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Article

Population Disaggregation on the Building Level Based on Outdated Census Data

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Abstract: A wide range of disciplines require population data with high spatial resolution. In particular, accessibility instruments for active mobility need data on the building access level. Data availability varies by context. Spatially detailed national census counts often present the challenge that they are outdated. Therefore, this study proposes a novel approach to hybrid population disaggregation. It updates outdated census tracts and disaggregates population on the building access level. Open and widely available data sets are used. A bottom-up population estimation for new development areas is combined with a top-down dasymetric mapping process to update outdated census tracts. A particular focus lies on the high flexibility of the developed procedure. Accordingly, users can utilize diverse data and adapt settings to a specific study context. Instead of requiring ubiquitous 3D building data, often unavailable free of charge, the approach suggests collecting building levels only in new development areas. The open-source software development was done using PostgreSQL/PostGIS as part of the co-creative development of the accessibility instrument GOAT in three German municipalities. A comparison with reference data from the population registry of one district was realized. On the building level, an R^2 of 0.82, and on the grid level (100 m $\times$ 100 m), an R^2 of 0.89 is reached. The approach stands out when land-use information is outdated; however, a spatially detailed census grid exists, but no ubiquitous 3D building information is available. Enhancements are proposed, such as improving the dasymetric mapping with machine learning and remote sensing techniques. Moreover, more reliable detection of new building development in already built-up areas is suggested to account better for urban densification.

Keywords: population disaggregation; accessibility; open data

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1. Introduction

Up-to-date high-resolution population data are essential for understanding a dynamic environment and thus conducting accurate urban and spatial planning studies [1]. High-resolution population data provide public authorities, non-governmental organizations, companies, and academics the possibility to design solid development metrics. This optimizes interventions in their respective communities [2], organizes an accurate response to natural disasters [2–5], and is the foundation for many other studies. In contrast, aggregated data risks masking important hotspots and smoothing out spatial variations inside the population [6].

In the field of transport, studies related to non-motorized modes (walking and cycling) require high-resolution population data at the building scale. For instance, walking accessibility studies require detailed population data to calculate the benefited population within a specified walking or cycling distance to a new public transport station or a set of points of interest [7,8]. Moreover, spatially disaggregated data are needed to define a more granular traffic analysis zone system, known as non-motorized traffic analysis zones (NM-TAZ), as an approach to analyzing walking and cycling inter-zonal trips [9].

Even though the demand for high-resolution population data is increasing, detailed databases often remain scarce or unavailable, due to limitations on the collection of individual micro-data [10,11]. For confidentiality reasons, public data are aggregated [6,12], or could be available but not digitized [9,13]. Therefore, the census population data are usually grouped by census tracts [14].

The use of raw census data has many implications to be considered before their use. First, census tracts polygons are designed according to administrative criteria to facilitate zone enumeration rather than specific demographic parameters [15,16], which can mislead results for demographic studies due to the effect of the modifiable area unit problem [17]. Second, due to their complexity and high cost, censuses are only conducted every 5, 10, or even 20 years, and therefore misrepresent the current population conditions; for instance, the latest German census was conducted in 2011 [18], while between 2011 and 2020, the populations of cities such as Munich have experienced a growth rate of 9% [19,20]. New population distribution cannot be easily anticipated. However, new development areas attract new inhabitants at higher rates than established neighborhoods. While census tracts are not frequently updated, up-to-date population counts are often available on the city, district, or even sub-district levels. The lack of high-resolution data is treated through the application of spatial disaggregation methods [21]. Spatial disaggregation is the process by which information on a coarse spatial scale is transformed into finer scales [2]. There are a variety of approaches, each based on different assumptions about the distributional information [16]. Disaggregation methods can be grouped into two categories: areal interpolation methods and statistical modeling methods [22]. Statistical methods consist of constructing stochastic models to generate simulated (or synthetic) distributions of population [23], for example, the iterative proportional fitting method [10,24].

Areal interpolation methods consist of transforming data from a source zone to many smaller and non-intersecting target zones [12,14]. Areal interpolation methods can be further classified into two categories, based on whether they use ancillary data or not [12]. Areal interpolation with ancillary information uses external data, usually land use or transportation networks, to refine population interpolation. Dasymetric mapping is one of the most popular methods in this category [25], which consists of refining polygons by discarding uninhabited areas obtained from ancillary data [9,26,27]. Areal interpolation without ancillary data can be either point-based or areal-based [22]. Point-based methods rely on census points to create a continuous representation of the population [12,16,28]. The continuous surfaces then support a wide range of spatial analytic processes [29]. The areal-based methods, also known as volume-preserving methods, target the calculation of the proportional distribution of the population with weighted factors [1–3,9,12,22]. Their advantage is the use of control units, which preserve the total number of the population.

Most recent studies propose to combine different methods to increase the accuracy, often starting with a dasymetric process [6]. The hybrid process combines a dasymetric analysis with a fit regression model, dasymetric techniques with machine-learning algorithms [11,30]. A two-step disaggregation is proposed based on a dasymetric processing and a weighted distribution method using 3D building information [2].

As the finer population at the building level has gained importance, different research has studied population disaggregation at this level. LiDAR data were used to detect building characteristics, such as footprint and volume to obtain detailed population data [31,32]. Bast et al. (2015) disaggregated population on the building level using OSM and population counts on the municipality level [33]. The population was recently also disaggregated to a 10 m $\times$ 10 m grid for the whole of Germany. Using remote sensing techniques, building settlement structures and buildings volumes were derived from Sentinel-1 and Sentinel-2 data. The disaggregation combines a bottom-up population estimation with a top-down dasymetric mapping process [34].

The review of the presented studies is far from complete, but it can be concluded that: First, a comprehensive spectrum of disaggregation approaches exists depending on the available information type and the study purpose. Second, there is no systematic framework for data disaggregation [12], and in the worst case, each study has to develop their own models. This problem tends to occur due to the diversity of input data and use cases that makes the standardization process more complex. Furthermore, deriving accurate population data on the building level without ubiquitous 3D building information is particularly challenging. Besides the fact that 3D building data does not exist in every context, it is often expensive to procure. For example, standardized building data are available nationwide in Germany in the CityGML specification LOD 1 and LOD 2, but the data are not openly accessible in many German states [35].

In this context, this paper proposes a standardized four-step hybrid approach to calculate high-resolution population data at the building-access level, based on widely available data sources. It uses a bottom-up population estimation for new development areas and a top-down dasymetric mapping process. Outdated census tracts are updated to a respective target year and then disaggregated to the building access level. There is no intention to derive additional demographic characters. Particular attention is paid to the balance between standardization and flexibility of the data used for the procedure. Accordingly, mostly open-source databases, like OpenStreetMap (OSM) or National Open Data Portals, are utilized. A focus is placed on developing a re-usable and highly flexible script that can cope with varying data quality. This process is realized with population data on the district level and land-use data from the target year. While it is generally expected that 3D building data would improve the procedure results, the presented approach aims to work without ubiquitous 3D building data. Instead, it suggests the collection of building levels only for selected building footprints in new development areas.

