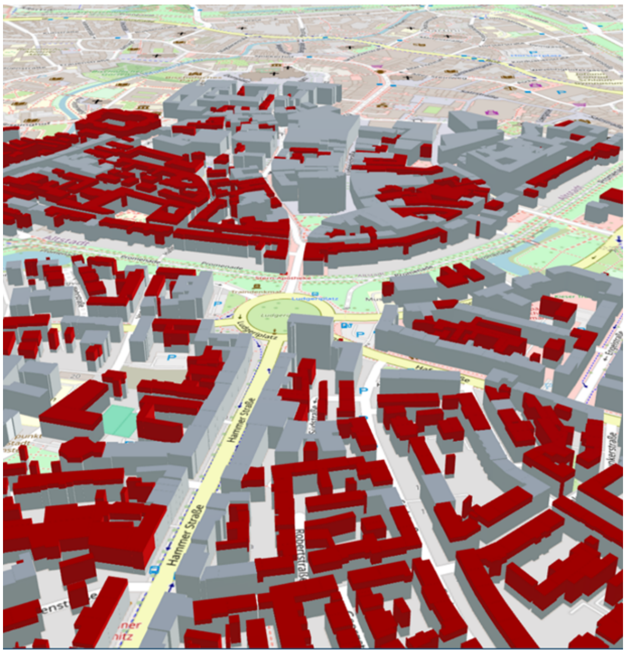

Figure 8. Potential of vertical extension based on 3D point clouds, where the extension is highlighted in red. Underlying map data from OpenStreetMap (openstreetmap.org/copyright).

the model is able to predict potential infill sites. Next to the railway tracks in the left image sample, a large infill site was identified that is not included in OSM data, although a few potential infill sites are marked for this area. The middle image shows a high potential in a region with sports grounds. Areas like this are unrealistic for potential densification. This example highlights that the results require the refinement mentioned earlier by intersecting the mapped infill site potentials with additional land-use information.

Figure 10 presents the potentials of vertical extension. The bright green highlighted building in the middle image shows a large vertical extension potential. The reason for this is that a building footprint already exists, but no building is present in the point cloud due to the different recording times of the point cloud and building footprints as described in Section 3.4. Consequently, the vertical extension potential of 11 m corresponds to a full building height that was placed in the infill site after the point cloud was captured. Most of the other vertical potentials higher than 10 m belong to garages and other small objects that are commonly not considered living spaces and are unrealistic for a vertical extension.

The left image sample along the railway tracks in Figure 10 shows another case where vertical extension on industrial buildings is indicated but seems unrealistic as potential for housing. However, as in the case of Münster, with additional information about industrial building locations such areas can be filtered out either in the used footprint data or in the resulting vertical extension map.

Overall, the results for Neuss show a behavior similar to that of Münster, even though neither fine-tuning of the model nor changes to the data processing are applied. This demonstrates the usability of our processing pipeline to generate a low effort data basis for densification potentials for different municipalities. In addition, despite differences in the available input data, comparable densification potentials are mapped for GIS-

