Streamlining urban tree data collection: a case study on Olomouc housing estates

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Abstract

Data collection on urban greenery plays a key role in its management and in evaluating the benefits it provides to society, including ecological, aesthetic, and health-related advantages. To manage urban greenery effectively, it is essential to seek ways to optimize the process of its inventory and assessment. Technological advancements in data collection methods offer new possibilities for making these processes more efficient. The aim of this study was to utilize and integrate available technologies and methods for the inventory of urban greenery and to evaluate their effectiveness. The results show that the combination of drone imagery with open-source software tools and data provides an accurate and cost-effective solution for monitoring urban vegetation. In conclusion, the proposed methodology enables efficient and economically beneficial management of urban greenery, which supports its broader implementation in urban areas.

1. Introduction

In the Czech Republic, a complete inventory of urban trees is often lacking, despite their significant potential to improve residents' quality of life. Although urban greenery is essential for a healthier and more ecological environment, tree inventory processes are still frequently time-consuming and costly, which limits their availability and sustainability. In the city of Olomouc, for example, tree mapping efforts are primarily focused on major urban parks and representative areas, while housing estates, which are among the most densely populated parts of the city, lack such tree inventories.Yet it is precisely these housing estates where greenery could substantially contribute to better living conditions and support biodiversity, as most residents spend their daily leisure time in these areas. However, greenery mapping and inventory can also be approached differently than through traditional field surveys. With the development of remote sensing, advanced GIS technologies, and artificial intelligence, innovative and accessible methods are now available that can significantly simplify and broaden access to urban greenery inventories. The aim is to propose a procedure that allows for the easy application of mapping methods in housing estate green spaces, even with limited technological and data resources, and to identify potential limitations and ways to address them.

2. State of Research and Approaches to Urban Greenery Data Collection and Tree Mapping:

Tree mapping using remote sensing is currently being extensively studied by many experts. Matese et al. (2015) point out that it is important to consider how we intend to use the remote sensing platform, as each has its own advantages and disadvantages. A key factor is the desired level of detail and the part of the electromagnetic spectrum to be captured. To achieve sufficient detail, it is appropriate to use aerial or UAV imagery, while satellites offer continuous coverage and are often equipped with sensors capable of capturing additional spectral bands. Based on their research, Niedzielko et al. (2024) highlight aspects that may pose limitations for urban greenery mapping. In general, remote sensing methods are costly, as acquiring satellite or aerial imagery is very expensive. One of the key advancements in the field of remote sensing is the use of deep learning, which significantly facilitates data collection and enables effective mapping without the need for user presence in the field (Hennig, 2021; Freudenberg et al., 2022; Weinstein et al., 2019).

Weinstein et al. (2019) state that even RGB imagery can be a valuable data source for tree detection. A deep learning model for detecting individual tree crowns was trained specifically on RGB images. This model was trained on various locations to be able to detect trees regardless of species. During model training, it was found that the most accurate models are those that detect any tree species and are not focused on specific types. Such models also achieve the highest accuracy in locations where trees are freely spaced (Hennig, 2021). Additional inaccuracies occur with smaller trees whose crowns have an area of less than 10 m² (Freudenberg et al., 2022; Weinstein et al., 2019). A general issue with detecting trees using pre-trained deep learning models lies in their inability to generalize outputs. This means that models may perform better in regions with typical vegetation compared to areas with different vegetation types. Therefore, it is advisable to use models trained specifically for the given area. Another challenge in detection is the inability to accurately identify trees in dense stands (Weinstein et al., 2019). It should also be noted that these tree mapping methods require higher computing performance, which may pose an additional limitation (Hennig, 2021).