2. Materials and Methods

2.1. Study Context

The approach is developed as part of the Geo Open Accessibility Tool (GOAT) project [36], an open-source planning instrument focused on modelling active mobility and local accessibility. One of the main data sources for the application is population numbers at the building access level. GOAT was developed in a co-creative process in collaboration with practitioners from the City of Munich, Freising and Fürstenfeldbruck in southern Germany. Therefore, the development of the presented procedure was applied to the mentioned municipalities visualized in Figure 1.

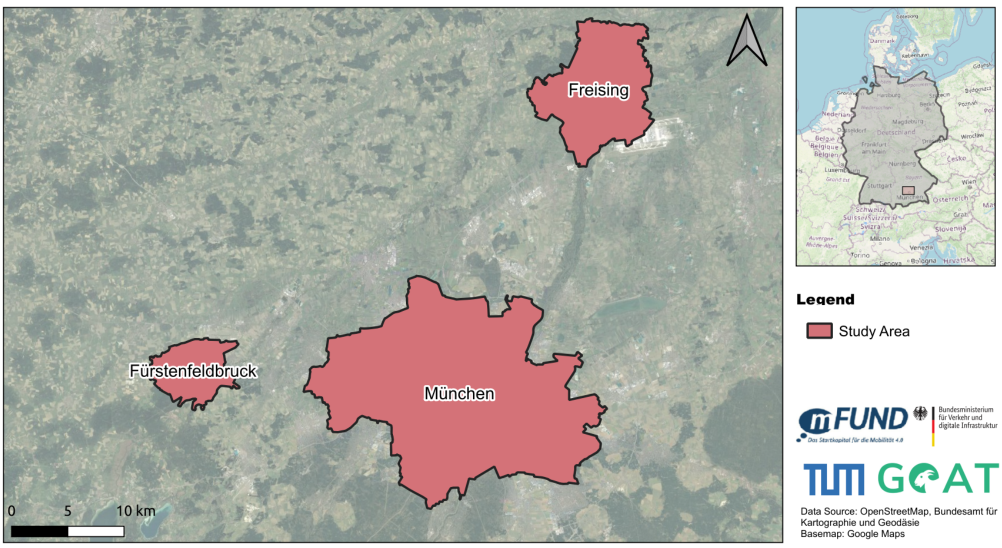


Figure 1. Studied municipalities.

In the last few years, all three municipalities have experienced significant population growth. Munich is the Free State of Bavaria capital, with approximately 1.488 million inhabitants, and Germany's third-largest city. It thus outnumbers the much smaller municipalities of Freising (48,872 inhabitants) and Fürstenfeldbruck (36,843 inhabitants) [20]. All three municipalities have a historical center and contain areas with diverse spatial typologies. The City of Munich is the most densely populated municipality in Germany, with a population density of 4777 inhabitants per km^2 [37]. Accordingly, urban spatial typologies dominate many districts. However, the outer districts also comprise suburbs with relatively low density and high-rise housing estates developed in the 1960s and 1970s. Freising and Fürstenfeldbruck are less densely populated and contain rural settlement structures in their outer districts. In the City of Munich, new housing development is almost exclusively realized in multi-family dwellings, either in new development areas or through densification in the existing built environment. Moreover, in the municipalities of Freising and Fürstendfeldbruck, a trend toward multi-family dwellings can be observed.

2.2. Data

The Table 1 lists all data sources used in this study with their respective reference year. The listed data can be considered a sample, as the developed procedure works with data from other contexts representing the same objects. Furthermore, if not available, only parts of the data sets are required (see Section 3.1).

Table 1. Data used for population disaggregation.

Data Set	Official Name	Data Provider	Reference Year
Land-use	Urban Atlas LCLU 2018 [38]	European Environment Agency (EEA)	2018
Land-use	OpenStreetMap raw files [39]	OpenStreetMap contributors	2021
Land-use	ATKIS Basis-DLM [40]	Landesamt für Digitalisierung, Breitband und Vermessung Bayern	2020
Points of Interest	OpenStreetMap raw files [39]	OpenStreetMap contributors	2021
Building attributes	OpenStreetMap raw files [39]	OpenStreetMap contributors	2021
Building footprints	ALKIS Hausumringe [41]	Landesamt für Digitalisierung, Breitband und Vermessung Bayern	2020
Census Germany	Census Germany [18]	Statistische Ämter des Bundes und der Länder	2011
City districts with population numbers	Stadtbezirksteile	City of Munich, Freising, Fürstenfeldbruck	2021

All data are represented as spatial vector data in the XML format, as Shapefile or GeoPackage. The presented data sets are either openly accessible or provided free of charge by the local public authorities. The data were downloaded in the specific raw formats for the study and converted into the spatial reference system EPSG 4326. Later, the data were imported into the spatial database system (see Section 2.3) for processing. In Figure 2, most of the used data sets are visualized. Three different sources were used for land-use data. While the land use data originating from the official ATKIS Basis-DLM contain only formally defined land-use categories, the data from OSM also contain categories that contributors defined. Furthermore, the land use data from OSM can contain overlapping geometries, which is not the case for the other land use data. The land use information from Urban Atlas is standardized by the European Environment Agency and again contains a different classification. As reference data set for the comparison with the disaggregated population (see Section 3.6), counts on the address level were provided by the City of Freising for their largest district, Lerchenfeld. These data originate from their municipal population register. In Germany, there is an existing obligation to register at a specific address. Therefore, the data can be regarded as remarkably accurate.

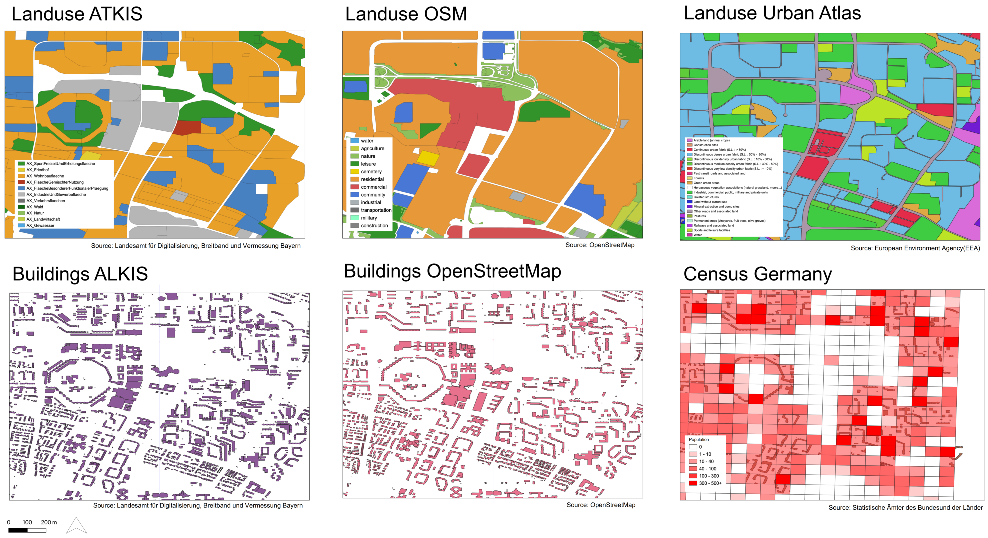


Figure 2. Core spatial data used.

