Accepted Manuscript

# Generating 3D city models without elevation data

Filip Biljecki *, Hugo Ledoux, Jantien Stoter
3D Geoinformation, Delft University of Technology, The Netherlands

ORCID

FB: http://orcid.org/0000-0002-6229-7749
HL: http://orcid.org/0000-0002-1251-8654
JS: http://orcid.org/0000-0002-1393-7279

* Corresponding author at f.biljecki@tudelft.nl

This is an Accepted Manuscript of an article published by Elsevier in the journal *Computers, Environment, and Urban Systems* in 2017, available online:
http://doi.org/10.1016/j.compenvurbsys.2017.01.001

Cite as:

Biljecki F, Ledoux H, Stoter J (2017): Generating 3D city models without elevation data. *Computers, Environment, and Urban Systems*, 64: 1–18.

## Abstract

Elevation datasets (e.g. point clouds) are an essential but often unavailable ingredient for the construction of 3D city models. We investigate in this paper to what extent can 3D city models be generated solely from 2D data without elevation measurements. We show that it is possible to predict the height of buildings from 2D data (their footprints and attributes available in volunteered geoinformation and cadastre), and then extrude their footprints to obtain 3D models suitable for a multitude of applications. The predictions have been carried out with machine learning techniques (random forests) using 10 different attributes and their combinations, which mirror different scenarios of completeness of real-world data. Some of the scenarios resulted in surprisingly good performance (given the circumstances): we have achieved a mean absolute error of 0.8 m in the inferred heights, which satisfies the accuracy recommendations of CityGML for LOD1 models and the needs of several GIS analyses. We show that our method can be used in practice to generate 3D city models where there are no elevation data, and to supplement existing datasets with 3D models of newly constructed buildings to facilitate rapid update and maintenance of data.



*Keywords:* 3D city models; GIS; building height; lidar; urban models; urban morphology; random forest; CityGML; LOD1


## Highlights

- Lack of elevation data hinders the construction of 3D city models.
- We infer heights of buildings solely from 2D footprints and attributes.
- LOD1 models are generated by extruding footprints to the predicted height.
- We achieve sub-meter accuracy in the predicted heights.
- The resulting 3D models satisfy the CityGML standard quality recommendations and those of several spatial analyses.

## 1 Introduction

The usual prerequisite to generate 3D city models are footprints and elevation measurements, the latter commonly obtained from photogrammetry and lidar. Despite the fact that footprints are now widely available as open data from governments and volunteered geoinformation (Hecht et al., 2015; Hartmann et al., 2016), elevation datasets remain expensive and time-consuming to acquire, hindering the production and availability of 3D city models (Wendel et al., 2016).

In addition, when elevation datasets are available, they may not always be suitable to generate 3D models. First, they may be outdated, resulting in a lesser completeness than footprints, which are fairly easy to update in contrast to point clouds, and are also usually produced at more frequent intervals. Second, their resolution and quality may not always be sufficiently adequate to produce 3D city models. For example, the popular Shuttle Radar Topography Mission (SRTM) offering free elevation data with worldwide coverage has been to a great extent taken advantage of in geosciences (Farr et al., 2007; Sathish Kumar et al., 2013). However, such datasets are not suited for producing 3D city models, mostly because of their insufficient accuracy and coarse resolution (e.g. 30 m) (Hamilton and Morgan, 2010; Varga and Bašić, 2015).

To goal of this paper is to explore and evaluate alternative ways to construct 3D city models in the absence of elevation data. First, we investigate what are the current alternative ways to obtain 3D models not involving elevation measurements (Section 2). A method we have commonly found is using the information of the number of storeys (floors, levels) of a building, which gives the impression of being a fairly good proxy for a building height. However, while several 3D datasets around the world have been constructed in such a way, this method was never evaluated, which we seek to accomplish in our paper. Second, we investigate whether there are other *predictors* that hint at a building's height, and assess their usability with machine learning techniques (Section 3). To train and test predictive models we use data from the Dutch authorities, and perform a proof of concept on the cities of Rotterdam (Section 4), and Leeuwarden (Section 5).

While a 3D building model derived with such an unorthodox method would obviously not be the most accurate one, we argue that it not only can serve as a provisional solution until an elevation dataset becomes available, but it can in fact be useful to carry out several spatial analyses. Hence the paper also discusses the usability of such datasets, and performs experiments to demonstrate that they give a good indication of the urban morphology, which is useful for various applications (Section 6).

To give a hint of the possibilities of the work we show a use case that benefits from the work we developed: our approach can be used to supplement existing 3D models by updating newer buildings for which footprints are available, but a lidar survey has not yet been carried out (Figure 1). This example shows 2D footprints of several buildings (left), but missing from the elevation data, since they were built shortly after the lidar campaign, which is not conducted as frequently as updates to the 2D cadastral database. Such situation results in a 3D city model with the omitted buildings, since the footprint cannot be extruded (centre). Using our approach the heights of the missing buildings were inferred from 2D data and the local context, so that the footprints can be extruded to a predicted height approaching reality quite well to generate a provisional 3D dataset with the improved completeness (right).

## 2 Background and related work

After a further explanation of LOD1 models, this section describes how different researchers have used other information to estimate the height of buildings.

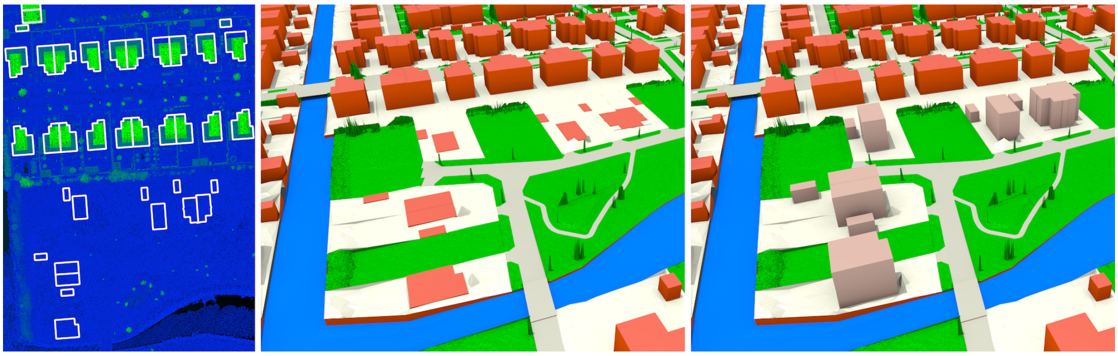


Figure 1: Besides generating 3D models from scratch, our method can be used to maintain existing 3D datasets by mitigating outdated point clouds, i.e. generating 3D models of buildings constructed after the most recent acquisition of a point cloud. The supplemented buildings based on predicted heights from our approach are shown in lighter colours in the updated 3D model on the right.

## 2.1 LOD1 models

The CityGML standard describes five levels of detail (LODs) of 3D city models, reflecting their geometric and semantic complexity (OGC, 2012; Gröger and Plümer, 2012).

An LOD1 model, the one that is relevant to our paper (shown in Figure 1), is described as a block model with flat roof structures (Kolbe, 2009). The most common approach to obtain LOD1 models is to extrude building footprints according to the height of the building, usually the median or maximum of all elevation samples located in the footprint (Ledoux and Meijers, 2011).

Although LOD1 models are simple, they are widely used in a multitude of applications, such as estimating shadows (Strzalka et al., 2012), solar potential estimations (Peronato et al., 2016; Jaugsch and Löwner, 2016), urban air flow analyses (Jurelionis and Bouris, 2016; Petrescu et al., 2016), determining the sky view factor (Ha et al., 2016), satellite visibility predictions (Ellul et al., 2016), and simulating floods (Varduhn et al., 2015). In fact, they may sometimes be preferred over the more complex LOD2 models due to simplicity, ease of acquisition, and fairly good results they provide.

It should also be noted that the notion of the building height in LOD1 is subject to different interpretations, depending on the purpose of the data and context (Biljecki et al., 2016c; Brasebin et al., 2016). For instance, data producers may choose that the top surface represents the height of the eaves or the top of the roof (ridges). In our paper we have chosen the latter in order to encompass the extent of the building as relevant for many applications.

In this context, the key piece of information is the height of the building, usually obtained from point clouds and photogrammetry. In this paper we investigate if the value of the height of a building can be obtained in alternative ways that do not involve those often costly and infrequent acquisition procedures.

## 2.2 Existing unconventional methods to infer the height of buildings

The methods we have found to derive the height of buildings for producing 3D city models without elevation data are inherently different and require different data sources, hence we group them into three categories.

