A Categorization and Parametric Modeling Approach Using Open Geodata Enabling Building Vulnerability Assessment

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Abstract

Due to the increase in the frequency and intensity of natural disasters such as heavy rainfall events, the evaluation of the vulnerability of the built environment is becoming increasingly important. Evaluation techniques for each separate building often require detailed geometric models of the supporting structures and time-consuming simulations. One possibility to overcome this problem is to categorize the buildings in a first step and use representative building models for each category. This paper presents a semi-automated approach for categorizing buildings and creating parametric models for the respective building categories. Using these models, the buildings of a category can be collectively examined for their vulnerability to various impacts. First, this paper introduces open geodata that can be used for this process. For the categorization of the buildings, the collected data is further processed to extract additional information such as building age classes or floor plan geometries of the buildings. This results in a data set, with the help of which the buildings can be categorized. However, information about the load-bearing structure is often missing in the different data sources. By including information on typical construction methods that are associated with the previously determined characteristics (age, floor plan geometry, usage), representative models can be created for individual building categories. In this study, the approach was tested in a selected reference area in Berlin. The results indicate that the presented approach is a promising first step towards deriving geometrical models from open geodata that can be used to evaluate the vulnerability of buildings.

1. Introduction

Heavy rainfall events have been causing severe damage in different parts of the world in recent years. Not only do these types of events pose a high risk for significant financial damage, but they also increasingly cost human lives. Additionally, buildings often have important relationships to other critical infrastructures such as the electricity network or fresh water supply as part of the urban infrastructure (Martini et al., 2023). Therefore, it is important during these events to keep an overview of the situation and to be able to assess the impact on people in the affected areas as quickly as possible. The investigation of the vulnerability of the built environment is a critical task for local authorities in this context.

Various methods are available to evaluate the susceptibility of structures to natural disasters. Most of these approaches are based on empirical review and surveying of previous events (for example Schinke et al., 2016 and Maiwald et al., 2022). Although vulnerability assessments can be made from these observations, the resulting findings are heavily dependent on the investigated area and the prevalent building typologies and cannot easily be transferred to other regions. Another approach to assess the vulnerability of building models and evaluate their ability to withstand the effects of heavy rainfall events is using Finite Element Method (FEM) simulations. However, these methods have significant drawbacks when they are applied in a case-by-case manner. Firstly, detailed structural models are necessary for the computation, and secondly, FEM simulations can be computationally expensive and time-consuming. These types of simulations are not suitable to assess the vulnerability of a large building stock or a complete city.

Integrating the categorization of the building stock into the FEM simulation process for representative geometric models for each building category, can combine advantages of the different approaches. In the past, probabilistic FEM simulation frameworks have been developed mainly for seismic hazards (Pitilakis et al., 2014 or Maio and Tsionis, 2015). By varying different parameters of the simulation model, the effects of uncertainties can be included in the analysis. Uncertainties can result from the lack of knowledge about material parameters or the exact geometry of the load-bearing structure as well as the variability of the load. The resulting fragility curves describe the probability of damage depending on a certain load magnitude. Including uncertainties for material parameters and loads for the creation of fragility curves is not a new concept. However, the generalization of models inherent in the categorization process of the buildings, incurs additional uncertainties. While parameters like the number of stories were integrated in the past, geometric parameters of the load-bearing structure such as the distance between walls are not as easy to integrate and require more complex parametric models for the analysis.

This paper presents an approach to categorize building stocks and develop parametric models for each category as basis for subsequent probabilistic analysis to assess the vulnerability of buildings. It reviews recent approaches on how to categorize building stocks and the generation of geometric models based on these categories. The presented approach is separated into two steps. In a first step available open geodata is collected and processed. Using the resulting data, the buildings are then categorized. In a second step, information on typical construction periods and typical load-bearing structures of these construction periods are used to develop a parametric structural model. Using the collected open geodata, the stochastic distribution and limits of the geometric parameters are identified wherever possible as a basis for the probabilistic analysis.