Building footprints were used from the official source ALKIS and OSM. The building footprint of ALKIS usually consists of one building per address. A building in OSM may correspond to several buildings in ALKIS, and vice versa. While building footprints are not mapped everywhere in OSM, almost all buildings exist in OSM for the study context. Furthermore, the OSM data on the building footprints were usually more up-to-date than the available data from ALKIS. Due to the active OSM community in the study area, new buildings are usually mapped during construction. Although the building type is collected in ALKIS, this information was not shared by the public authority. Accordingly, the available building footprints in ALKIS do not contain information on the use of the building. This information, however, exists for approximately 66.17% of the buildings in OSM in the City of Munich.

Finally, the Census of Germany is a vector layer with the population for each census tract. In this case, each census tract is represented by a 100 m $\times$ 100 m square grid and was last updated in 2011. In addition to the total population, census tracts contain demographic information, such as age groups and citizenship. The German census is repeated every ten years (the next one in 2022); the currently available data is out-of-date.

2.3. Software

GOAT is a WebGIS application created with various open-source software (see Figure 3). For the development, the software was installed on a ThinkPad T470 with 16 GB of RAM and an i7 processor running the Linux distribution Ubuntu LTS 18.04. The setup was running with a Docker container. To set up the application, a step-by-step guide exists on the project website [42].

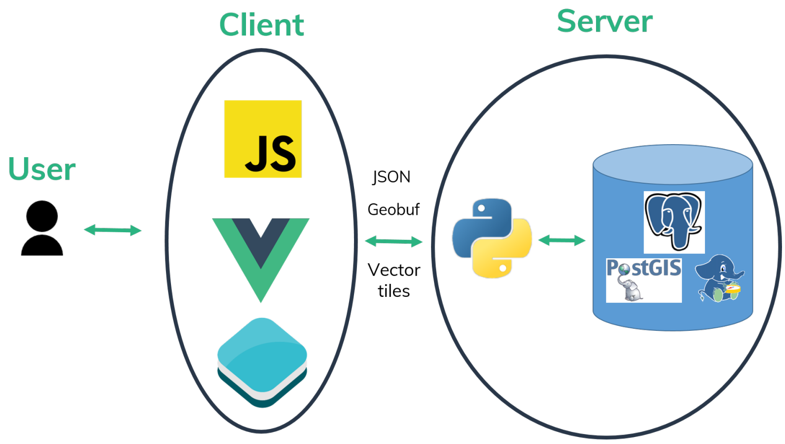


Figure 3. GOAT Architecture [43].

The core of the application is a spatial database system consisting of PostgreSQL 12 and PostGIS 3. A custom Debian-based database image was used as the database docker image [36]. Accordingly, the presented procedure is written in SQL, making extensive use of the spatial functions provided in PostGIS. Besides classical SQL, the SQL Procedural Language PL/pgSQL is used to develop database functions and in anonymous code blocks. In addition, Python functions are developed to execute the different SQL scripts automatically and to import the required data. These functions are integrated into the GOAT setup routines. If running the GOAT setup, the procedure is executed automatically, but can also be triggered manually. Customization can be realized in the configuration file "goat_config.yaml" and when preparing the raw data. A detailed description of data preparation and the options for configuration are provided on the project website [44]. For the data visualization and the creation of maps, QGIS is utilized. The developed source code has been frequently published on Github and is available here [42]. If data were collected, it was performed directly with the OSM iD editor and JOSM. The most recent changes in the OSM database were frequently fetched using the daily dumps and the Overpass API.

3. Results

The population disaggregation approach presented in this paper is composed of four steps: 1. Fusion of Building data and Dasymetric mapping, 2. Detection of building entrances and new development areas, 3. Updating of census tracts, and 4. Population distribution. As part of the workflow, data verification and collection is suggested in the respective areas. To ensure high flexibility of the procedure, users can customize important settings in a configuration file.

The overview of the procedure can be seen in Figure 4. The developed table schema will be presented in the following section, and then the individual steps will be elaborated further.

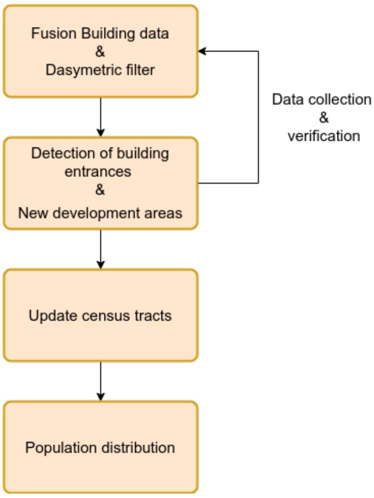


Figure 4. Overview procedure.

3.1. Table Schema

For the presented data (see Section 2.2), a suitable table schema was developed. Two schemas are defined for a high flexibility on the data used: required (see Figure 5) and optional (see Figure 6).

Buildings OSM

PK	gid	int4
not null	osm_id	int8
not null	building	text
	amenity	text
	building_levels	int2
	roof_levels	int2
	street	text
	housenumber	text
not null	area	int4
not null	geom	POLYGON

Study Area

PK	gid	int4
not null	name	text
not null	sum_pop	int4
	default_building_levels	int2
	default_roof_levels	int2
not null	geom	POLYGON

Census Tracts

PK	gid	int4
not null	pop	int4
not null	geom	POLYGON

Landuse OSM

PK	gid	int4
not null	osm_id	int8
	landuse	text
	amenity	text
	tourism	text
	name	text
not null	geom	POLYGON

Figure 5. Required input tables.

For required tables, there are only defined minimum data requirements. Accordingly, only data from OSM, census tracts and administrative boundaries with up-to-date population data are needed. While the required data is sufficient to make the procedure work, especially when OSM Data lacks completeness, the optional data tables are suggested to obtain better results. Furthermore, not all attributes, but only the attributes labeled with 'not null' in Figures 5 and 6, are required.

As output schema, the tables in the Figure 7 are produced as either intermediate or final results. While the presented table attributes and data types are identical to the SQL implementation, the table names differ slightly to read the figures better. A translation of the table names into the names used in the SQL scripts is in the Appendix A.

Buldings Custom

PK	gid	int4
	building	text
	amenity	text
	building_levels	int2
	roof_levels	int2
	height	float
not null	area	int4
not null	geom	POLYGON

Landuse Custom 1

PK	gid	int4
not null	landuse	text
	name	text
not null	geom	POLYGON

Landuse Custom 2

PK	gid	int4
not null	landuse	text
	name	text
not null	geom	POLYGON

Fixed Population

PK	gid	int4
not null	population	float
not null	geom	POINT

Figure 6. Optional input tables.

Fused Buildings

PK	gid	int4
	osm_id	int8
not null	building	text
not null	residential_status	text
	amenity	text
not null	building_levels	int2
not null	building_levels_residential	int2
not null	roof_levels	int2
	height	float
	street	text
	housenumber	text
not null	area	int4
	gross_floor_area_residential	int4
not null	geom	POLYGON

Census Tracts New Development

PK	gid	int4
not null	pop	int4
not null	geom	POLYGON

Updated Census Tracts

PK	gid	int4
	pop	int4
	new_pop	int4
not null	geom	POLYGON

Population

PK	gid	int4
not null	population	float
not null	geom	POINT

Residential Entrances

PK	building_gid	int4
not null	gross_floor_area_residential	float
not null	geom	POINT

Figure 7. Data structure output tables.