### 2.2.1 Using attributes (number of storeys)

Many 2D building datasets contain the information of the number of storeys of buildings. Because the number of storeys is generally accepted to be a self-evident proxy for the building height, it has been used for 3D city model generation, especially in volunteered geoinformation, e.g. OpenStreetMap (Uden and Zipf, 2013; Noskov and Doytsher, 2013; Goetz, 2013; Fan et al., 2014; Fan and Zipf, 2016). In fact, we have found a substantial number of occurrences of 3D models generated by simply extruding a footprint to the height obtained by multiplying the number of storeys with an assumed storey height (Coors et al., 2009; Şengül, 2010; Buhur et al., 2009; Yu et al., 2007; Coors, 2003; Guney et al., 2012; Sugihara and Shen, 2016; Wróżyński et al., 2016; Nichol and Wong, 2005; Ratti and Richens, 2004; Schläpfer et al., 2016; Perez et al., 2013; Teo and Cho, 2016; Santana et al., 2017). The storey height seems to vary among papers, ranging from 2.8 and 3.5 m (Kurakula and Kuffer, 2008; Vermeulen et al., 2015; Guney et al., 2012; Goetz and Zipf, 2012). Models constructed in this way have proven useful in a variety of applications, such as visibility analyses and energy simulations (Wróżyński et al., 2016; Perez et al., 2013). To a lesser extent, some of the obtained 3D models are used for interactive querying, e.g. browsing 3D cadastre registrations (Olivares García et al., 2011), rather than 3D models of reality for spatial analyses. Furthermore, the number of storeys has been used as an indication for the building's height in research where no 3D models are reconstructed, e.g. in investigating the relation between price of construction and building height (Chau et al., 2007), meaning that it is widely used also outside 3D GIS.

An advantage of this method is that the number of storeys is available from open data of governments and volunteered geoinformation in many places around the world (Agugiaro, 2016a; Dalmau et al., 2014; Lwin and Murayama, 2009). Alternatively, the number of storeys has been obtained from a simple visual inspection of buildings, using terrestrial or airborne imagery (Wendel et al., 2016; Deakin et al., 2014; Basiouka et al., 2015; Figueiredo and Martina, 2016).

A common observation about these papers is that they are reserved about the details: the generation of (accurate) 3D models is not their principal topic (it is merely described in a sentence or two), and none evaluates the quality of the predicted heights. A somewhat exception is the work of Over et al. (2010) stating that "the computation of building heights using the number of floors alone is not a reliable method to measure the height of a building.". Unfortunately an error metric is not directly given nor a quality analysis, but the paper mentions that the error is outside the permitted margin for block models according to the CityGML standard (we will revisit this matter in Section 3.4).

The absence of quality analyses of 3D models derived in this way is unusual considering their amount, and taking into account that a potentially large uncertainty in the 3D data may substantially degrade the quality of a spatial analysis (Biljecki et al., 2015a).

Number of storeys is the only characteristic associated with a building that we have found being used for this purpose. In our paper we evaluate the accuracy of the 3D models generated by using the number of storeys, and we investigate if several other characteristics can be useful in determining the height of the building for extruding its footprint.

### 2.2.2 Using local regulations

Another way to predict the height of buildings is to use maximum allowed height values as prescribed in building regulations. Many jurisdictions around the world impose building height restrictions for: (1) aesthetic reasons, (2) to maintain environmental quality, (3) to prevent increased traffic congestion, and (4) to limit the strain on urban infrastructure (Bertaud and Brueckner, 2005; Joshi and Kono, 2009). In urban and densely populated areas with scarce land, height restrictions are usually exploited to the last centimeter, hence it is reasonable to assume that in such cases the height of most buildings corresponds to the maximum permitted height.

This reasoning has been capitalised on in Singapore by Chen and Norford (2016). Their method relies on the data on the maximum permitted floor area ratio (FAR) from the local master plan—the ratio of a building's total floor area and the area of land parcel on which it sits. Regulating the FAR effectively limits a building's number of storeys rather than directly the height (Bertaud and Brueckner, 2005), which can then be indirectly used to estimate the height, using the method described in the previous section.

A validation was performed against the number of storeys obtained with a visual inspection. On average the method overestimated the number of storeys by 20%, mostly due to the mix of building heights within a plot (an area with the FAR regulation), since the restrictions apply to multiple buildings in a plot.

Additional papers relevant in this context are (Brasebin et al., 2012), which similarly proposes the generation of 3D buildings from footprints using different local rules and constraints; and the one of Allani-Bouhoula and Perrin (2008), which presents a method to generate 3D buildings from local regulation and various architectural principles. The latter work is also interesting to mention because it attempts to deduce the shape of the roof from the same set of information.

We did not replicate these methods because in the Netherlands there is no corresponding dataset, but since in our work we examine the usability of the number of storeys and floor area we indirectly evaluate them as well.

### 2.2.3 Using sun ephemeris (shadows in imagery)

Shadows cast by buildings have been used as an indication of its height, with a large number of papers on this mature topic in remote sensing (Irvin and McKeown, 1989; Lin et al., 1994; Nevatia et al., 1997; Sırmaçek and Ünsalan, 2008).

The height of a building can be estimated from the length of its shadow and solar altitude at a given latitude and the date and time at which the image was captured (Peeters and Etzion, 2012). In contrast to the previously described method using the number of storeys, the quality of such predictions is often reported. For instance, Lee and Kim (2013) report an accuracy of 3 m, Cheng and Thiel (1995) outlines 3.7 m, while Shao et al. (2011) achieves an accuracy of 13 m in estimating the height of high-rise buildings. As main challenges, researchers report overlapping shadows, measuring them on slopped terrain, and the interference of vegetation (Liasis and Stavrou, 2016).

This unconventional method continues to capture interest, recently being a topic in this journal (Peeters, 2016), and has current uses. For instance, Tong et al. (2013) and Tu et al. (2016) detect partially and totally collapsed buildings after an earthquake by comparing the height of a building from a pre-disaster database with the one obtained from shadows from post-disaster imagery.

Because this method has been much investigated, and because of the nature of the data (we use vector building footprints and not imagery), we do not focus on it. Furthermore, this method requires satellite imagery, which suffers from the same problems as point clouds: acquisition and the fact that the most recent dataset available may be outdated.

### 2.2.4 Conclusions from the literature review

As it can be concluded from the literature review, common observations of these specific methods to predict the heights of buildings from non-elevation data are: (1) they are using only one predictor of the height; (2) not all of them are focused towards producing accurate 3D city models; and (3) comprehensive quality analyses are seldom performed, and when they have been performed—they are limited to smaller areas such as a neighbourhood, not investigating how the solution scales to larger area such as a city. In the subsequent sections we seek to overcome these limitations.

# 3 Methodology and data

## 3.1 Overview and considerations

We have developed supervised learning models using different attributes of buildings (predictors) to estimate their heights to generate 3D city models in LOD1. Supervised learning involves training data to develop the predictive model. Hence for this purpose we use a subset of buildings in our study area.

Besides discussing the usability of the predictors alone, we combine different predictors, envisaging different scenarios where various combinations of attributes are available and to investigate the importance of each in combination with the other. This is also important in our method, because in our dataset we did not have all the attributes for all buildings. For instance, the information on the building use was not available for all buildings. Hence different predictive models can be used depending on what attributes are available for each building.

When developing the method, the following use cases are foreseen:

1. In case a 3D model of a city is not available: measuring the heights of only a small subset of a city and applying the inferred predictive relationships to the unmeasured buildings. This involves having heights of certain buildings, but they may be available from an old point cloud, from the cadastral database, or by measuring a small subset of a city which can also be done from ground (e.g. with a total station). We focus on this case when developing and validating the method (Sections 3 and 4).
2. In the case of having an outdated 3D model (and outdated point cloud) which has to be supplemented, we can analyse patterns from existing buildings and infer the heights of the new ones, built after the elevation data has been obtained (the case shown in Figure 1).
3. Inferring the relationships from one city where the elevation data is available, and applying them to another city where elevation data is not available. We have run experiments in another city to investigate this possibility (Section 5).

We have used Random Forests (RF), a supervised learning method for classification and regression that works by creating a number of decision trees on random subsets of data, and uses averaging to improve the predictive accuracy and control over-fitting (Breiman, 2001). It has been used in remote sensing and GIS for various purposes (Mutanga et al., 2012), for instance, for classifying movement trajectories (Zhou et al., 2016), for assessing fire risks (Conedera et al., 2015), and for identifying the typology of buildings (Hecht et al., 2015).

One of the method's strong points is that it can assess the importance of each used predictor (feature importance) (Grömping, 2009). This property is useful because it provides the ranking the importance of predictors in the regression, enabling designing predictive models by choosing only predictors that are important, minimising their amount.

In our experiments we have also evaluated Support Vector Machines (SVM) and Multiple Linear Regression (MLR). However, the results obtained with SVM and MLR have not been as good as with the ones achieved with RF. Hence in this paper we focus on RF.

For the implementation, we have used Scikit-learn, an open-source Python module for machine learning (Pedregosa et al., 2011).

## 3.2 Data and study area

Rotterdam is the second largest city in the Netherlands, and it contains a variation of more and less urbanised areas with large differences of building heights. Hence it is a good option for a case study. The city covers an area of 326 km$^2$, and has a population of 620 000 people. The extent of the municipality covers a sizeable industrial area, that is, it hosts Europe's busiest port (Port of Rotterdam), adding to the diversity of the analysed structures.

**2D footprints and their attributes** We have obtained the 2D dataset of building footprints from the City of Rotterdam. For each building we have the following attributes: (1) building use, (2) year of construction, (3) number of storeys above ground, and (4) the net internal area (sum of floor area in all units in a building).