The paper is structured as follows. Section 2 describes an overview of existing work. Subsequently, the methodology of the paper is presented in Section 3. Berlin is chosen as an exemplary city to showcase the presented approach in Section 4. All findings of this paper are discussed, and possible future research fields are presented in Section 5. Section 6 concludes this paper.

2. Related Research

It is important to note that different categorization methods exist for different applications. For example, there is a method that categorizes buildings for subsequent energy simulations (IWU, 2016). This categorization method was developed in the context of the TABULA project. The crucial parameters used here for categorization are the country and the region in which the buildings are located, the age class of the buildings, and predefined size classes of the respective buildings (for example, single-family homes). Important parameters for assessing the load-bearing capacity are not considered in this typology. Nevertheless, projects such as TABULA can serve as an inspiration. The procedure of categorization and the creation of representative models for subsequent simulations is also applied in that project (Ballarini et al., 2014). A recent study utilizes content from the TABULA project for the energy demand calculation of existing buildings based on open geodata and CityGML models (Harter et al., 2020). However, this method is highly dependent on additional user input data, as the data in the existing CityGML model alone is not sufficient for the calculations.

The aim of this literature research is not to list all existing taxonomies, but to identify parameters that are considered important for the characterization of buildings in terms of their load-bearing capacity. Several typologies have been developed for categorizing buildings in terms of their load-bearing capacity and structural resilience, often tailored to different regions. A more detailed overview about existing typologies and their disadvantages and advantages is presented by Silva et al., 2022. Some globally applicable typologies exist, including the World Housing Encyclopedia (EERI, 2000) and the GEM Building Taxonomy (Brzev et al., 2013). Both typologies were developed for assessing building vulnerability to earthquakes. However, the GEM Building Taxonomy has been further developed into the GED4ALL Taxonomy, which can also be applied to multi-hazard scenarios (Silva et al., 2018 and Silva et al., 2022). Because the GED4ALL Taxonomy was designed to include the use case discussed in the presented contribution, the parameters mentioned are considered particularly important for categorization. The developers of the GED4ALL Taxonomy identified 13 parameters that are relevant for the categorization of buildings to assess the vulnerability of the load-bearing system:

1) Direction of load-bearing system,
2) Material of load-bearing system,
3) Load bearing-system,
4) Height,
5) Construction date,
6) Occupancy,
7) Building position within a block,
8) Shape of the building plan,
9) Structural irregularity,
10) Exterior walls,
11) Roof (shape, material, …),
12) Floor (material, wall connections, …),
13) Foundation type.

It is possible to use OSM (OpenStreetMap) data to match the parameters of an existing typology for buildings (Nievas et al., 2023). While the theoretical foundation of the OSM data sets contains many definitions that can be directly mapped to the parameters of the GED4ALL Taxonomy, unfortunately, this data is often not available. Thus, the buildings can only be categorized based on the available data. To overcome the problem of incomplete or missing data, various approaches exist to achieve automated enrichment of the existing data using machine learning or laser scanning (In Section 5, it will be discussed to what extent these approaches could be helpful for this application). However, this paper is dedicated to presenting the general approach for making the best possible use of the available geodata and preparing it for subsequent analysis.

Automated modeling based on available open geodata and building categories has so far only been partially addressed in the literature. A framework was developed to automatically generate FEM simulation models from given CityGML models (La Russa et al., 2022). In addition to attributes like roof type, elevations, and façade orientation, these models include a specifically defined file in which the openings in the building envelope are defined as input. The approach is not solely based on available open geodata and requires an additional collection of data for openings of the buildings. The inner walls and structures of buildings are not integrated in the generated models of this work. A similar approach introduced the integration of the inner structure into the transformation of the simulation model (La Russa et al., 2023). However, the internal partitions and locations of the walls were identified in a manual process. Both approaches are focused on creating a simulation model for a specific building. For the definition of a generalized, parametric model for a complete building category, these approaches are insufficient.