3.2. Fusion of Building Data and Dasymetric Mapping

As visualized in Figure 8, this first step consolidates the different building data sets. Therefore, the OSM data (if available, custom building data) are fused by spatial intersection. If available, a priority is given to the custom building data set, and fusion is performed based on the largest share of spatial intersections, in case there are multiple intersections. If available, attributes such as building type and building levels are combined from OSM and custom building footprints. If the height of buildings is known, the number of floors is computed using average height per building level. If neither the height nor the building levels are available, a default number of building levels is assigned per district of the study area. In the study, this average varied from one to five, depending on the district and municipality. This value was derived from the author's knowledge of the study context, and was assigned to each district. Another option will be assigning the observed average from a reference data set, such as OSM if building levels are available for a statistically significant number of buildings.

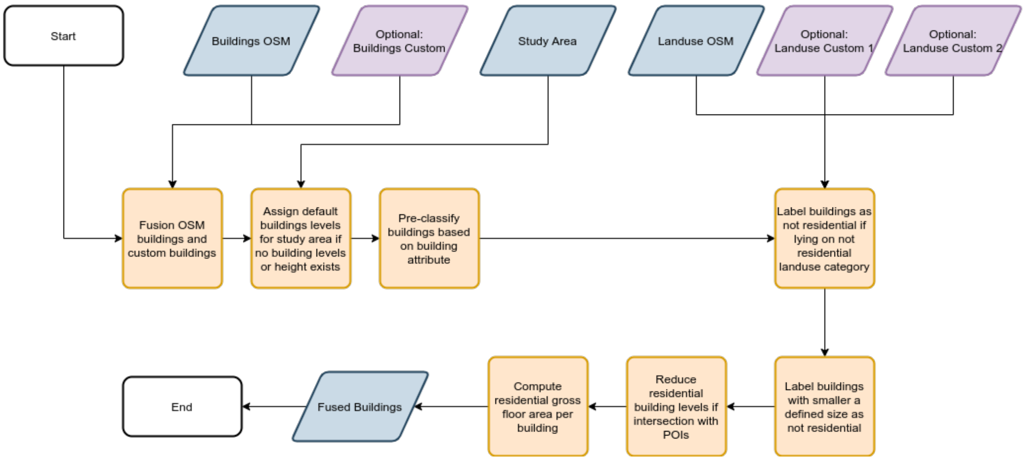


Figure 8. Fusion building data and dasymetric mapping.

Next, dasymetric mapping is performed to identify buildings with residents. Simplified binary classification is applied to categorize buildings into "with residents" and "no residents". Therefore, buildings are first classified using the attributes building and amenity, which specify the use of the building. For the classification, users can define a list of residential and non-residential categories in the configuration file. However, as is common in OSM, there is no specification on the building type. Therefore, other auxiliary data are needed to classify the buildings further. Land use data from OSM is used as the default data set, and (if available), two more custom land-use data sets can be provided. For each of the land use data sets, a configuration of different categories contains information on whether the buildings are residential or not. Accordingly, land use categories such as industrial or commercial can be labeled as non-residential, while residential use can be labeled as residential. If multiple files are provided, a hierarchy between the land-use files can be defined if the data sets assign contradicting categories to the buildings.

A particular challenge, however, is the detection of outbuildings such as detached garages or garden houses. In this case, a final filter is applied using a minimum residential building size of square meters to label these non-residential buildings. Similar to other settings, this filter can be customized to the local study context. After that, ground floor commerce is identified using a set of points of interest from OSM. If buildings have ground floor commerce, the residential floor levels are reduced by one floor. If no ground floor commerce exists, it is assumed that all floors are residential. Finally, the residential gross floor area is calculated per building using the following equitation:

$$G = A \times (NBL + 0.5 \times NRL) \quad (1)$$

where G is the residential gross floor area in m^2, A is the area of the building footprint in m^2, NBL is the number of residential floors and NRL is the number of roof levels. As the final result of this step, a fused building data table is saved and made available for the subsequent steps. The final result of the process is visualized in a chosen neighborhood in Munich in Figure 9.

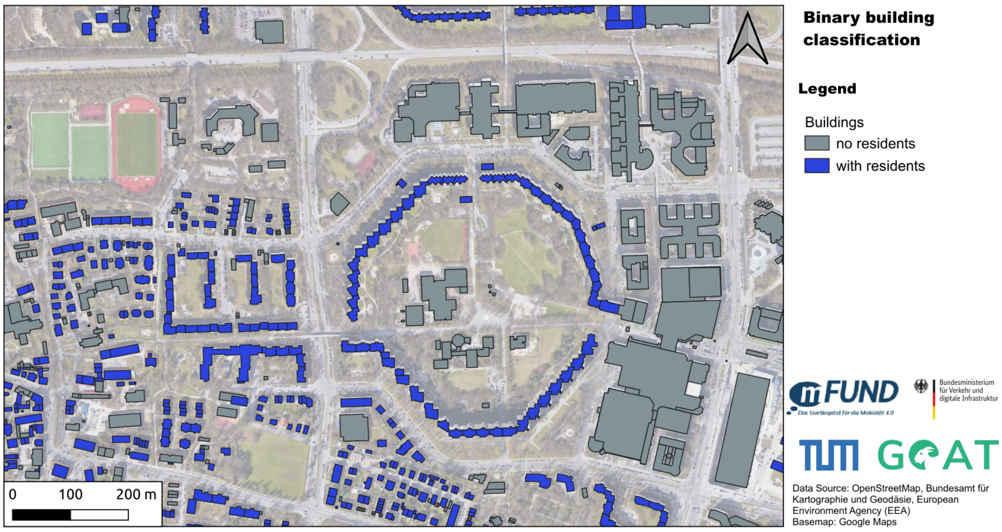


Figure 9. Binary classification buildings.

3.3. Detection of Building Entrances and New Developments Areas

In this step, the procedure is intended to estimate access points to buildings and identify census tracts recognized as areas of new residential development (see Figure 10). The entrances and addresses are identified from OSM point data (if available) or based on the edge of the building closest to the OSM street network. If several access points are identified in one building, the residential gross floor area is equally distributed. It is also possible to complement data by feeding in custom population point data sets. This optional data set allows one to specify the exact number of residents for a given access point. If buildings intersect points from the custom population data set, their population is considered static for the upcoming steps.

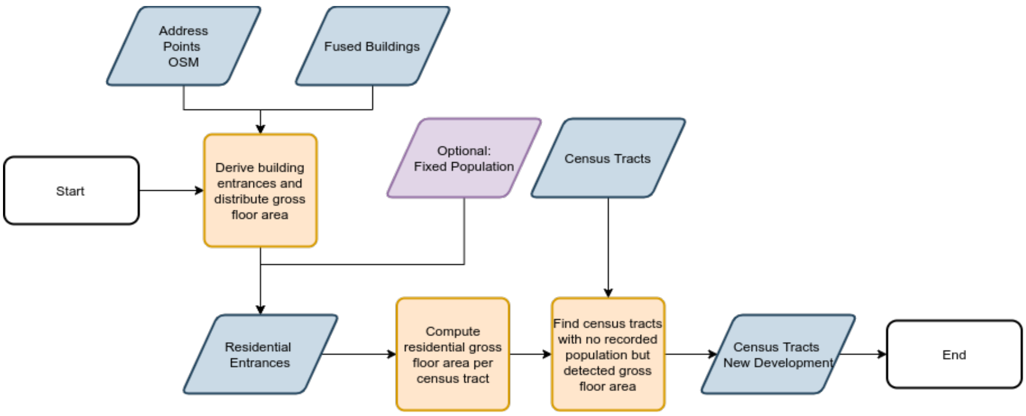


Figure 10. Detection of building entrances and New development areas.