Researchers in several countries report the availability of these attributes from cadastral datasets (Agugiaro, 2016b; Dalmau et al., 2014; Stoter et al., 2015; Aringer and Roschlaub, 2014; Roschlaub and Batscheider, 2016; Salimzadeh et al., 2016; Lwin et al., 2016; Neidhart and Sester, 2004; Kolbe et al., 2015; Strzalka et al., 2012; Ahmed and Sekar, 2015; Perez et al., 2013; Bahu et al., 2015). Furthermore, some of these attributes may be derived automatically and may also be available in volunteered geoinformation (Ural et al., 2011; Meinel et al., 2009; Hecht et al., 2015; Kunze and Hecht, 2015), enabling a wider applicability of the method presented in this paper.

**Geometric properties** On top of these attributes we investigate the following metrics derived from the geometry: (5) footprint area, (6) shape complexity, and (7) number of neighbouring objects.

We will elaborate on them in the continuation, and explain the rationale behind their selection.

**Statistical data** In addition, we have obtained census data from Statistics Netherlands (CBS), a possibly useful piece of information to predict heights. Rotterdam is divided into 92 statistical neighbourhoods, and for each we have access to the following potential predictors of the height of buildings: (8) population density, (9) average household size, and (10) average income.

**Completeness** Our dataset contains 200 000 buildings. However, not all of the buildings contain all attributes. For instance, about a third of the buildings does not contain the number of storeys, use, and net internal area; these were usually smaller buildings without a cadastral registration, such as sheds. This reflects real-world situations of varying completeness of data, hence it is important to investigate the performance of different kinds of attributes and different combinations of availability. Figure 2 gives an illustration of the study area and the datasets.

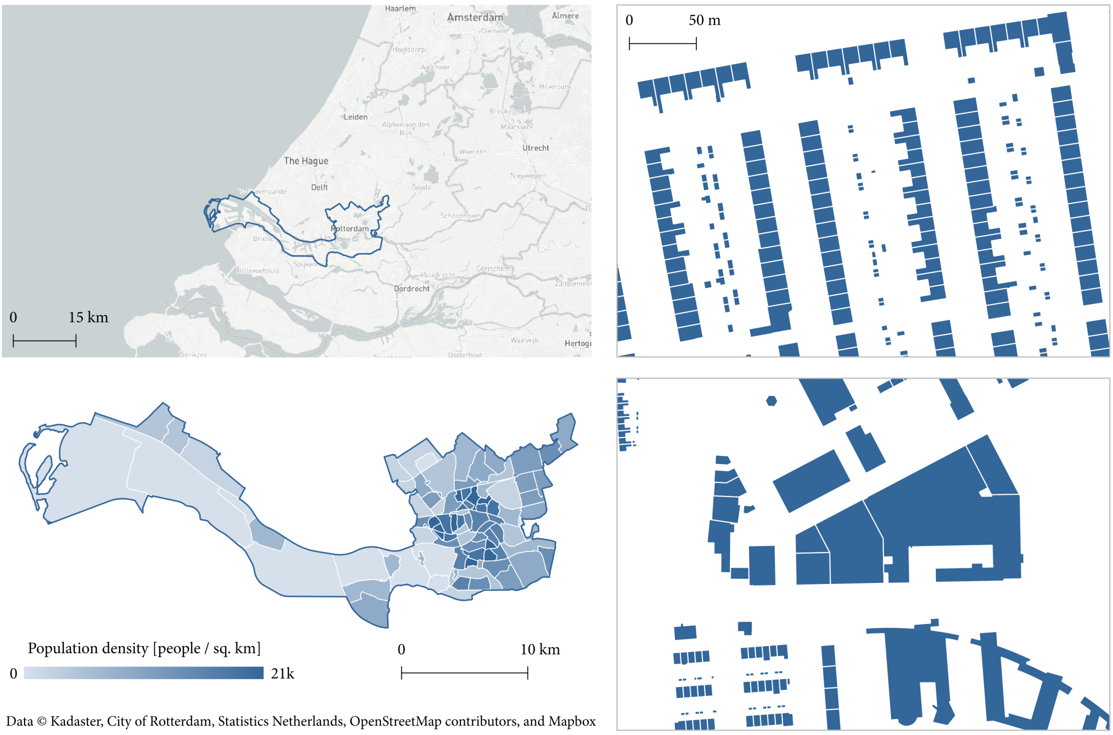



Figure 2: Illustration of the study area (top left), the census neighbourhoods (bottom left), and the dataset of 2D buildings (right). Can you guesstimate the height of most buildings just by looking at the geometry of their footprints and neighbourhood?

**Heights for validation and ground truth 3D model** For training the predictive models and for validating the results we have used a point cloud provided by the City of Rotterdam, from which we have calculated the ground truth heights of buildings.

The methodology (illustrated in Figure 3) is based on calculating the elevation of the bottom (ground) and the elevation of the roof of the building. The former is calculated as the 5th percentile of the elevations of the points that fall within the buffer of the footprint, while the latter has been determined as the 90th percentile of the points within the building footprint. This particular percentile value for the top of the building was taken in order to filter out not only outliers but also chimneys, antennas, and similar constructions (similar values have been used in related work, e.g. see the overview in Biljecki et al. (2016c), and an example in Eeftens et al. (2013)). The difference between the two elevations is taken as the reference height of a building. This method has been realised with the open-source software 3dfier*.

For training we use a relatively small subset (10%) of randomly selected buildings, and validate the performance with the remaining buildings (90%). In order to minimise inconsistencies in this reference dataset, we have filtered out a minor number of buildings with obviously erroneous

*Available at `https://github.com/tudelft3d/3dfier`

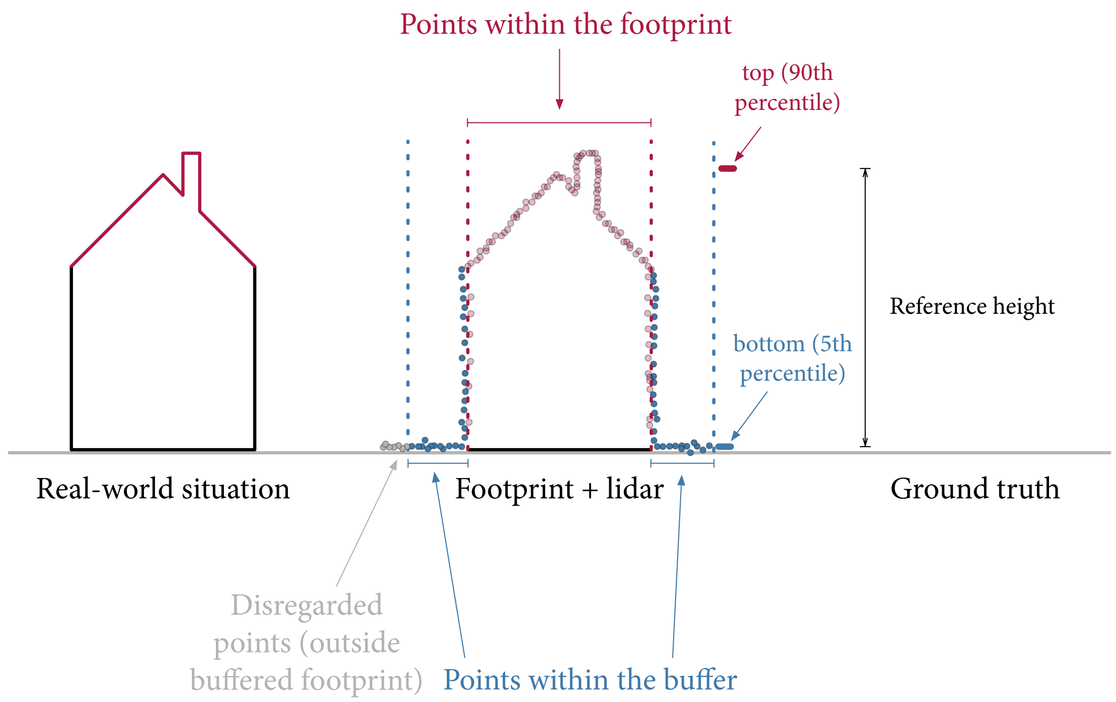



Figure 3: Anatomy of the approach to determine the reference (ground truth) heights of buildings. For each building, the software analyses separately two sets of points: those that are within the footprint (red), and those that are within the buffer of the footprint (blue).

values, e.g. with the measured height lower than 2 m; these were caused by cases such as the buffer overlapping with other constructions.

## 3.3 Overview of the predictors

### 3.3.1 Building attributes (cadastre)

While using the *number of storeys* and multiplying it with an assumed floor height is straightforward, it is prone to many errors. Most importantly:

- Storey height differs between buildings due to different ceiling heights and slab thicknesses (Vartanian et al., 2015). For instance, a church has only one storey but it can be more than 25 times taller than a single-storey residential house. Furthermore, a building may have variable ceiling heights, e.g. a lobby may be considerably taller than the upper storeys.
- The building height that needs to be derived in our research is the overground height (from the base to the rooftop), excluding possible underground structures such as garages. The data on the number of storeys may include the total number of storeys, instead of only storeys above ground, resulting in overestimations. In our dataset we conveniently have

the number of storeys above ground. But there are many datasets rather containing the total number of storeys.