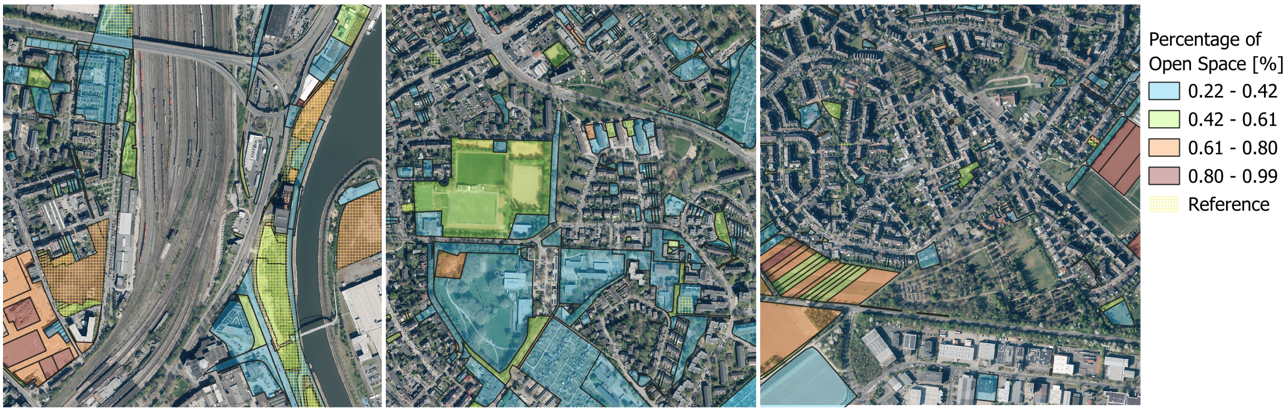

Figure 9. Potential infill sites in three regions of Neuss.

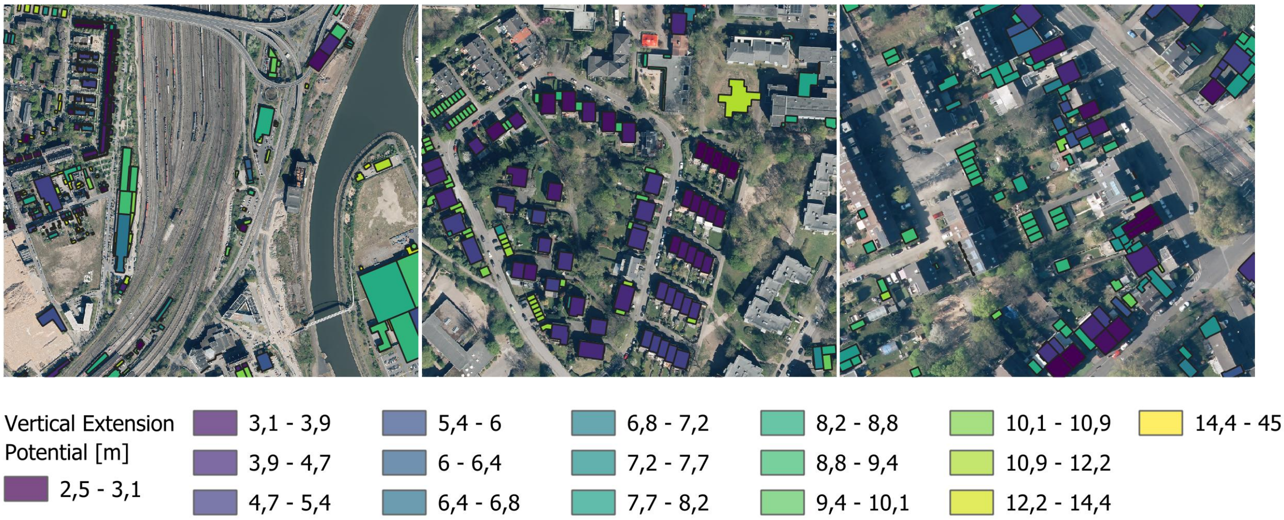

Figure 10. Potential vertical extensions in three regions of Neuss.

analysis, addressing the issue of existing maps that are often not comparable between different locations.

5. Conclusion

We introduced a new QGIS plugin which generates GIS-compatible maps of potential infill sites and vertical extensions. In contrast to other GIS-based approaches, our method only needs common geodata as an input and requires no specialized densification-specific data. Further improvements of the results can be achieved using additional information such as urban zones or specific land-use. Even without such refinements, the plugin enables a quick initial assessment of densification potentials. Due to the developments in the context of foundation models, improvements for the segmentation quality are expected. In addition, detecting the roof type and other semantic metadata such as the number of storeys remains for future work.

Acknowledgements

We thank the city of Münster, which provided the high-resolution orthophotos, point clouds and street lines. We thank the Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen (BMWSB) and Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR) for the funding.

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