In terms of greenery mapping, Hennig (2021) combined remote sensing and automatic detection to map fruit trees in orchards, using RGB imagery for crown detection. Hartling et al. (2021) applied deep learning for tree species detection, using LiDAR data, thermal imagery, and hyperspectral images as input data. Incorporating multiple data sources increases reliability, especially when the goal is to identify tree species. Both authors thus utilize remote sensing methods for tree mapping. Niedzielko et al. (2024) state that including LiDAR data is highly suitable for accurate species identification, as reliability significantly decreases without it. Reliability also declines with a lower number of spectral bands used during imaging. This research supports the conclusions of Hartling et al. (2021).

In the Czech context, the detection, classification, and inventory of greenery using remote sensing is primarily focused on forest mapping. Research most commonly targets the health of trees or the overall state of the ecosystem. Kupková et al. (2018) monitored changes in forest cover and its health using Landsat time series data, observing changes related to the occurrence of acid rain. Klouček et al. (2024) investigated the use of multispectral UAV imagery to assess forest health in relation to bark beetle infestation. Komárek et al. (2024) conducted studies evaluating whether data acquired using a more affordable drone, capable of providing information on tree height, can be sufficiently accurate to eliminate the need for traditional field surveys or expensive laser scanning. This research focused on protecting infrastructure from falling trees. The results of the study indicate that even more accessible drones can perform such tasks. Therefore, it is not always necessary to use technologies that are financially demanding and thus less accessible to the broader public.

2.1 Public Science in Greenery Data Collection

In the context of collecting certain types of information, it is appropriate to utilize other freely available data on trees. Data collection does not always have to be directly tied to the work of a researcher. It is possible to use data already gathered by the public or to organize public data collection initiatives. In this context, the concept of PPGIS (Public Participation GIS) can be applied (Kahila-Tani et al., 2019), which is a method within participatory mapping (Ollivierre et al., 2021). Participatory and community mapping involves various techniques and tools that support community involvement in map-making and allow them to adapt formal mapping procedures to their needs (Peluso, 1995). The strengths of these techniques include data collection at various scales and relatively easy engagement of large numbers of participants. However, challenges such as technical difficulties and the digital divide must be considered (Kahila-Tani et al., 2019). Among the main disadvantages are inaccuracies in identifying tree species and other parameters. One of the key advantages is the relatively fast data collection process (Crown et al., 2018; Roman et al., 2017). Crown et al. (2018) notes that if participants are at least partially trained and provided with identification tools, the accuracy of species identification can reach 77,6 %. However, the accuracy of measuring the trunk circumference at breast height was significantly lower, only 32 %, even with an acceptable deviation of 2,54 cm. The study by Roman et al. (2017) confirms a relatively high success rate in identifying tree genera (84,8 %) and similarly low accuracy in trunk circumference measurement with a 2,54 cm deviation (54,4 %). Both studies agree that using volunteers for tree inventory is suitable if the client does not require completely precise results and the accuracy levels are sufficient. It is not entirely appropriate for volunteers to assess the exact condition of trees. Measurements of trunk diameter at breast height should be accepted with greater tolerance. The identification of genera is very accurate, and species identification is relatively accurate as well (Crown et al., 2018; Roman et al., 2017).

3. Data a methods

3.1 Study Area

Rigatti (2000) states that each housing estate exhibits a regular structure in which smaller repeating units can be identified. These units, referred to as housing blocks, represent the basic research unit in this study. For research purposes, housing blocks were randomly selected from various housing estates in the city of Olomouc. In some cases, the boundary of a housing block coincided with the boundary of a land parcel. When this was the case, the block was defined by this parcel boundary. In situations where the parcel boundary did not correspond to a land boundary, the block was delineated using physical infrastructure such as roads or sidewalks. Each delineated housing block was intended to include one residential building and its associated green space. In Olomouc, four housing estates were selected (Figure 1), each built in a different time period, as it is assumed that the structure of the environment varies (Kłopotowski, 2017).

i) Olomouc – Norská: This is the first post-war, purpose-built housing development (1948–1955) constructed from scratch in Olomouc. The buildings are arranged in rows, with green space filling the areas between them (Skřivánková et al., 2016).