Subsequently, these entrances containing building-related data are compared with census tracts. If the census tract has no recorded population but contains a residential access point, it is labeled a census tract with new development. The population is computed bottom-up using the residential gross floor area and an average gross floor area per resident for these selected new census tracts. The average gross floor area per resident is defined per municipality. According to official statistics, the net living area per person is 39 m^2 in the City of Munich and 49 m^2 in the Munich region [45]. Following this, parameters for average gross floor area 50 m^2 for the City of Munich and 60 m^2 for Freising and Fürstenfeldbruck were chosen. However, the procedure allows one to freely chose a suitable gross floor area in the configuration. For the bottom-up estimation, the building data quality in the tracts with new development is critical. Therefore, the table "Census Tracts New Development" is created. It is suggested that the building type and the number of building levels are collected directly in OSM for buildings located in these tracts. An alternative could be to acquire commercial building data for the selected areas. While the upcoming procedures also work without further data collection, it is highly suggested to improve the final result. Since only a fraction of census tracts are usually affected, the resources needed for this step are relatively small. Once data collection is realized, the previously described steps should be repeated. The final result of the process is visualized in Figure 11 for an exemplary neighborhood in a new development area in Munich. The buildings visualized in the new census tracts have four to five stories and flat roofs with no commerce on the ground floor. This area can be classified as a typical new development area in the outer districts of Munich.

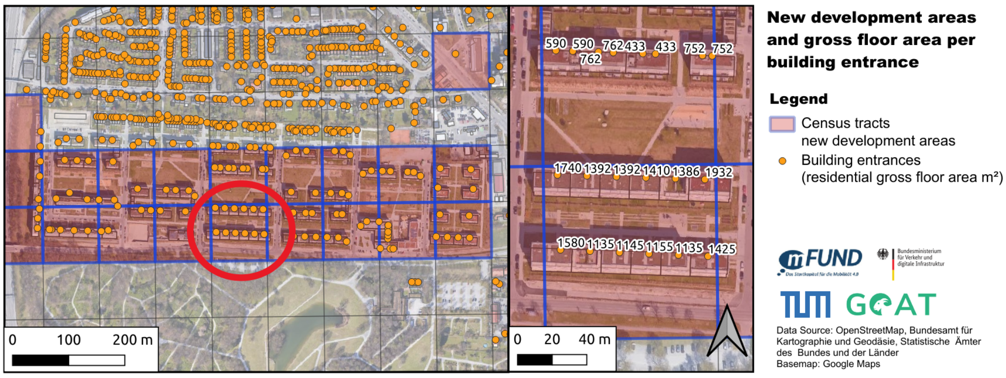


Figure 11. New development areas and gross floor area per building entrance.

3.4. Updating of Census Tracts

In this step, the population per census tract is updated to meet the population number of the study area as a control unit in the respective reference year (see Figure 12). Therefore, a combination of a bottom-up and top-down approach is implemented. First, the population is computed using a bottom-up approach for the census tracts detected as "new development areas". Accordingly, for all census tracts, the intersecting building entrances are taken, and population numbers are computed using an average gross floor area per resident as follows:

$$P = \sum_{i=1}^{c} GA_i / AGR \tag{2}$$

where P is the computed new population for the census tracts, c is the number of intersecting building entrances, GA_i is the gross floor area assigned to the entrance, and AGR is the average gross floor area needed per resident.

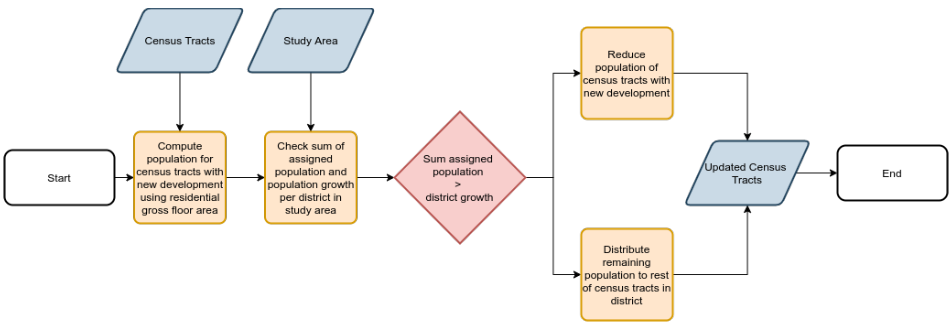


Figure 12. Update census tracts.

Consequently, the population assigned by the bottom-up distribution will be corrected using the total population of the related district of the study area as a control unit through a top-down approach. It is checked whether the sum of the newly assigned population growth matches the overall growth in the related district. In case the population in the new development areas exceeds the overall population, the newly assigned population in the tracts is adjusted. If the distributed population is lower than the overall growth, the remaining population is distributed proportionally according to the residential gross floor area to all remaining census tracts. By that, densification in already built-up areas should be modeled. As a final result, a census table with updated population numbers is stored. The combination of bottom-up and top-down approaches ensures that the population in the census tracts does not exceed the total population of the respective study area.

3.5. Population Distribution

In a final step, the population from each census tract is distributed proportionally to the residential entrances using the residential gross floor area (see Figure 13). Inaccuracies which come with assigning default building levels per district are reduced, as due to small grid sizes, building levels are likely homogeneous within the grid. The disaggregated population data are saved as vector point data sets in the database.

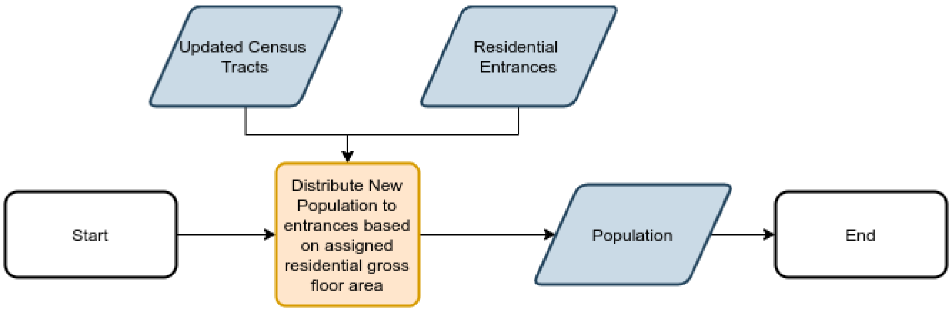


Figure 13. Population distribution.

The data are aggregated on a hexagonal grid with an edge length of 150 m for visualization purposes. The map in the Figure 14 shows the distribution of the population in the City of Munich. Despite the overall very high density, the large green areas within the city and main transport infrastructures are clearly visible as uninhabited. The zoomed-in map further visualizes how the population is distributed on the building entrance level. To the author's knowledge, the displayed buildings have five stories and consist of ten flats per building, of varying sizes.