For subsequent probabilistic analysis it must be ensured that different geometric parameters of the generated model can be varied. In the literature, fragility curves are commonly based on simplified models that vary only a few geometric parameters and mainly focus on variation of material properties. Building height is the most frequently varied geometric parameter, either as a continuous variable or a discrete number representing the number of stories. Adding more geometric parameters to the model would require a more complex parametric model (Maio and Tsionis, 2015). In the field of architectural informatics, studies have been performed using a parametric city model to evaluate the influence of changes in building codes. In this context the outer envelopes of the buildings are parametrized based on a building typology. The outer dimensions and dependencies of the buildings are modeled in a parametric way to simulate changes in the regulations and evaluate the possible influences on the cityscape (Seifert et al., 2016). To evaluate the structural vulnerability of buildings this approach is not feasible due to the limitation to the outer shell of the buildings.

In the present paper, elements of categorizing buildings based on open geodata and parametric modeling are combined to set up a pipeline for the vulnerability assessment of buildings. New ways of interpreting existing geodata are shown and linked to existing typologies. In addition, typified parametric models are presented as a basis for probabilistic analyses. The linking of the analyzed geodata and the parametric model for a subsequent analysis is also investigated.

3. Methodology

3.1 Collection and Processing of Open Geodata

In a first step, various data sources are initially examined and combined to obtain as much input data as possible for the buildings. Widely available OSM data can be combined with data from local geoportals of the municipalities. For example, the city of Berlin maintains its own geoportal that provides various data sets for different kinds of data for the buildings (SenStadt, 2024). Local geoportals often offer more detailed data than the OSM data. The quality of the data depends on the completeness of the OSM data and the availability of additional data sources.

Although the presented data sets are freely available, they do not cover all the necessary parameters required for assessing the characteristics of the structural behavior according to various typologies as presented in Section 2. Important information about the construction materials of the load-bearing structure and about the load-bearing structure itself is missing in most sources of open geodata. Section 5 discusses some existing ways to enrich the existing data.

Different methods are applied in this paper to map the available geodata to the important parameters identified in Section 2 of existing typologies. Georeferenced raster data can be used to extract data on building level. The presented method could be applied similarly for various existing raster data to obtain additional information about the buildings. One example of data mapping used in this research is the implementation of an automated detection of the building age class, which extracted the building ages of the buildings from a georeferenced analogue map from 1992 (see Figure 1).

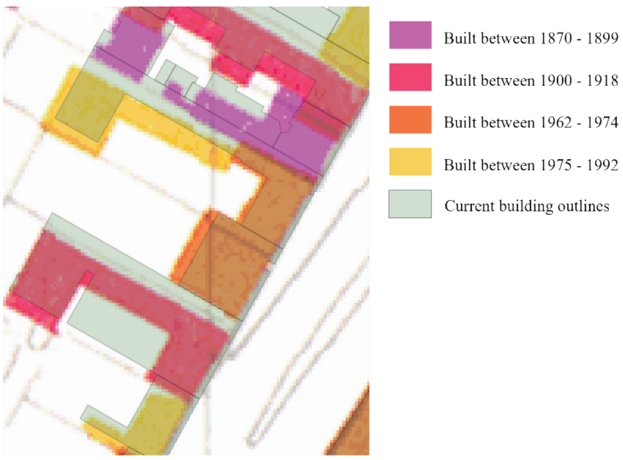

Figure 1. Automatic age class detection of buildings by mapping building polygons with a georeferenced analogue building age map using the example of Berlin. © Geoportal Berlin / ALKIS Berlin Gebäude, © Geoportal Berlin / Gebäudealter 1992/93.

To detect the building age classes from the georeferenced raster data consisting of color pixels, georeferenced polygonal building outlines are used. For each polygon in this data set, the frequency of each color pixel is automatically counted. Using the color legend of the raster data, the building age classes can then be assigned to the current building stock.