- Buildings on sloped terrain may also contain an ambiguous number of storeys above ground (one side of the building may have a different number of overground storeys than the other side). While another convenience is that we are dealing with the flat topography of the Netherlands, we recognise that this could be a problem in other areas.

Furthermore, the complexity of the derivation of the height is indicated also by researchers in 3D geoinformation who work on the inverse problem: deriving the number of storeys from the height citing similar issues (Alahmadi et al., 2013; Boeters et al., 2015; Shiravi et al., 2015).

To give a general impression of the data on the number of storeys, Figure 4 indicates the relation between the number of storeys of a building and its height. While there is a strong correlation, the plot also shows that there is a lot of variation in the heights of buildings with the same number of storeys. This is especially the case with buildings with one storey.

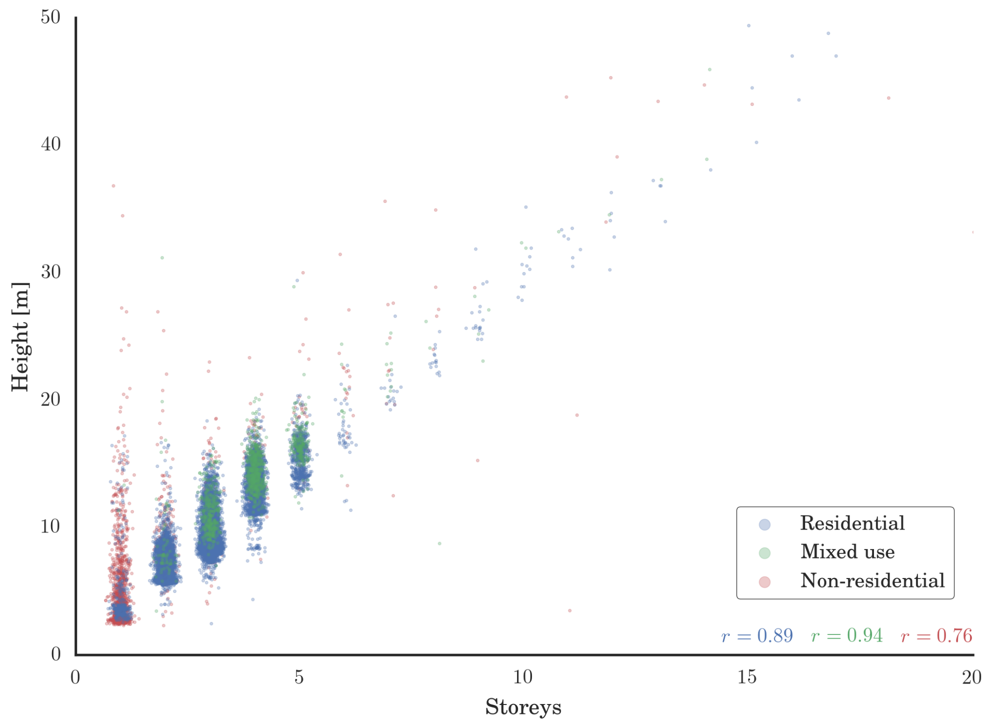



Figure 4: The relation between the number of storeys and building height, coloured by building use. The number of storeys are integers, but jitter is added to expose the variation. The $r$ values are correlation coefficients for each subset according to the building use.

The observations are coloured according to the *use of the building*, which gives more insight in the patterns. For instance, it shows that residential buildings have a slightly more consistent pattern than non-residential registrations. Hence we test if, along the information on the number of storeys, the building use may improve the predictions, as it influences the storey height.

Another predictor that should come in handy here is the *age of a building*: older buildings tend to have taller storey heights (Figure 5), so we will use this attribute to tackle the problem of the varying storey heights between buildings.

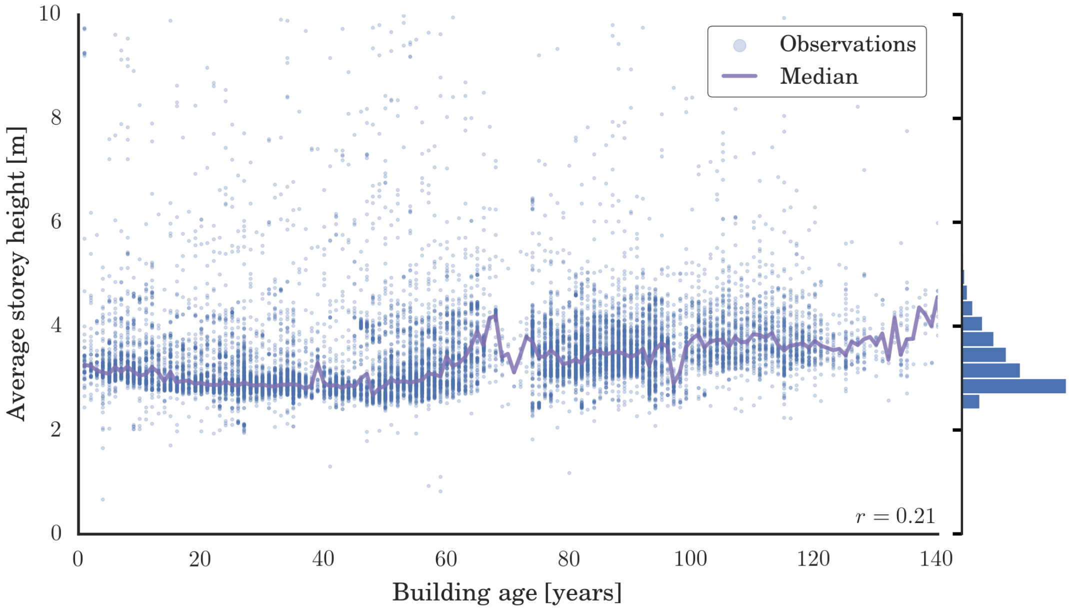



Figure 5: Storey height is somewhat associated to the age of the building. We take advantage of this information to improve the predictions. The plot also shows the distribution of storey heights in the dataset (the same scale of the left $y$ axis applies), indicating that multiplying the number of storeys with an assumed storey height is inherently subject to large deviations.

Before carrying out any experiments, it is obvious that the number of storeys appears to be a very useful predictor of the building's height, but it can be problematic to obtain in practice (Fan et al., 2014; Bast et al., 2015). This is also evident from our study area for which for a third of buildings we do not have this attribute.

Moving away from the conspicuous number of storeys, our dataset contains the information about the *net internal area* (NIA), which denotes the usable floor area of the units in a building. This area metric is the usual data recorded in real estate management and it differs from the gross area and other related measures. For instance, in the Netherlands the floor area of stairs and escalators and one that has a ceiling height lower than 1.5 m (e.g. in the attic below a sloped roof) is not counted in the NIA, meaning that it can differ substantially from the gross floor area (NEN, 2007). Another limitation of the NIA, similarly to the number of storeys, is that underground floor area is counted.

Using the floor area of spaces inside a building could be a predictor of the height in two ways: (1) buildings containing more floor area may generally be taller; and (2) dividing the NIA with the footprint area may derive the number of storeys, which can then be used as a predictor when the number of storeys is not available directly.

Figure 6 shows the relation between the NIA divided by the footprint area (to indicate vertical extent), and the height of a building. It appears that here building use provides more distinction, but also that there are many outliers.

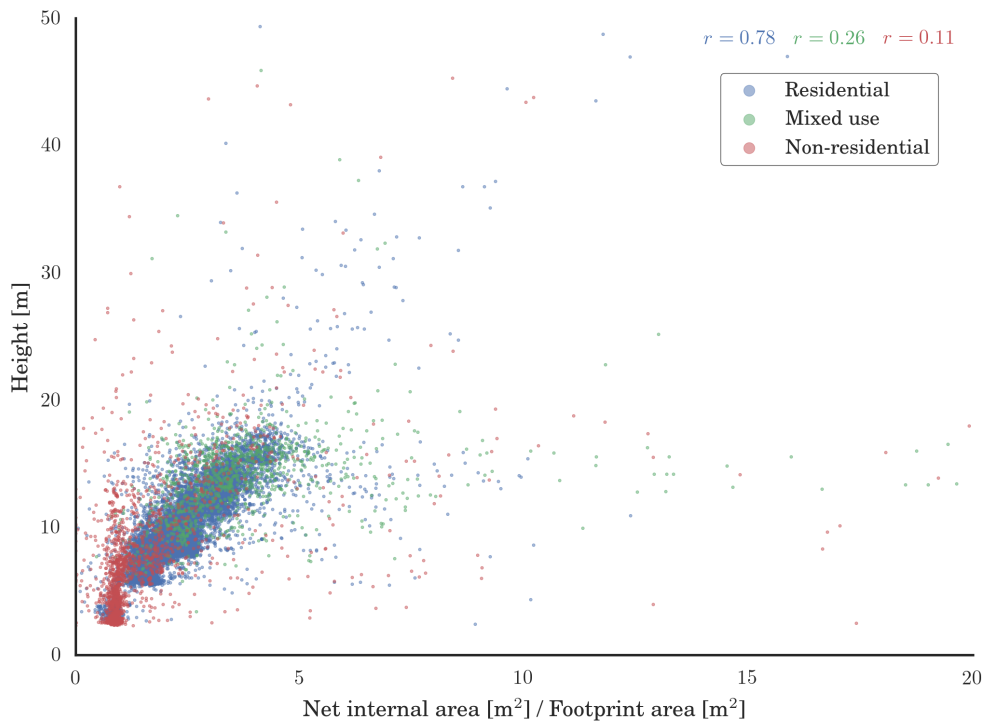



Figure 6: Relation between the net internal area and the building height with the denoted building use.