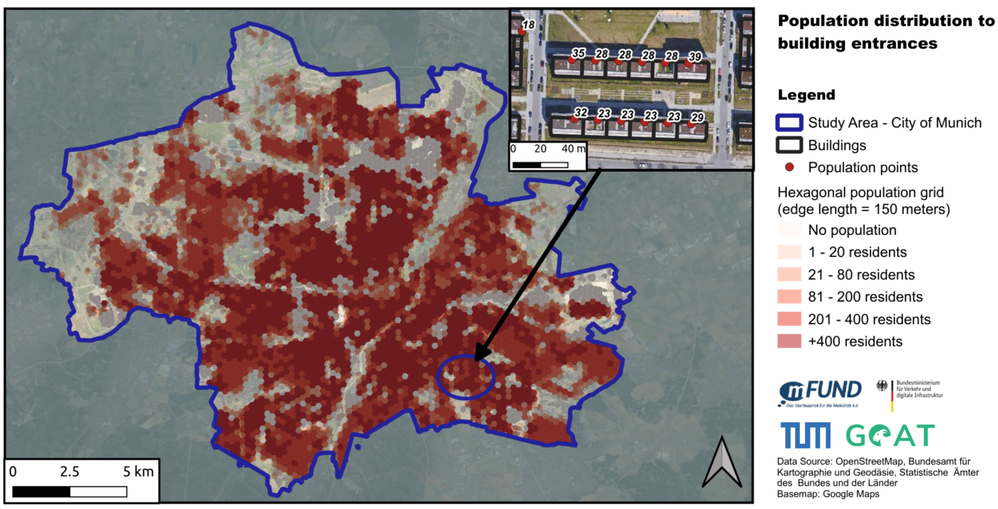


Figure 14. Population distribution.

3.6. Comparison with the Municipal Population Registry

For the comparison, the district of Lerchenfeld in Freising was selected. The reason for this was the availability of suitable reference data. The district had, in 2020, a population of 13,135 inhabitants, and had growth of 13.8% since 2011. It is very heterogeneous in terms of building structure and demography. It is characterized by single-family housing, detached housing, and multi-story building of up to nine building levels. There are also major commercial and industrial areas in the district. Urban growth has happened since 2011, mostly in new multi-story buildings with three to four building levels. Besides greenfield development, existing neighborhoods were densified. A particularity in the area is the existence of two complexes for the housing of refugees, particularly with high population density. Although the reference data can be regarded as very accurate, there are two significant limitations. First, assigning the provided population on the address level to a specific building was not always possible. Not all buildings had address information, and sometimes, one population point represents several buildings. Second, the inspection revealed implausible outliers. There were buildings with a comparatively low living area, but many residents and non-residential buildings with residents. In the population registry, persons can be registered at a specific address, but live at another location. Nevertheless, the provided data are considered the most suitable one for the comparison.

The disaggregated and recorded population point data were summed up on the building level, and their relative difference is visualized in Figure 15. There could be both over- and underestimations of population detected. Moreover, there are also neighborhoods with an exceptionally high correlation of disaggregated and recorded data. The highest mismatch was yielded on the building complexes for refugees. There were up to 450% more residents registered compared to the disaggregation (see Figure 16). Another significant outlier was a nursing home for the elderly classified as a non-residential building, due to consideration of this edge case in the dasymetric mapping not being appropriate. While these strong outliers are few, they affect the quality of the disaggregation for the whole district, as the missing population is assigned to other buildings, resulting in an overestimation. This was observed mainly for single-family houses. It can also be observed that identical buildings face a high relative mismatch of population numbers for single-family houses. This is most likely related to differences in the household structure and age. However, with the available data, differences in age or household size could not be considered on the building level. Overall, an R^2 of 0.82 was achieved for the disaggregation on the building level, as shown in the Figure 17.

Further comparisons were realized on the level of the census grid (100 m $\times$ 100 m), as shown in Figures 17 and 18. Due to the lower spatial resolution, the correlation between disaggregated and recorded populations was higher. As a result, an R^2 of 0.89 was reached. Despite the higher correlation, still, significant outliers are visible, mainly in the previously described cases. A correlation between unmodified population numbers from the census registered in 2011 and the recorded population in 2020 is shown in Figure 19. Without updating the population data, a significantly lower R^2 of 0.78 on the grid level would be achieved.

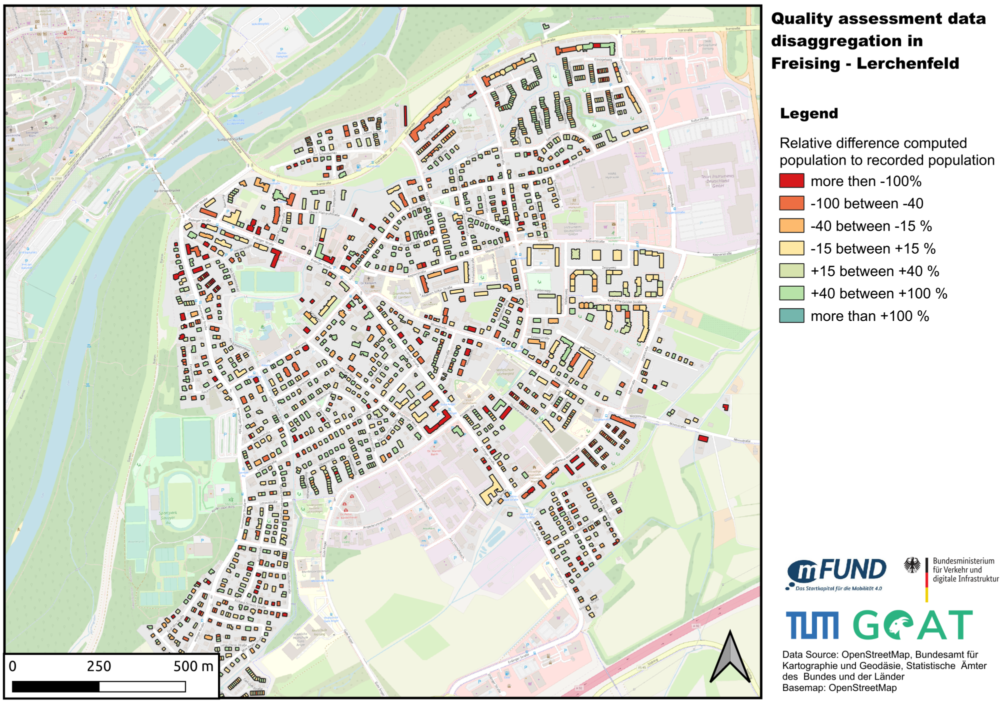


Figure 15. Comparison disaggregated and recorded population data on the building level.