ii) Olomouc – Lazce: The buildings here are arranged in an unconventional layout, forming incomplete hexagons. One of the reasons for this arrangement was to create larger, continuous green spaces. This housing estate was built between 1978 and 1985 (Skřivánková et al., 2016).

iii) Olomouc – Holandská čtvrť: This is the newest of the studied housing estates, constructed after 2014 (ČUZK, 2025).

iv) Olomouc – Hodolany (třída Kosmonautů): This estate was built in the first half of the 1960s on the edge of the Kosmonautů Avenue boulevard (Kuča K., 2000 in Kladivo, P., & Šimáček, P., 2011).

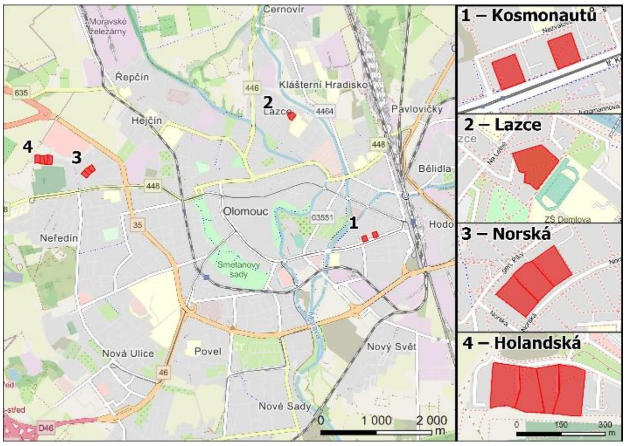

Figure 1. Location of the Studied Housing Blocks within the City of Olomouc

3.2 Field Mapping

In the first step, a point layer was created in an online GIS environment. The attributes of this layer included only the geographic coordinates and tree species. Initially, trees recorded by the public were edited and uploaded to this online layer. In the Czech Republic, data collected by the public is available through the mobile application *Tree Check* (Nadace Partnerství, 2023). In this app, users can collect tree data through several steps, assisted by AI species recognition. The app allows users to input trunk diameter and upload photos of other organisms present on the tree, such as fungi or mistletoe. It also includes gamification features, awarding points for collecting data, watering trees, or simply visiting them. Data from this platform within the area of interest were imported into the point layer in the GIS environment. Subsequently, field data collection was carried out to add missing trees and attributes, and to verify the validity of the data collected by the public. During the field mapping, geographic coordinates were automatically generated when marking a point, and species identification was conducted by the author. The primary aim was to identify individual tree species, which represented a key aspect of the entire study. The point layer was essential for accurately determining the location and count of trees in the area, serving as a basis for validating the following steps of the study. Other attributes such as frost resistance, toxicity, salt tolerance, hazard potential, and drought resistance are directly linked to the tree species. Therefore, collecting these attributes in the field is considered inefficient (Málek et al., 2022).

3.3 Pre-trained Deep Learning Models and Input Remote Sensing Data

For the purposes of this study, two pre-trained deep learning models were selected: Segment Anything Model (SAM) (esri_analytics, 2025a) and Tree Detection (esri_analytics, 2025b). Both models recommend the use of 8-bit RGB imagery. For the Tree Detection model, the recommended pixel resolution is between 10–25 cm. However, this model was originally trained on data from the United States, and in this study, it was applied to data from the Czech Republic. As Weinstein et al. (2019) noted, this may result in reduced model accuracy due to differences in tree species and data characteristics. Since this study aims to utilize low-cost or freely available sources, aerial imagery freely provided by the Český úřad zeměměřický a katastrální (ČÚZK) was used. These datasets are freely downloadable, and the most recent available imagery for the selected area at the time of the study dated back to 2022. These images are in RGB format with a resolution of 12.5 cm (ČÚZK, 2025a), which meets the requirements of the pre-trained models. Satellite imagery with lower resolution was deemed unsuitable because the study focuses on working with trees as individual objects. One limitation of aerial images from ČÚZK and similar sources is the lack of height information for the objects. A potential workaround could involve the use of the Digital Surface Model (DSM 1st generation) and Digital Terrain Model (DTM 5th generation), which would allow for height estimation by subtracting the two layers. However, the DSM 1st generation is outdated, as it was scanned between 2009–2013 (ČÚZK, 2025b). For this reason, drone data were required to determine tree heights.