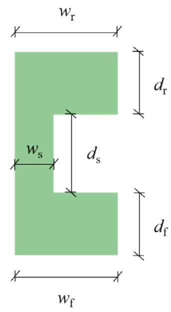

Figure 2. Parameters of a floor plan geometry.

In a further step, the georeferenced polygons of the building footprints are automatically assigned to their respective floor plan geometries. Various types of floor plan geometries can be defined for this purpose (e.g., rectangular, l-shape, …). For each desired floor plan geometry, a polygon is created in parametric form, which includes the possible parameters of the floor plan geometry (for example, width and depth of the front or rear building and the side wing, see Figure 2). To automatically assign the building polygons to the respective floor plan geometry, the polygon of the building is overlaid with polygons of different floor plan geometries. For each floor plan geometry, the parameters are then chosen so that the error of the overlay is minimized. The error is defined as the sum of the uncovered area, and the excessively covered area, shown in Figure 3. The best fitting floor plan geometry is now recognized based on the shape with the smallest deviation from the building polygon. The identified parameters of the selected floor plan geometry are collected and represent an approximation of the existing parameters of the building.

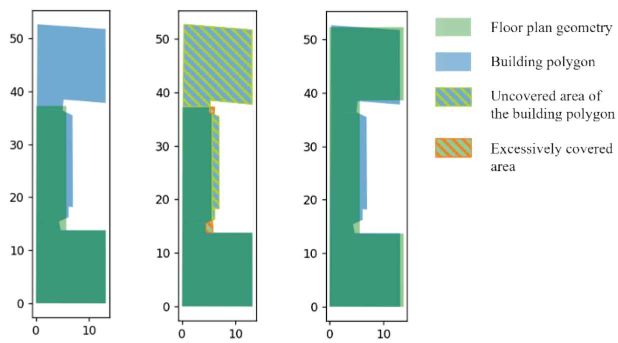

Figure 3. Left: overlay of the buildings' polygon and a floor plan geometry. Middle: errors of the overlay are marked in two different colors. Right: overlay of the chosen floor plan geometry and the buildings' polygon.

By using the presented methods, important information can be obtained from the limited available data. This shows, that readily available open geodata can be used for the categorization of each building. Depending on the nature of the available data, additional steps (such as the age detection described above) are necessary. However, the information derived from geodata is not sufficient to create a simplified geometric model for the purpose of vulnerability assessment.

3.2 Deriving Parametric Models from Literature Research

The existing geodata and the recognized building age classes can be mapped to the typologies, but some of the parameters identified as important for the automated classification of the buildings regarding their load-bearing capacity are still missing. In Section 4 the ability of mapping available information to the parameters of the typologies is presented for the considered reference area in Berlin (see Section 4.2). In the absence of additional structural data for the respective buildings to be evaluated, typical construction methods for the given building age classes and types can be reviewed in documented literature to deduce further properties. In many cases, specific construction methods can be identified that are typical for construction periods. Especially in times when large quantities of buildings had to be built quickly to expand cities, repetitive and standardized construction methods were used. Such construction methods are often described in the literature and additional data can be obtained in this way. Through literature research, information about typical load-bearing systems as well as the typical construction materials can be collected. By examining typical construction methods in the literature, representative parametric models can be developed for such cases. These models then cover the basic features of the load-bearing system and can be used to investigate the load-bearing capacity of buildings of the entire category. From the previous automated recognition of the floor plans and the remaining open geodata, the stochastic distributions of the various parameters of the parametric model of the category can be derived. The developed parametric model can then serve as a basis for further investigations, in this case vulnerability assessment.

4. Case Study

To test the presented approach in an urban environment, Berlin was chosen as an exemplary city. In Berlin a reference area in the center of the city is selected to reduce the number of buildings for test cases.