### 3.3.2 Geometric attributes

In our method we compute three attributes from the geometry of buildings that we seek to use as predictors. Researchers in related work have used similar attributes to derive building-related characteristics, e.g. building type and architectural style from footprints (Henn et al., 2012; Dehbi et al., 2016). Hence, our hypothesis is that these information may also be useful in predicting the heights of buildings.

First, the *footprint area* is computed. This attribute is introduced in the previous section to put the value of NIA in a vertical context. However, we investigate if the footprint area per se is commensurate with the height of the building.

Second, another shape metric worth considering is the *shape complexity* of a building footprint. Various shape metrics to quantify the characteristics of a polygon are frequently used in remote sensing to classify buildings and plots (Belgiu et al., 2014; Hermosilla et al., 2012). Hence we investigate if the complexity of the building footprint can be similarly used to predict the height of a building by analysing their patterns. We use the Normalised Perimeter Index (NPI)—the ratio of the perimeter of the equal-area circle and the perimeter of the shape: $\frac{2\sqrt{\pi A}}{P}$ (where $A$ is the area of the polygon, and $P$ the perimeter). It is normalised to make it independent of the size of the polygon, and the values range between 0 and 1 with lower values indicating smaller compactness of the shape (Angel et al., 2010).

Third, for each building we compute the *number of neighbouring buildings*. We have noticed that shorter buildings have more neighbours, so we deem that this metric can be used as a predictor. For this purpose we have selected a buffer of 30 m.

The advantage of these three predictors is that no additional attributes and data sources are required to calculate these, as they can be always computed from the geometry, and should be available at all times. This is also valid for the number of neighbours, now that the completeness of volunteered geoinformation has much improved, especially in urban areas (Hecht et al., 2013; Fan et al., 2014).

In our estimations in Section 4 we also test whether it is possible to predict the heights using solely these three attributes, in cases when we have footprints without any attributes.

### 3.3.3 Census (demographics and socio-economic parameters)

In a population estimation study using 3D city models, Biljecki et al. (2016a) indicate that in residential neighbourhoods there is an association between the average building height in the neighbourhood and its population density, as more populous districts accommodate people in taller buildings. This finding was used to estimate the population density from the information on the general vertical extent of buildings in the district. We take advantage of this conclusion in the reverse direction: we use the data on *population density* to infer the vertical extent of neighbourhoods (Figure 2 illustrates the 92 neighbourhoods of Rotterdam and their population density).

Figure 7 shows the distribution of heights of buildings per neighbourhood of a specific population density in our dataset. The small white dots present the median of all building heights in the same class of population density.

However, while on average there is an association, there are several downsides about this predictor. First, this reasoning applies mostly to residential areas, since we are dealing with population. Second, this predictor encapsulates hundreds, if not thousands of buildings, from which the height of individual buildings cannot be predicted (due to privacy reasons it is not possible to obtain the number of residents down to the level of a building). Third, all neighbourhoods contain both short and tall buildings, preventing a generalised conclusion. Nevertheless, we have tested if this predictor is useful in conjunction with others.

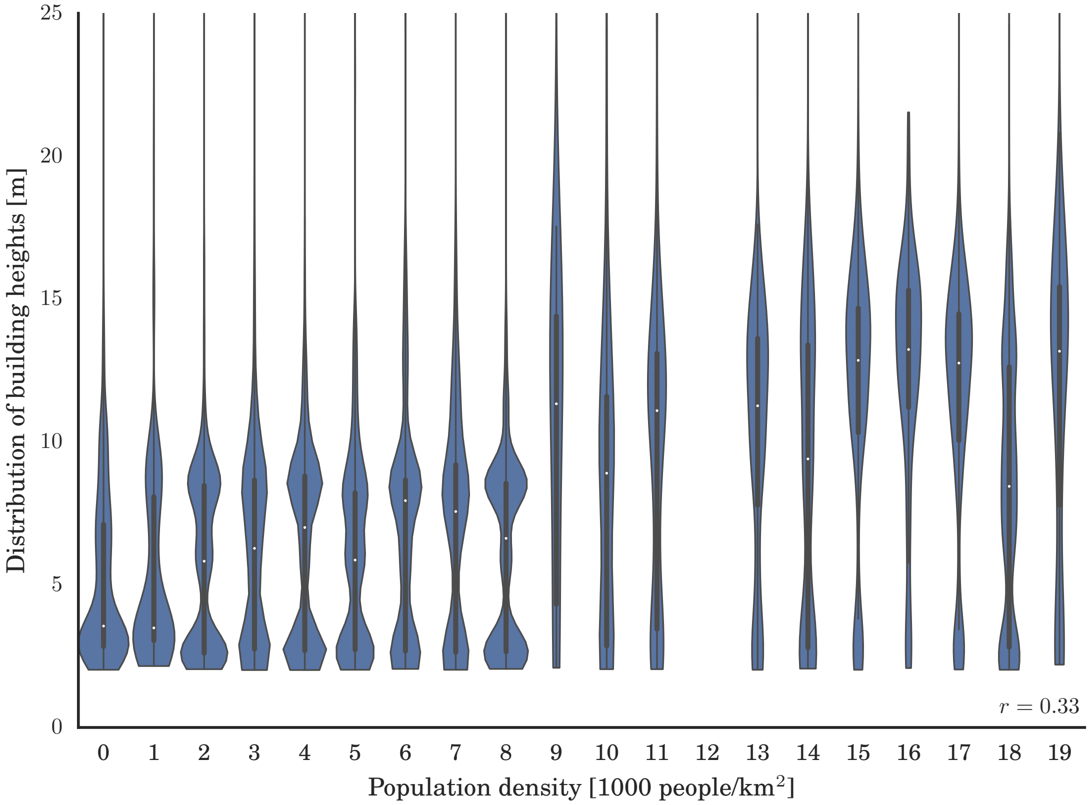



Figure 7: Violin plots (Hintze and Nelson, 1998) indicating the distribution of heights per class of population density of the neighbourhood in which the buildings are located. The average building height in a neighbourhood is moderately associated with the population density. We investigate if we can make use of this relation.

In addition to the population density, our dataset contains the information of the *average household size* and *average income* in each neighbourhood. We also include them in the training to investigate if they can improve the predictive models.

### 3.4 LOD1 quality measures

We assess the quantitative accuracy of the methods with both the mean absolute error (MAE) and root mean square error (RMSE). The latter metric is sensitive to outliers, but we include it as well following the reasoning of Chai and Draxler (2014).

On the other hand, the qualitative assessment of the results is not simple. Technically, we can reconstruct an LOD1 model with any value of the height, and deem it valid, as there is no commonly agreed idea in terms of accuracy that would make an LOD1 model acceptable or not.

While CityGML (OGC, 2012) mentions an accuracy benchmark ("In LOD1, the positional and height accuracy of points should be 5m or less"), it is in our opinion far from perfect. First, we are of the impression that this value has not really been picked up on and it is not widely accepted by the 3D GIS community. Second, a common misconception is that the standard imposes this requirement. On the contrary, the value is rather described as a recommendation: "The accuracy requirements given in this standard are debatable and are to be considered as discussion proposals.". Third, the standard declares that the "Accuracy is described as standard deviation $\sigma$ of the absolute 3D point coordinates.". The standard deviation is not suited for non-normal distributions, which may appear in geographical data (Zandbergen, 2008). Finally, the standard states that the "Relative 3D point accuracy will be added in a future version of CityGML", hence it is not clear whether we can consider the recommendation of 5 m when it comes to the height of buildings.

Despite the shortcomings, and because we are not aware of any national or international standard other than CityGML mentioning LOD1 accuracy requirements, in the results section we will come back to this recommendation as an indication of quality of the generated 3D building models. To bridge this uncertainty, we will tackle the results with two other descriptions that may indicate the quality of the results:

- Comparability: is the accuracy of the constructed 3D models comparable to some occurrences in research and practice? Section 2.2.1 describes a myriad of publications using 3D models constructed from attributes, hence our method already satisfies this requirement. However, we also compare the results to papers that expose the quality of the reconstructed 3D models.
- Usability: can the derived 3D models be used in spatial analyses? In Section 6 we run experiments to support the accuracy with applications (error propagation).

# 4 Results and discussion

An illustration of the 3D model generated from the inferred heights is shown in Figure 8.

## 4.1 Overview of the models and their performance

We have trained predictive models based on different combinations of predictors. This is important because not all attributes covered are always available, but also to test the performance of each in combination with others.

We have selected 17 combinations of predictors. After training the models, we performed the estimations on the test dataset and we present the accuracy of the inferred heights in Table 1, along with an overview of the used models as different combinations of predictors.