For this study, the Phantom 4 Pro drone was selected, as it allows for data collection with high accuracy and resolution while remaining relatively affordable. Mission planning was conducted using the Pix4Dcapture Pro: drone flight application (Pix4D, 2024), which enables the setup of flight missions in various modes. In this study, the "grid" mode was chosen, where the drone first flies in parallel paths and then captures additional imagery in a second set of parallel paths-oriented perpendicular to the first. The image overlap was set to a high value of 80 %, ensuring sufficient coverage for subsequent data processing. The camera angle was set to 30 ° to capture detailed information about objects and their spatial relationships. The flight altitude was set to 50 meters. The captured images were then stitched into an orthophoto in ArcGIS Pro (esri, 2025) using the Ortho Mapping Workspace, which facilitates the creation, management, and visualization of orthophotos, such as those produced from drone imagery. This tool automates the processing of images, including alignment, block adjustment, and orthophoto generation. As part of this process, the images were georeferenced and merged into a final orthophoto.

3.4 Criteria for correct data selection

When preparing a comprehensive workflow, it is essential to focus on the maximum accuracy and functionality of each step to prevent the accumulation of errors when connecting them. For this reason, it is crucial to carefully verify the correctness and suitability of each step. Even during the field mapping phase, attention must be paid to the precise placement of points. Points should be inserted exactly where the tree is located, and it is not sufficient to rely solely on the GPS position provided by the mobile device, as it may lead to relatively large deviations. The average deviation was calculated during a trial mapping session without manual point adjustment and amounted to 2,7 meters.

The SAM segmentation model (esri_analytics, 2025a) is not specifically designed for tree segmentation, but rather for segmenting the entire image. Therefore, it is necessary to manually select polygons corresponding to trees or shrubs. In this study, these polygons were filtered using several criteria:

- The first criterion was the use of positional matching with the point layer created in the field.
- Polygons larger than 450 m² were removed, as this tool tends to merge multiple tree crowns into a single polygon. This threshold was chosen because the largest polygon capturing a group of trees was just below this value.
- Pixel values within the generated polygons were also used as a filtering criterion. Only those polygons were selected in which all enclosed pixels met the condition of green dominance. The condition expression used for this filtering could look like this: ("Green_Band" > "Red_Band") & ("Green_Band" > "Blue_Band") & ("Green_Band" > value) In this case, the "value" was set to 100. This parameter is expected to vary depending on the characteristics of the image.

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- Spatial overlap with polygons generated by the Tree Detection tool (esri_analytics, 2025 b) was also considered. These polygons also had to be filtered accordingly.

  - Only quadrilaterals with a value of the automatically generated Confidence attribute of at least 15% were selected. While this may seem like a low threshold, the goal was to avoid removing polygons that do represent actual trees, and to filter out false positives using additional characteristics.
  - Another criterion applied to this tool was a minimum polygon area, which was set to 2 m².