4.1 Data Sources

Because Berlin has a well-maintained geoportal with various data available, no OSM data is used for this example. The main data set used is the ALKIS data set of the Berlin property cadaster (SenStadt, 2024; data set name: ALKIS Berlin Gebäude). In addition to building polygons, this data set provides parameters such as the occupancy, address, number of stories, and a uniform ID for buildings that can be directly linked to other data sets of the Berlin geoportal. Although similar information is contained in the OSM data, there are small differences in the data sets available for this region. These differences mainly include small deviations of the building polygons or missing buildings compared to the other data set (buildings included in the OSM data were missing in the ALKIS data set and vice versa). However, it was not possible to determine that one of the two data sets contained significantly more or better data. Because of the easy possibility of linking the data sets using the uniform ID, the ALKIS data set was chosen as the basis of the presented example. The ALKIS data set also forms the basis for the 3D CityGML model that is available for Berlin. Both ALKIS data and CityGML models are available for large parts of Germany. The only advantage of the CityGML models is the 3D geometry of the buildings. All additional semantic data contained in the CityGML model of the city of Berlin can also be found in the ALKIS data set. For the categorization method used in this paper, the 3D geometry of the buildings is not necessary. The extraction of the semantic attributes from the CityGML data is more complex than using the ALKIS data set directly. Additionally, the linking between multiple two-dimensional data sets can be designed in a simple way. Since no additional advantages arise from the use of the CityGML model, the ALKIS dataset is used.

In an additional data set, the Berlin geoportal provides information on building heights and roof shape. Information on the age of the buildings is available in two different versions on the Berlin geoportal. In a vector layer, the distributions of age groups are available block by block. However, for data protection reasons, no conclusions can be drawn about the actual age of individual buildings with this data set. In a raster layer, an old map is available that divides the buildings into age groups up until 1992 using a color scheme (SenStadt, 2024; data set name: Gebäudealter 1992/93; visible in Figure 1). This raster layer was chosen for the automated age recognition described in Section 3.1.

4.2 Data Processing and Categorization

The existing ALKIS data set was initially filtered. The data set includes many objects that are not considered in this paper. In total, the selected reference area includes 2874 objects. However, there are many objects that represent individual building parts such as passageways. After filtering these objects, 804 buildings remain. For these buildings, the different data sets mentioned in Section 4.1 were merged using the building IDs.

For the determination of the building age, the automated recognition of the building age classes detailed in Section 3.1 is applied to the existing map from 1992. Here, the buildings are divided into age groups up until 1992 (before 1869, 1870-1899, 1900-1918, 1919-1932, 1933-1945, 1946-1961, 1962-1974, 1975-1992). The automatically recognized age classes could be checked by manually assigning the buildings to their building age classes using the map. It was possible to correctly identify the age group for 89% of the buildings out of 804 automatically. Some buildings were assigned an age group even though they were built after 1992 and therefore no age group should have been assigned (7%). Only 4% of the buildings that were built before 1992 were assigned a wrong age group. The reason for this is the slight deviations in the georeferenced position of the map and the building polygons (visible in Figure 1). Especially for smaller buildings this was a problem. Looking only at the buildings for which it would have been possible to assign an age group with this map (all buildings built before 1992), the age group is correctly recognized for 615 out of 651 buildings (94,5%).

Literature research was carried out, to examine typical construction methods in the given construction age classes. In the presented study, the so-called "Berliner Mietshaus" (engl. Berlin tenement building; Geist and Kürvers, 1984) was identified for further categorization and generation of a parametric model. This type of building was built before 1918 in Berlin and represents a typical apartment building with multiple flats. Comprehensive and detailed references for this typology are readily available (e.g. Geist und Kürvers, 1984). The typical construction method of this period comprises masonry buildings with typically five stories. Both the rough dimensions and the arrangement of different parts of the building (front house, side wing and rear house) are documented and similar for all buildings from this period. Figure 4 shows an example of such a building.

The use of recurring arrangements of building parts allows the categorization of the floor plans into shapes. Figure 5 shows five simplified variants of floor plans. For these floor plan geometries, the respective parameters required for the automated identification process of the building polygons can be defined. As an example: for type 3 there is the width and depth of the front building, the side wing, and the rear building (see Figure 2).