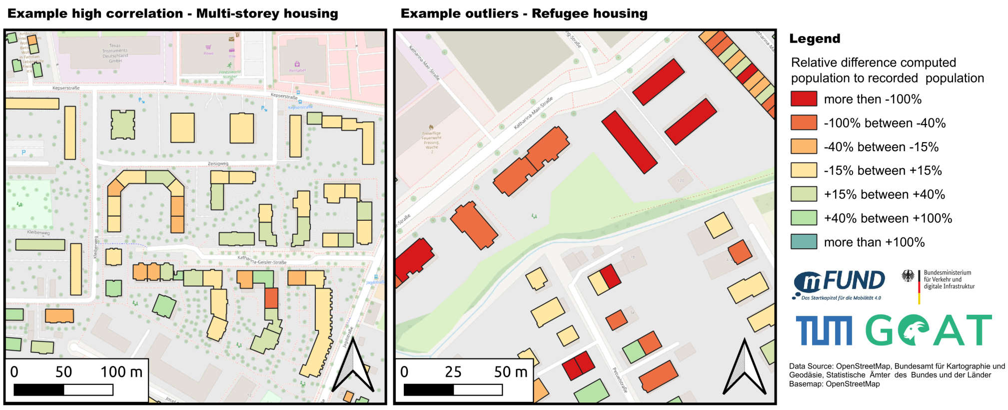
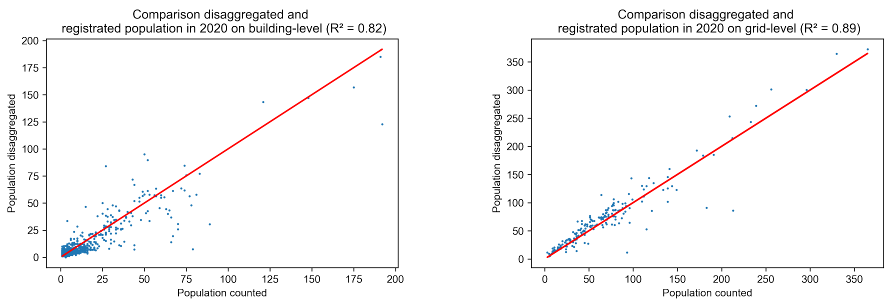


Figure 16. Comparison disaggregated and recorded population data correlation examples.



(**a**) (**b**)

Figure 17. Correlation disaggregated and recorded data on (**a**) building-level and (**b**) grid-level (100 m × 100 m).

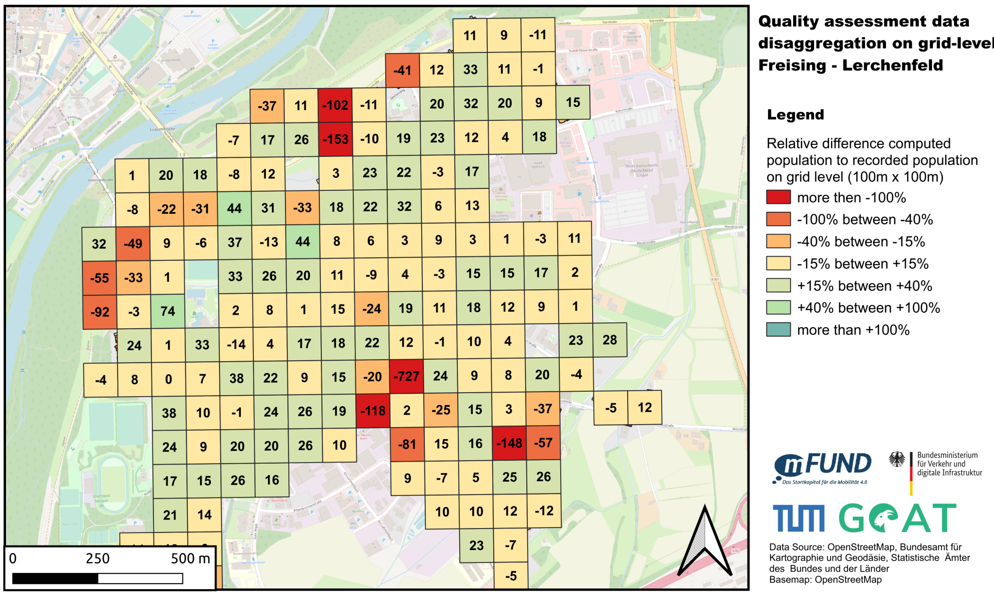


Figure 18. Comparison disaggregated and recorded population on grid-level.

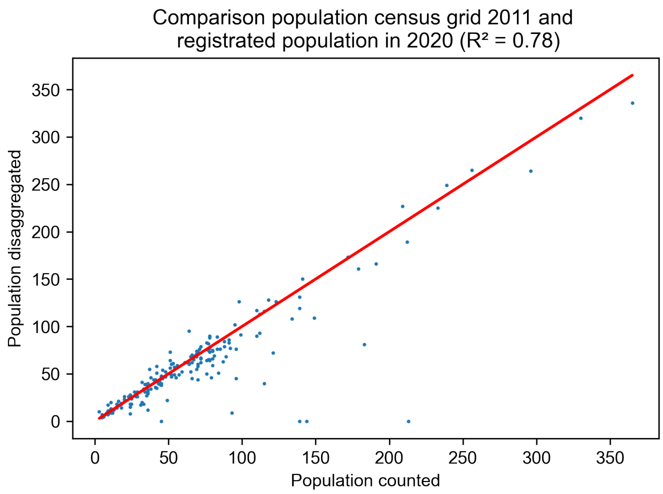


Figure 19. Comparison census population from 2011 and recorded population 2020.

4. Discussion

The methodology was applied in three growing municipalities in southern Germany. The results were used for accessibility analyses in planning workshops, with urban and transport planners in the studied municipalities. A comparison with recorded population data on the address level for a selected district in the municipality of Freising indicates a relatively high quality of the produced data. However, it also shows that the population is significantly over- or underestimated for selected buildings. As the total population is used as a control unit for the district, significant deviations for selected buildings can strongly influence the results for the remaining buildings. The comparison of data from the census of 2011 and the recorded data from 2020 shows that the procedure updates the data successfully, and quality is higher than without the update.

An explicit limitation of the presented approach is that the procedure expects, a priori, that the population grows in the respective study area. It would be feasible to adjust the scripts to model population decline. However, it has not yet been implemented. Further testing would be needed to see if the procedure produces relevant results when the population declines. Another methodological weakness of the presented solution is the insufficient attention paid to new housing development in areas with a population in the outdated census tracts. As the population is initially assigned to census tracts that previously had no population and only afterward is the remaining growth assigned to all other already inhabited census tracts, the phenomena of urban densification are not captured well enough. However, detecting new development in a separate tract without historical building footprints is particularly challenging. The procedure assigns the same average gross floor area for all districts within a study area with the current design. This is a limitation as the average living area can vary significantly between different neighborhoods and building types.

While collecting data on building levels improves the results of the procedure, it requires additional resources. Therefore, fallback values in the configuration files can be favorable in larger regions and regions with homogeneous buildings levels. An interesting source for further exploration could be building heights derived through remote sensing. Due to the absence of area-wide building heights, emphasis is placed on estimating building heights using freely available data such as products from Sentinel and Landsat. Building heights were estimated on a 1 km grid for Europe, the USA, and China using a random forest model and training data sets from the different regions [46,47]. A validation showed an R^2 of 0.81 for the building height estimation [46]. On the national scale, significantly higher resolutions of 10 m were achieved using Sentinel 1 and Sentinel 2 data. Machine learning regression models were utilized with robust training data sets composed of almost 15 million buildings in LOD 2. A frequency-weighted RMSE of 2.9–3.5 m was achieved [48]. Despite the increasing availability of data on building footprints and land-use, this might not be the case in every context. Accordingly, the procedure is not recommended for areas with missing building footprints and missing land-use information. The procedure also expects census data on a high resolution, and grid sizes of 100 m were used for the tests. Although not tested yet, it is expected that larger grid sizes would weaken the detection of new housing development areas, as census tracts with new development are identified by searching tracts with no population recorded in the reference year but having residential buildings in the target year. Moreover, the resolution of the districts of the study area influences the results of the disaggregation. Generally, it can be assumed that a higher resolution of the districts will improve results, and vice-versa.