4 Results

By synthesizing several tools in the ArcGIS Pro environment, specifically using Model Builder, a workflow was designed that optimized data collection and effectively integrated individual processes and tools (Figure 2). Although a functional working scheme was successfully created, its full utilization is conditioned by the availability of field survey data. A key aspect is at least the knowledge of the exact location of the tree, since based on the aerial image it is not always possible to determine whether it is one or more trees, a shrub, or whether there is another tree under the canopy. Fieldwork is also necessary to determine the tree species. As Hartling et al. (2021) point out, data with various spectra should be used for this identification. However, the aim of this work was to work exclusively with freely available data, and therefore it was not possible to apply this method. This is also related to the assessment of the health condition of the trees, which was not examined in the field survey, however, for its assessment using remote sensing (RS), it is necessary to work with the NIR spectral band, with an advantage being a single-species vegetation (Kupková et al., 2018), which urban housing estates certainly are not. The result of this work is thus a working scheme that is not fully automated and requires continuous user intervention, as not all tools work reliably despite efforts to eliminate errors. The final product of the proposed procedure is a point layer containing information about the tree species, information directly linked to the species (frost resistance, salinity tolerance, hazard: thorns and toxicity, drought tolerance, nativeness, leaf-out period), tree height, crown dimensions: area and perimeter, crown radius (either determined from the area calculated using the SAM tool:

$$r = \sqrt{\frac{s}{\pi}}, \tag{1}$$

where r = tree crown radius
s = tree crown area

or determined as the geometric mean of the sides of the quadrilateral generated by the Tree Detection tool:

$$r = \frac{\sqrt{a*b}}{2}, \tag{2}$$

where, r = tree crown radius
a = north-south width of the tree
b = west-east width of the tree

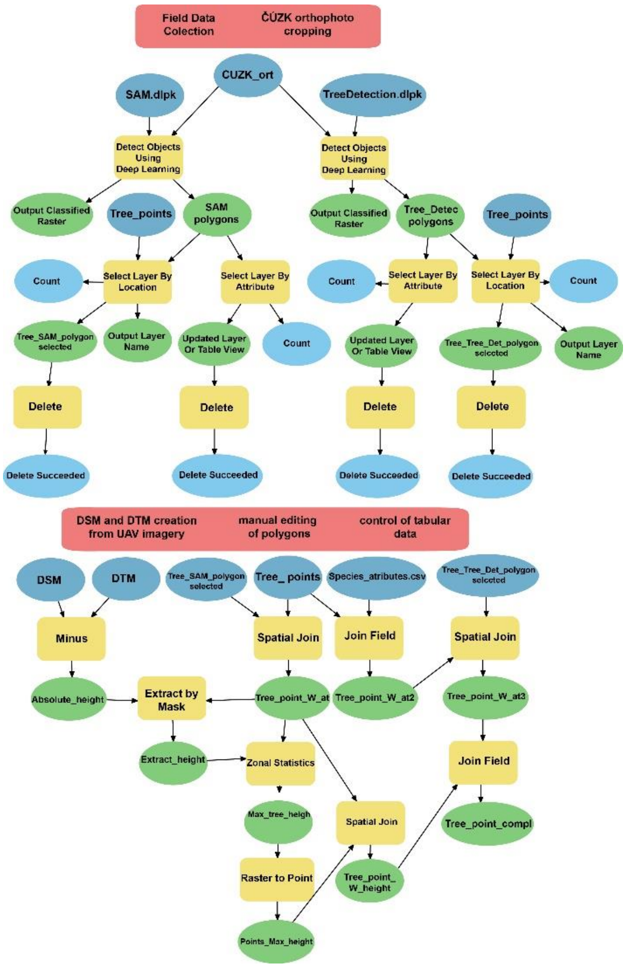

Figure 2. Proposed methodology for mapping trees and selected attributes visualized in Model Builder in ArcGIS Pro

4.1 Time Efficiency

The time requirements of individual data processing steps vary significantly depending on the chosen method and the user's computing equipment. Not only the specific workflow (e.g., a combination of segmentation and detection) plays a role, but also any potential modifications of these methods based on individual preferences.

The most time-consuming operations are those associated with segmentation using the SAM tool and the subsequent tree detection (Tree Detection). Depending on the size of the input data and the performance of the device, these processes may take several hours. For this reason, an effective strategy proved to be dividing the processing into smaller sections—specifically by individual residential blocks. Once the operations for one block are completed, the process can continue with the next one, which optimizes both time and computing resource usage.