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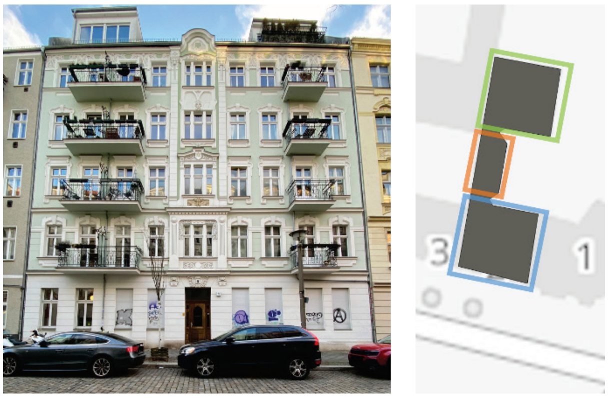

Figure 4. Exemplary street view and building polygon of a typical Berlin tenement building. The different parts of the building are marked in the building polygon (blue: front building, orange: side wing, green: rear building). © GeoBasis-DE / BKG (2024) CC BY 4.0, © Geoportal Berlin / ALKIS Berlin Gebäude.

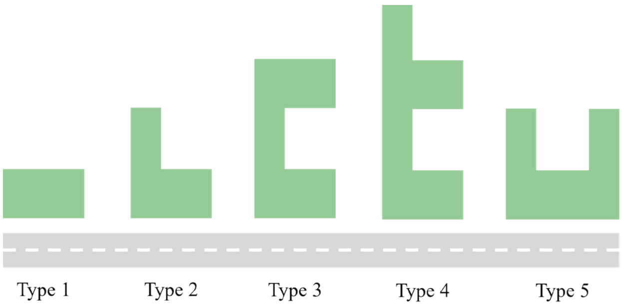

Figure 5. Different floor plan types of the typical tenement building type in Berlin before 1918 and their relative position to the street. Types 3 and 5 differ in the limits of the parameters and are therefore considered distinct from each other.

For the automatic recognition of floor plan geometries, the five types in Figure 5 are used. These five floor plan geometries cover 85% of the entire building stock in the construction age class before 1918 in the chosen reference area. 15% of the building stock in this construction age class cannot be assigned to one of these floor plan geometries because of irregularities. However, only 76% of the floor plan geometries which can be assigned to one of these five floor plan geometries are recognized correctly (see Table 1).

	Type 1	Type 2	Type 3	Type 4	Type 5
Total	44	62	27	8	45
Correct	31	51	14	5	42
%	70 %	82 %	52 %	63 %	93 %

Table 1. Recognition rate of floor plan geometries.

The reason for the partially high deviations of the recognized floor plan geometries is the similarities between the different types of floor plans. Many buildings, especially buildings with floor plan geometries of type 2, 3 and 4, cannot easily be assigned to a specific category, even manually. Figure 6 shows some irregularities of building polygons in the real world and the difficulty to find a matching shape type, even manually. Irregularities occur quite often, so in reality, the boundaries between the categories blur.

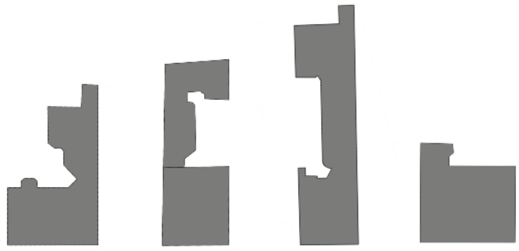

Figure 6. Examples of irregularities in building polygons. © Geoportal Berlin / ALKIS Berlin Gebäude.

For the categorization of the buildings, the collected data can now be used. Table 2 shows which parameters mentioned in Section 2 were available in the open geodata and which parameters needed to be extracted or researched in the literature for the discussed category. In Figure 7, the buildings of the age classes up to 1918 are assigned to their respective categories, using the identified floor plan geometries.