The MAE varies between 0.8 m and 3.1 m (RMSE from 1.8 m to 4.3 m), depending on the used predictors, satisfying the first two aspects discussed in Section 3.4, as we have encountered a

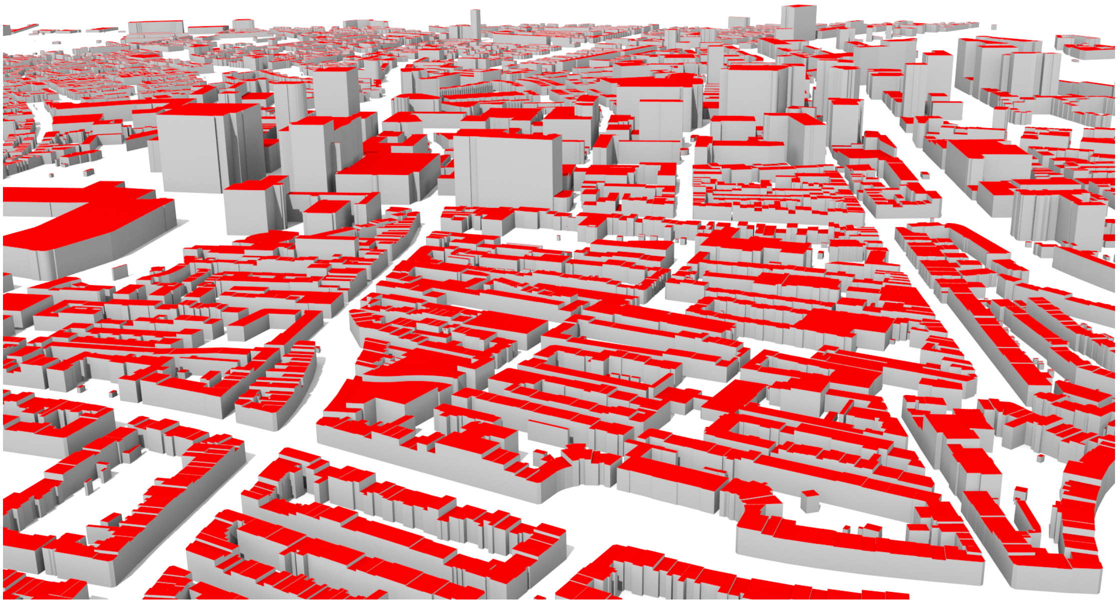


Figure 8: 3D model of Rotterdam generated without elevation data. An evaluation of these predictions will be shown later in Figure 11.

number of papers reporting accuracy of 3D models in that range or with an even larger error (e.g. Macay Moreia et al. (2013), Duan and Lafarge (2016), Gupta et al. (2015), Al Amouri and Kolbe (2009), and Tack et al. (2012)). As a result, we argue that it is feasible to generate 3D city models with this approach.

In the continuation we will address each model separately. The reader should also follow Figure 9 which illustrates the importance of each predictor in a particular model, a value useful to indicate the relation between different predictors, along with the accuracy of each predictive model.

Starting from the number of storeys alone (model 1) is already a convincing motivation for using attributes to generate 3D city models that roughly convey the size and shape of a building. Its MAE is 1.3 m, hence using the number of storeys to extrude building footprints in absence of elevation data is for a reason a relatively popular method to obtain 3D building models without elevation data—the accuracy of the heights obtained with this attribute can be sufficient for a number of spatial analyses. However, no study has critically evaluated these numbers so researchers have used such models without insight into the quality.

As a side experiment, as in related work we have taken two assumed storey heights (2.8 m and 3.5 m), and simply multiplied them with the number of storeys for each building to assess the approaches in related work. The errors are 1.6 m in both cases, showing that even with an assumed storey height of a relatively large range without a training process it is possible to achieve a relatively good accuracy.

Table 1: Overview of the predictive models and their performance (accuracy).

| | Predictors | | | | | | | | | | Accuracy [m] | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Cadastre | | | | Geometry | | | Census | | | | |
| # | S | U | A | NIA | FA | NPI | N | PD | AHS | I | MAE | RMSE |
| 1 | • | | | | | | | | | | 1.3 | 2.1 |
| 2 | • | ○ | | | | | | | | | 1.3 | 2.2 |
| 3 | • | ○ | • | | | | | | | | 1.1 | 2.0 |
| 4 | | | | • | | | | | | | 1.7 | 3.4 |
| 5 | • | ○ | • | • | | | | | | | 1.0 | 2.0 |
| 6 | | • | • | • | | | | | | | 1.8 | 4.0 |
| 7 | | | | | • | | | | | | 2.3 | 4.2 |
| 8 | | | | | • | • | • | | | | 1.8 | 3.5 |
| 9 | • | ○ | • | • | ○ | ○ | ○ | | | | 0.9 | 1.9 |
| 10 | | | | • | • | | | | | | 1.3 | 2.6 |
| 11 | | | | • | • | • | • | | | | 1.1 | 2.5 |
| 12 | • | | | | • | • | • | | | | 1.1 | 2.0 |
| 13 | | | • | | • | • | • | | | | 1.4 | 3.2 |
| 14 | | | | | | | | • | • | • | 3.1 | 4.3 |
| 15 | | | | | • | • | • | • | • | • | 1.3 | 2.9 |
| 16 | • | ○ | • | • | ○ | ○ | ○ | ○ | ○ | ○ | 0.8 | 1.8 |
| 17 | • | | • | • | | | | | | | 0.8 | 1.8 |

— Legend: S—storey, U—use, A—age, NIA—net internal area, FA—footprint area, NPI—normalised perimeter index, N—neighbours, PD—population density, AHS—average household size, I—income.
— The sign ○ denotes that a feature was used but in this particular combination it turned out to be marginally relevant for the RF regressor. Figure 9 illustrates the predictor importance in more detail.

Adding the building use (model 2) does not improve the results. However, if age was added to the combination (model 3), the error was reduced down to 1.1 m.

Using only NIA (model 4) achieved an accuracy of 1.7 m, and when added to the previous combination the accuracy improved further to 1.0 m (model 5). Again, building use was the least important piece of information. The same combination without the number of storeys (model 6) did not fare well as the previous combinations (1.8 m).

Moving to the geometric predictors, using the area of the footprint (model 7) did not give good results. But when combined with the other two geometric attributes (model 8), the accuracy was 1.8 m. This value is not so accurate as model 5 consisting of cadastre attributes, however, model 8 consists of predictors that are always available, hence it is pleasing to see that the worst case scenario of data availability results in an accuracy that can produce models which are for sure of interest, and might be useful in different application domains.

When combining all the 4 building attributes and 3 geometric predictors (model 9) we achieve sub-meter accuracy. This combination helped to put the predictors in perspective: again the