In this study, the average segmentation time (SAM) for one residential block was 40 minutes, while tree detection using the TreeSegmentation tool took approximately 4 minutes. The average area of one block was 4 465 m², including built-up areas. The total time required for complete processing of one block, including the identification of additional attributes and manual adjustments, averaged 102 minutes. A standard notebook with an

AMD Ryzen 5 processor, 12 GB RAM, and an integrated AMD Radeon Vega 8 graphics card was used in this study. Although in some cases processing may be slower than fieldwork (especially with lower hardware performance), the main advantage of the digital approach remains its high level of automation, minimal dependence on the individual user, and the ability to perform the analysis at any time, regardless of weather or time of day.

For comparison collecting the same parameters in the field, including subsequent digitization and data processing, took approximately 125 minutes per block. However, it is important to emphasize that the duration of field data collection varies depending on the individual's experience, the type of terrain, and the chosen methodology. Similarly, the performance of computing equipment significantly affects the speed of digital processing.

4.2 Tree detection success rate

The TreeDetection tool identified 71,9 % of trees in housing blocks from the total number of existing trees. However, the model also included other objects mistakenly identified as trees. These false detections made up 32,4 % of the total number of detected objects (polygons). Undesired objects were successfully filtered out using the criteria described above. Nevertheless, some incorrectly detected polygons remained, and some were not detected at all. In these cases, manual intervention by the author was necessary, including hand editing or deletion.

When using the segmentation tool SAM, several specific limitations appeared. One of the main issues was the duplication of polygons, where some objects were identified repeatedly. There were also situations where one polygon was assigned to an entire group of trees, while others represented individual canopies; in some cases, even a combination of both occurred. In such cases, introducing a maximum polygon size criterion proved effective in eliminating overly extensive segments. At the same time, these larger segments provided an advantage in the form of manual splitting based on visually recognizable canopy boundaries on the orthophoto. Another significant complication was the occasional merging of tree canopies with their shadows, which often led to incorrect interpretation of the shape and extent of individual crowns. An attempt to refine the boundaries using height analysis from drone-acquired data was not successful, as the recording was not sufficiently detailed.

After applying the filters and removing duplicate or irrelevant segments, the final number of polygons corresponded to 44,3 % of the trees recorded in the field. However, this proportion should not be interpreted as a direct indicator of success in many cases, one polygon included multiple trees. Nevertheless, it can be said that the SAM tool was partially capable of capturing the vegetation structure, and although the segmentation success rate may initially seem low, the results are relatively sufficient considering the complexity of the task.

4.3 Tree Height Estimation

The height mapping was performed using the Phantom 4 Pro drone and the Pix4Dcapture Pro application (Pix4D, 2024). The data were then processed in ArcGIS Pro within the Ortho Mapping Workspace, where the Digital Surface Model (DSM) and Digital Terrain Model (DTM) were created. These layers were subsequently used in the overall process shown in Figure 1, where they were subtracted, and their maximum heights were converted into point vector layers. Tree heights obtained via drone-based measurements were compared with values recorded using a digital hypsometer on a sample of 21 trees in the field. While the average difference between the two measurement methods was 0,42 m, indicating a relatively notable discrepancy, it is important to acknowledge that the sample size was limited. This limitation is recognized and should be taken into account when interpreting the results. Future investigations should therefore focus on identifying whether this variation stems from limitations in the accuracy of drone-based measurements or from potential errors associated with hypsometer-based field measurements.