The application has shown that dasymetric mapping works particularly well with several land-use files. However, it is still challenging to properly classify buildings that have no specific information on the use of the buildings, either from OSM or other data sources. Especially in mixed land-use areas, it is not trivial to detect which building contains residents or not. Furthermore, the detection of outbuildings solely by size can be error-prone.

Dasymetric mapping could be improved by the use of remote sensing techniques and machine learning. Lu et al. (2014) classified buildings into single-family, multi-family, and non-residential buildings using LiDAR data. Four different machine learning techniques were used: decision trees, aggregated decision trees, support vector machines, and random forest. Accuracies of 60–88% were reached. The best-performing one was supported vector machines in both urban and suburban areas. Diverse attributes falling into categories such as building shape attributes and spatial relationships with other land-use features were used [49]. Although the mentioned study utilizes LiDAR data, the methods for the classification could partially be applied with the available vector data from OSM and public sources. With the wide availability of building footprints, the dimension of buildings could be utilized as a good proxy for building type classification. In the German context, officially labeled data on the building type could be retrieved from cadastre for states where the data are open access.

Moreover, street view imagery is utilized to classify building types. Using a convolutional neural network on geotagged imagery from Google StreetView, buildings were classified into diverse categories, such as industrial, office, and garages [50]. As part of a German-wide population disaggregation, building areas were classified using random forest on Sentinel 1 and Sentinel 2 data. The procedure reached an overall accuracy of

81.4% [34]. These mentioned examples indicate that the use of additional data sources and methods can improve the developed procedure.

While the presented solution produces population point data on a particularly high resolution, it lacks further socio-demographic attributes such as age, gender, or income. This makes it particularly unsuitable for activity-based land-use and transport models, which usually require a synthetic population. While advanced population synthesizers exist, as reported in [51–53], the objective of this study was to develop a well-performing and simple solution, which produces exclusively up-to-date population counts at a very high resolution under minimal data requirements. A high-resolution population is relevant for a wide array of use cases. In countries such as Germany, population registries exist, which provide an up-to-date picture of population data on the address level. However, these data are usually sensitive and not shared with upper administrative bodies, researchers, or private businesses at a high resolution. Therefore, the developed procedure could be of special value for official statistics at the higher administrative levels or public service providers in the studied context. Meanwhile, in contexts where citizens are not forced to report on their home location, the procedure can also be relevant for municipalities by providing a granular disaggregation of the population.

5. Conclusions

The new population disaggregation approach demonstrates that population numbers can be disaggregated on the building level based on outdated census data. Unlike other existing solutions, the procedure works without ubiquitous 3D building data. It suggests the collection of building levels in OSM for new residential areas, or suggests the definition of average building levels per administrative district. Furthermore, diverse but easily available data sets are fused and utilized. This significantly reduces the data requirements and makes it possible to utilize the census tracts' spatially detailed but outdated population information. It can adjust to local requirements through configuration files and fuses data from varying sources to remain useful in varying contexts. Different configurations should be tested in the future and best practices documented for different contexts. As the procedure was integrated into the setup of the software GOAT, it can be executed in a highly automated fashion and can be directly used in the application. However, it is also possible to use the scripts independent of the GOAT application. Overall, the development is a pragmatic contribution to the existing landscape of population disaggregation. The solution is advantageous if an inexpensive approach is favored and good open data are available, but no 3D building information exists. This study was mainly intended to prepare population data for accessibility analysis on the neighborhood level. Meanwhile, it could be useful for other applications.

So far, the scripts have been primarily tested in the studied municipalities. However, further testing will be conducted. Large-scale tests in Germany are currently prepared, and tests in regions worldwide are envisaged. To date, the results have been verified by comparing them with recorded population data from one district. As described in Section 3.6, it could be feasible to reach higher correlations with data from population registries in other areas with less dynamic growth and fewer outliers. Further strategies need to be developed to detect and handle outliers. Due to the unavailability of data, no large-scale comparison can be realized yet. Whenever possible, this should be done in the future. Furthermore, data verification using data produced by other disaggregation algorithms or newly published census data are being sought. To improve the detection of new development areas, historical data on building footprints should be examined further. A potential source could be the OSM database, as timestamps exist for each feature created or modified. In addition, remote sensing techniques on satellite imagery could be tested to detect areas with changes in the built environment. This improvement could particularly help in identifying urban densification. As described in Section 4, the dasymetric mapping could benefit from remote sensing and machine learning. Promising is, in particular, the extension of the current binary building classification towards multiple classes, such as single-family housing, multi-family housing, mixed-use and non-residential. Further experimentation with deriving building type and gross floor area for residential purposes with the help of points of interest is targeted.

Overall, it is seen that this work adds especially the following contributions:

- A standardized and adaptable yet pragmatic solution was developed to disaggregate the population on the building access level.
- Compared to many other solutions, no ubiquitous 3D building data or LiDAR data are necessary.
- An outdated census grid is updated to the target year, and therefore the spatially detailed but outdated census data are set in value.

Among others, the following are seen as the most important limitations:

- Dasymetric mapping is solely based on a boolean classification; accordingly, different residential buildings are not differentiated.
- A spatially detailed census grid, up-to-date population data on the district level, building footprints are necessary to obtain appropriate results.
- It is suggested to collect buildings level in new development areas, which means additional effort and limits scaling.
- More validation of the produced results is necessary to judge the accuracy finally.

Besides the aforementioned technical optimization, one might ask if it is sufficient to include only the static population. There are high temporal variations in the distribution of the population within a city region; most notably, the variations between day and night. Moreover, many applications such as accessibility instruments would benefit from showing the variations of population. Recent research [54,55] underscores the potential and feasibility of disaggregation procedures, which incorporate the tempo-spatial dynamics of the population in cities and regions. To specifically enrich accessibility instruments with temporal dynamic population data, further research and development are envisaged.

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Abbreviations

The following abbreviations are used in this manuscript:

ALKIS	Amtliches Liegenschaftskatasterinformationssystem
ATKIS	Amtliches Topographisch-Kartographisches Informationssystem
GOAT	Geo Open Accessibility Tool
LOD	Level of Detail
OSM	OpenStreetMap
PL/pgSQL	Procedural Language/PostgreSQL
SQL	Structured Query Language
WebGIS	Web geographic information system

Appendix A

Table A1. Table Schema Mapping in SQL.

Table Names Figures	Table Names SQL
Buildings Custom	buildings_custom
Buildings OSM	buildings_osm
Census Tracts	census
Census Tracts New Development	census_split_new_development
Fixed Population	fixed_population
Land-use Custom 1	landuse
Land-use Custom 2	landuse_additional
Land-use OSM	landuse_osm
Population	population
Residential Entrances	residential_addresses
Study Area	study_area
Updated Census Tracts	census_prepared

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