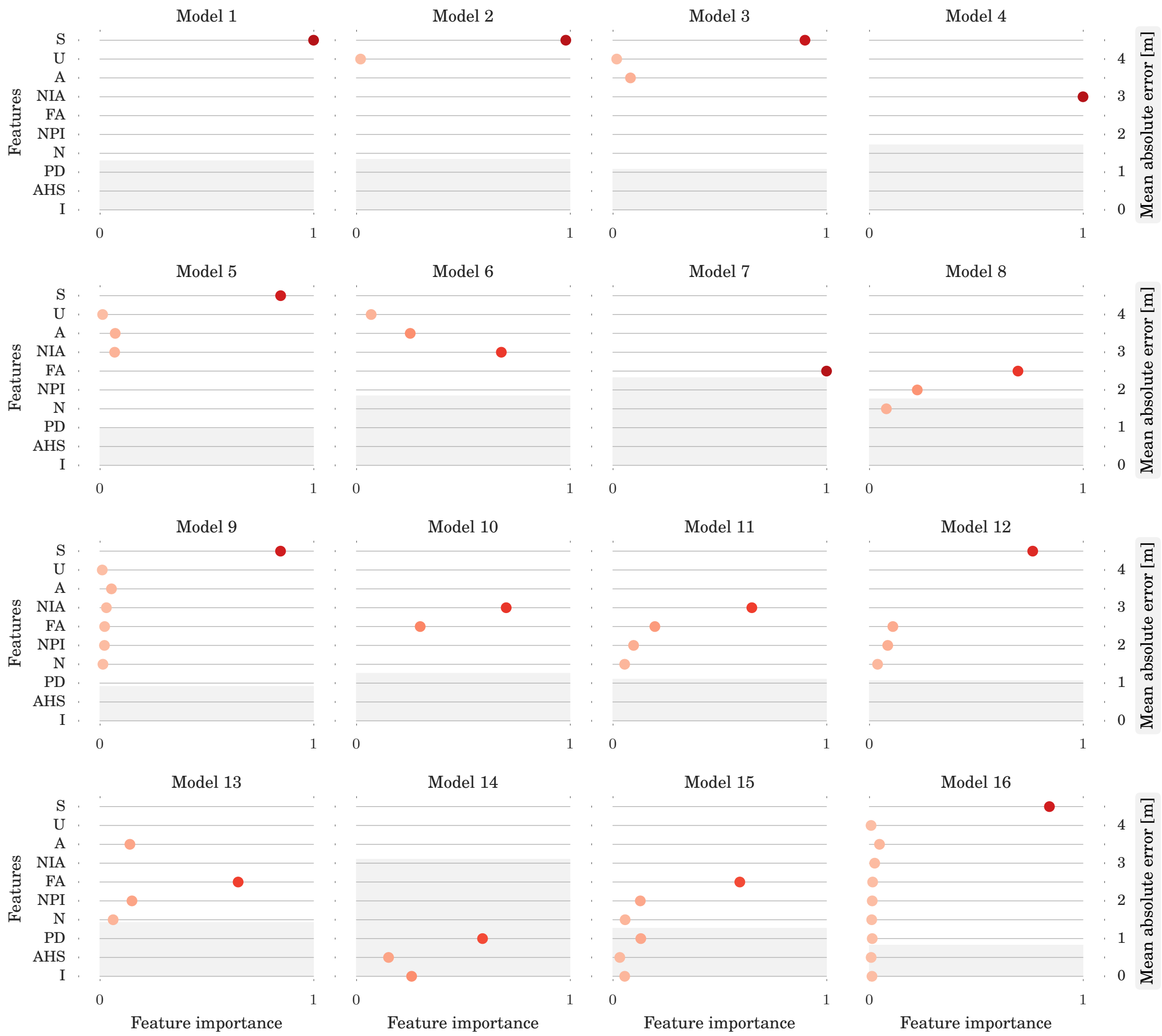



Figure 9: Visual illustration of predictor (feature) importance for the predictive models, and their performance to predict heights (mean absolute error). The accuracy of each model is illustrated with the filled bar (see the end right for the values—each horizontal line indicates an error of half meter). Models containing only one variable have obviously always the importance of 1, but are given here for comparing accuracies.

number of storeys has been the most important predictor, but as Figure 9 illustrates, there is a variation in the importance of the others.

Model 10 combines the models 4 and 7, which use only NIA and footprint area, respectively. As discussed in Section 3.3, having the footprint area might help putting the NIA in vertical perspective. Indeed, as the accuracy improves to 1.3 m.

In model 11 we add other geometric predictors to achieve an accuracy of 1.1 m. Model 12 is similar, with the number of storeys instead of the NIA, achieving the same accuracy. In a similar fashion model 13 includes the age of the building, but with an error of 1.4 m not being as accurate as the previous two.

In model 14 we move to the neighbourhood attributes (census). Evidently, using only these predictors will give the same height for all buildings in the neighbourhood. The error is 3.1 m, due to large variations in the building heights in the neighbourhoods. Nevertheless, this model might be worth considering in cases in which aggregated data per neighbourhood are required (e.g. average height of buildings). In model 15 we add the three geometrical predictors (which are always available so there is no reason not to use them), resulting in an error of 1.3 m.

Finally, model 16 includes all 10 predictors achieving an error of 0.8 m. While the error of this predictive model is the smallest so far, it is interesting because it enables us to evaluate the importance of all predictors together, and to find the minimum combination of predictors that yield a comparably good accuracy.

It appears that the number of storeys, building age, and net internal area have been the most useful predictors. Hence we construct the final combination comprising these three predictors (model 17), resulting in the same MAE of 0.8 m.

The sub-meter accuracy of this model was achieved only with three attributes, all of which are from cadastre, showing that the geometric attributes and neighbourhood characteristics have not been much of a use when cadastral data was available. When the number of storeys was used in a predictive model, all other features were much less important. However, there are other predictors that have proven useful, which is convenient because the number of storeys is not always available.

Using only the geometric attributes, which are available for all 2D datasets after trivial processing, have predicted the height below 2 meters. This makes sense, because just by looking at the building footprints in Figure 2, and judging the shapes of the buildings and their concentration it is possible to deduce that these are terraced houses which always have about 2 to 3 storeys.

On the negative side, as evident in Section 3.3 we have put much hope in the information on the building use while its contribution has been not much of use.

### 4.2 Generation of the 3D city model

In Figure 8 we have shown the generated 3D city model based on the inferred heights. The prediction models were used based on the availability of data for each building: we have used the predictive model 17, but since for 31% of buildings there was no storey and NIA information, the next best available predictive model that does not require that variable was used automatically (model 15). The heights of the supplemented 3D buildings shown in Figure 1 in the Introduction were predicted in the same fashion, as sheds did not have cadastral information, and nevertheless they turned out to be fairly accurately predicted.

## 4.3 Cumulative errors

So far we have presented the MAE and RMSE, which aggregate all errors in one value. In Figure 10 we analyse the errors in more detail for five selected predictive models. The plot shows that for most of the buildings in several predictive models the height was predicted within 1 m. In our best predictive model (no. 17) the heights of 77% buildings have been predicted with an error smaller than one meter.

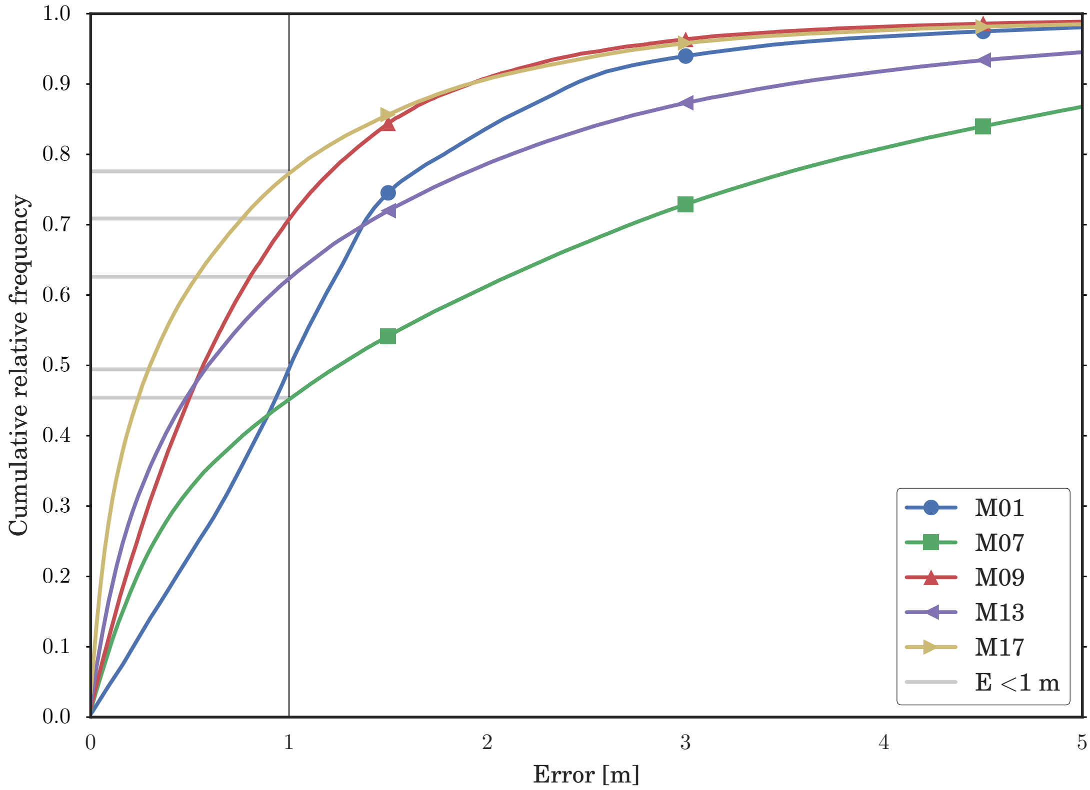



Figure 10: Cumulative plot of errors for 5 selected models. In several models the height of more than half of buildings was predicted with sub-meter accuracy.

## 4.4 Gross errors

Figure 11 supports these observations by exposing the errors of the 3D model shown in Figure 8: the coloured portion of the walls represents the error in the estimation of the height, while the colours classify the errors into negative (underestimation) and positive (overestimation) errors. Some of the heights were predicted with a negligible error having the value almost the same as from the lidar measurement, however, for some buildings the error was substantial.