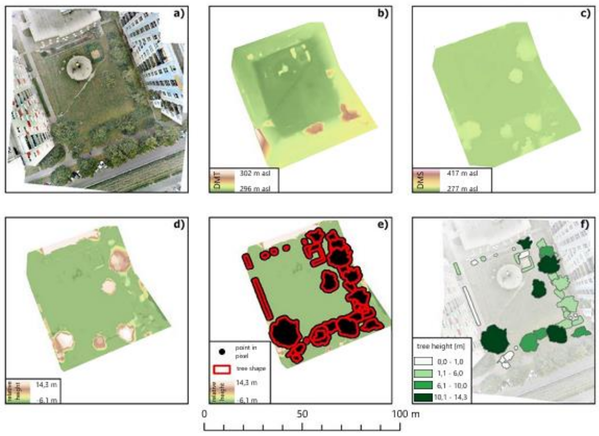

Figure 3. Calculations of object heights above the surface: a) drone-based orthoimage, b) DSM, c) DTM, d) Object height above the surface, e) Tree connection point generation, f) Polygon-point linking for max tree height

4.4 Reliability of Publicly Collected Data

The reliability of tree species data collected by the public was assessed by comparing species identifications submitted by users of the TreeCheck application with the author's own field records. A total of 50 trees were verified in this manner, with full species-level agreement in 45 cases (90,0 %) and genus-level agreement in 49 cases (98,0 %). While it is not possible to entirely rule out misidentification by the author, the high level of agreement between public data and expert verification indicates a high degree of accuracy in this citizen science approach. These findings are consistent with the results of studies by Crown et al. (2018) and Roman et al. (2017), although slightly higher accuracy was observed in this study. This difference may be attributed to the smaller sample size and the fact that TreeCheck incorporates AI-based species identification support. The most significant limitation of this method, however, is the incomplete spatial coverage. None of the surveyed residential blocks were fully mapped, and only three out of nine were at least partially covered within the scope of this study.

5 Conclusion

Based on this study, it can be stated that the integration of affordable modern technologies, such as drones, open-source tools and pre-trained deep learning models, represents an effective and accessible approach to improving the mapping and management of urban greenery. The study demonstrated that even with limited technological and data resources, it is possible to carry out accurate tree inventory in urban environments, specifically in housing estates, which are often overlooked. Field data collection supported by public science provided valuable insights into tree species and their distribution. Additionally, drone data made it possible to obtain missing information on vegetation height, which is one of the key parameters for assessing its condition. The collected data can be visualized according to user needs for example, to highlight potential risks as illustrated in Figure 4, to show only spatial distribution, or to display other collected attributes. Despite certain limitations of deep learning models trained on different geographical regions, their use proved to be beneficial and can significantly streamline the entire process. The proposed integrated approach thus supports broader adoption of these methods in urban planning and green space management.

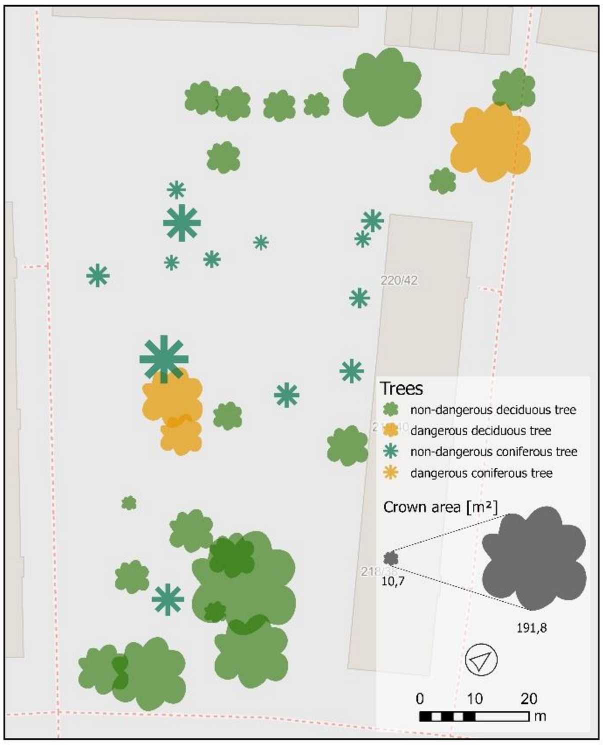

Figure 4: Example of possible data visualization (Norská housing estate)

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