	Directly available	Derivable from data	Found in literature	Not available
Direction of LBS			x	
Material of LBS			x	
LBS			x	
Height	x			
Construction date		x		
Occupancy	x			
Building position			x	
Building plan shape		x		
Structural irregularity				x
Exterior walls			x	
Roof	x			
Floor			x	
Foundation type			x	

Table 2. Availability of the identified parameters of existing typologies from Section 2 (LBS equals load-bearing system).

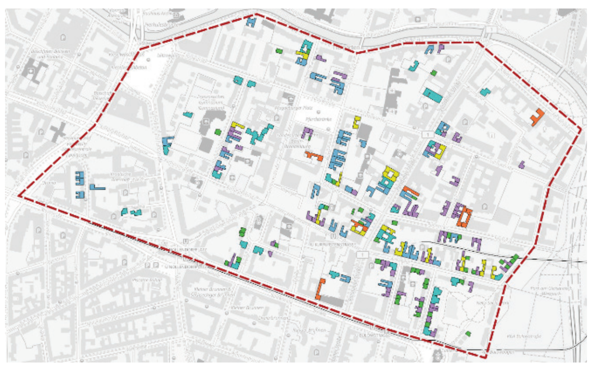

Figure 7. Reference area and predicted categories of buildings built before 1918. © GeoBasis-DE / BKG (2024) CC BY 4.0, © Geoportal Berlin / ALKIS Berlin Gebäude.

4.3 Parametric Model

For the considered building category (tenement building built before 1918) in the chosen reference area and the identified construction type, typical floor plans and the typical load-bearing structure of the respective categories can be derived from the literature (Geist and Kürvers, 1984). The parametric model can be developed manually on this basis.

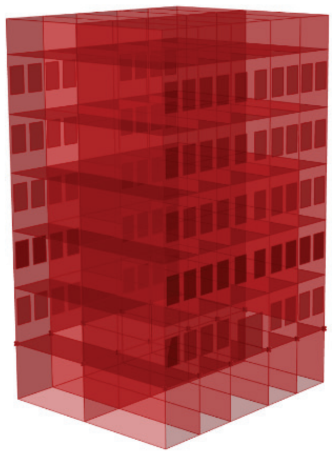

Figure 8. Parametric model of a building built before 1918 with a rectangular floor plan geometry (type 1).

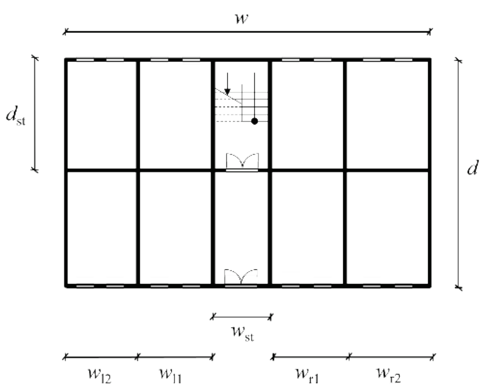

Figure 9. Reduced floor plan of the parametric model with the corresponding variable parameters.

As an example, Figure 8 shows the parametric model of the category with the floor plan geometry of type 1. The following parameters can be varied here (also shown in Figure 9):

- Total width w
- Total depth d
- Width of staircase w_{st}
- Depth of staircase d_{st}
- Width ratio of right-hand rooms w_{r1} / w_{r2}
- Width ratio of left-hand rooms w_{l1} / w_{l2}
- Height of floors
- Window dimensions
- Door dimensions

All parameters relating to the internal load-bearing structure and the position of the internal walls have been researched from the literature as described in Section 3.2. Limits are given within which these parameters normally lie. The stochastic distribution of the parameters of the external dimensions, i.e., the total width and the total depth, can be derived from the identification of the floor plan geometries based on geodata. Figure 10 shows the histograms of the total width and total depth of the category.

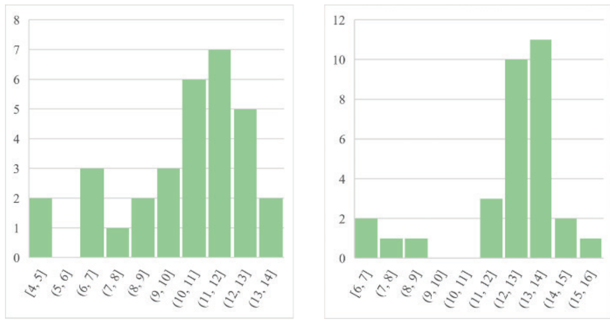

Figure 10. Histograms of the total width (right) and total depth (left) of the correctly recognized buildings of type 1. The x-axis describes the rounded width or depth. The y-axis shows the frequency of the corresponding values.

5. Discussion

This research aimed to explore the capabilities and limitations of using geospatial data sets as a basis for structural analysis at an urban scale, with Berlin serving as a case study.

Existing open data sources of the city of Berlin were used to enable a categorization of the building stock. Various existing data sources were combined in such a way that as much information as possible about the buildings was available. With the help of the demonstrated methods for automated recognition of building age and detection of floor plan geometry, additional information is derived that was not readily available in the original data sources. However, the central problem in the presented approach is the limited availability of data on the load-bearing structure of buildings.

Further enrichment methods for the existing geodata can be integrated in the future. For the recognition of the building age or the floor plan geometry, machine learning offers opportunities to support the previous efforts to expand the available data (Biljecki and Sindram, 2017). There are already approaches for recognizing seismic building structural types from laser scanning data with the help of machine learning (Geiß et al., 2015). This field also offers potential for gaining additional insights for the building categorization process. To integrate information about the load-bearing structure, laser scanning can be integrated into the presented approach. There have been many advances in the field of laser scanning and the automated recognition of building geometry (Ochmann et al., 2019 and Arachchige et al., 2012). The field of scan-to-BIM (Building Information Modeling) is a wide field of research with multiple different studies regarding the automatic generation of BIM models based on laser scanning. However, it is not feasible to scan a large building stock for this purpose because of the high effort for laser scanning.

Without additional data, the presented approach in this paper remains dependent on an extensive literature research and the identification of typical construction methods in different age categories. This process leads to the fact that the building categories identified, and information derived therefrom, are only applicable to the area in which these typical construction methods were used and buildings of the respective categories are widespread.

Despite the discussed open points for the categorization of buildings, the resulting parametric model can be directly used for probabilistic FEM analyses of building vulnerability. The parameters extracted in the process of detecting the floor plan geometries, such as the total width and depth of the buildings, can be used for such analyses. Some of the buildings are assigned to the incorrect floor plan geometries in the reference area in Berlin. Despite the deviations, it is possible to recognize from the histograms of the extracted parameters what statistical distribution these parameters have in the existing building stock. However, it is still necessary to investigate what influence the incorrect recognition of the floor plan geometry has on the subsequent analysis of the buildings.

6. Summary and Conclusion

This paper presented an approach for utilizing open geospatial data for the categorization and development of parametric building models for the subsequent FEM simulations or other analyses and investigation of the vulnerability of these buildings to various natural disasters. Existing geospatial data sources were identified. The automated detection of building age classes and floor plan geometries was presented. The buildings were categorized using the different data sources available. Using a manual literature research, a typical construction type was identified. Using this additional information, it was possible to develop a parametric model which forms the basis for subsequent probabilistic analysis of this building category. The different data sources were used to analyze the distribution of different parameters of the parametric model within the building category.

Further investigation is still necessary to improve the enrichment of the geospatial data and to test the actual ability of the developed parametric models to give reliable results regarding the vulnerability of the buildings. Nevertheless, the presented approach is promising for supporting probabilistic analyses for buildings and to help automating the process of assessing the vulnerability of buildings at an urban scale.

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