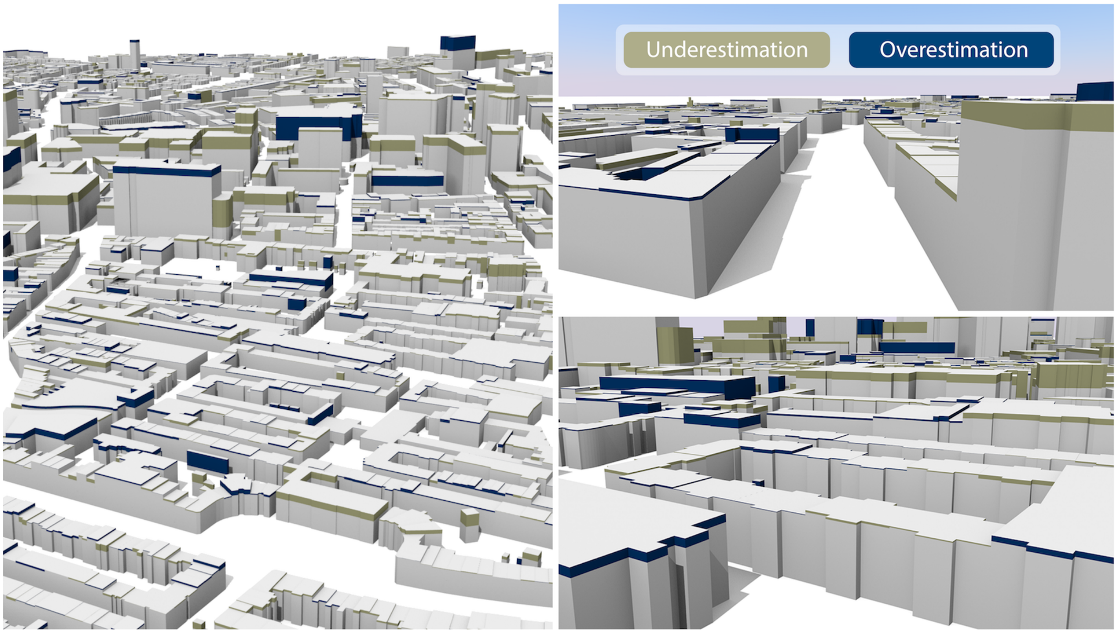



Figure 11: Evaluation of the 3D models presented in Figure 8. The colours represent underestimations (missing portions of buildings), and overestimations (excess heights).

In this section we focus on the predictions that were significantly erroneous (e.g. overestimations of more than double the height). Figure 10 suggests that in all predictive models a certain share of heights has an error of more than 5 m. Such gross errors considerably affect the MAE and RMSE values.

Most of the large errors were caused by limitations of the method, mostly due to predictor-specific factors described in Section 3.3. For instance, using the number of storeys substantially underestimated the height of tall constructions that contain only one or a few storeys (e.g. observation decks, religious buildings, and industrial objects such as warehouses, water purification and waste recycling plants). With the number of storeys there were cases of overestimation as well. For instance, the height of a car park of 5 storeys was predicted to be 17 m. But in reality it has a height of less than 8 m because the car park features split-level storeys each counted as a full storey. Moreover, the top surface of the building was also counted as a storey because of the parking function.

Other attributes also had some problems as discussed, e.g. a building with a large net internal area that has a few underground storeys, was extruded too much because the method falls short with the NIA portion below ground. The large errors visible in Figure 11 were mostly due to these reasons.

In general, if we consider the circumstances, we can conclude that the predictive models resulted in surprisingly good performance. However, due to gross errors researchers should exercise caution when using models derived from attributes. As we show in the literature review (Section 2.2), such models are not uncommon, and they are seldom critically evaluated being accepted as is, and sometimes used in spatial analyses where a relatively small error in the 3D model may cause a substantial error in the spatial analysis.

## 4.5 Limitations of the validation

It should be noted that many gross errors were caused by limitations of the validation, as the reference data is not without faults.

First, we have noticed at least a few errors in the attributes, such as the incorrect number of storeys in the cadastral registration.

Second, the reference height of the building which we have derived from the point cloud contains some inconsistencies (either too low or too high). While the point cloud is accurate, the height might not be always represent the top of the construction, as factors such as adjacent tall buildings, may influence it. Rotterdam has also a fair share of buildings that overlap each other, which also influenced the height. Figure 5 hints at errors in the measurement of the reference height: some of the storey heights were unrealistically small.

Third, a notable problem with the validation are the shortcomings of the LOD1 models in which a building may have the notion of multiple heights, hence an LOD1 often does no justice in representing it (Xiong et al., 2016; Biljecki et al., 2016b). Several buildings for which the predictions resulted in a gross error are discontinuous in height. For instance, a building with a sloped top that covers more than a few storeys. Buildings including setbacks also fall in this category (e.g. the floor area at the top is much smaller than at the bottom of the building). A few examples are shown in Figure 12.

Finally, we have encountered several large footprints comprising arguably multiple buildings. While the dataset we have obtained contains buildings at a quite granular level (e.g. terraced houses—see the buildings in Figure 2), due to the modelling conventions of the Dutch cadastre some of the footprints encompass a large area containing multiple buildings. We have considered partitioning such buildings depending on the continuity of the height, following methods such as the ones of Commandeur (2012) and Kada and McKinley (2009). However, in that case it would not be possible to meaningfully distribute attributes across partitioned buildings.

An example of such a case is shown in Figure 13. According to the number of storeys (33), in the predictive models involving this attribute, the height was predicted to be between 94 and 100 m, which corresponds to the height of the tallest tower. However, the height from lidar was predicted to be 17.5 m, flagging a large error in the validation.

Predictive models not involving the number of storeys were more promising (e.g. model 15 predicted 15.5 m), however, here it anyway does not make sense to talk about the height of a building.

Figure 12: Examples of buildings in Rotterdam with an ambiguous notion of height if extruding the building footprint to a single height was used. Imagery (c) Microsoft and Pictometry International Corp.

A byproduct of our method is that it can be also used to find errors in the underlying data: gross errors may indicate not the imperfection of the method, but rather inconsistencies in the reference data. Thanks to them we have found these errors and special cases.

# 5 Applying the inferred patterns to another city

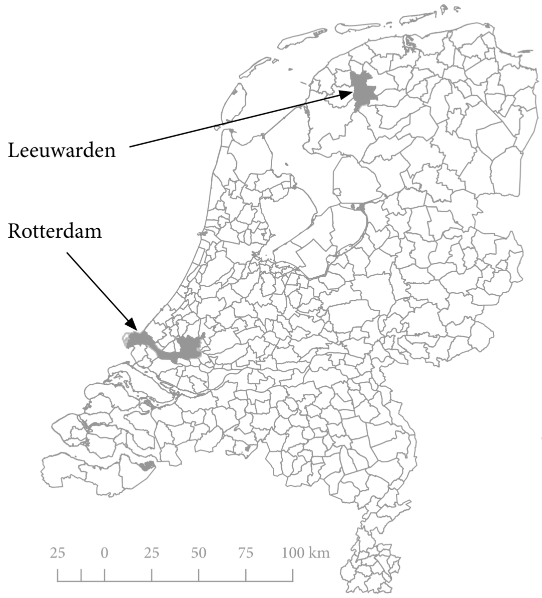
In order to train our prediction models, we have taken a small subset of buildings in Rotterdam. While the heights were predicted without elevation data, training involves reference heights and the patterns may be limited to a unique local context. Hence one might argue that this method is not entirely without elevation data. Furthermore, training data might be applicable only for a specific context that is not applicable somewhere else.

As stated in Section 3, we argue that our method can be used in other areas far from the training area and where there are no elevation data. To prove this assumption we apply the predictive relationships on buildings in Leeuwarden, one of the farthest Dutch cities from Rotterdam (170 km distance). Leeuwarden is not as urbanised as Rotterdam, and it is also a city with a different cultural environment and history, so it is interesting to investigate whether the predictive models developed in Rotterdam would obtain comparable results in such a different place (Figure 14).

We have applied the inferred relationships of 9 predictive models (we could not test the models including number of storeys because we could not obtain that data for Leeuwarden), and validated


Figure 13: Example of a footprint covering multiple buildings of significantly different heights. The labels represent the number of storeys for each footprint, which we have used to predict heights, and in this case resulted in erroneous predictions. In cases such as this one it is ambiguous to discuss building heights. Footprints (c) Kadaster and City of Rotterdam. Imagery (c) Google and Aerodata International Surveys. Oblique imagery (c) Microsoft and Blom.

the inferred heights with the heights obtained from the national height model of the Netherlands (AHN). The mean absolute errors of the evaluated models are shown in Figure 15. The heights in Leeuwarden estimated from the predictive models trained in Rotterdam are slightly less accurate,




| | Rotterdam | Leeuwarden |
|---|---|---|
| Average b. height [m] | 6.2 | 5.3 |
| Residential buildings [%] | 52 | 65 |
| Population density [1000 res. / sq. km] | 2.9 | 1.2 |
| Average income [k€] | 29.3 | 26.9 |

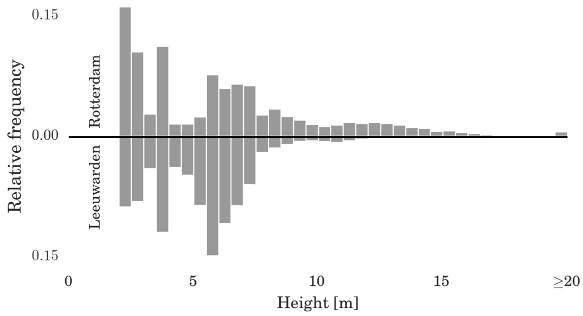



Figure 14: Location and comparison of Rotterdam and Leeuwarden. The two histograms show the differences in the heights of buildings.

with the interesting exceptions of models 4 and 14 which are more accurate in Leeuwarden than in Rotterdam, possibly due to less variation in the heights of buildings and architecture.

This evaluation shows that it is feasible to train a predictive model in one area where heights are available and use it for another one. Furthermore, we assume that we would obtain comparable results also beyond the border of the Netherlands, at least in Belgium and northwestern Germany.

For future work it would be beneficial to investigate the performance of the method in areas with a considerably different type of urban fabric, and to research whether the advancement of the sampling method can lead to an improvement in the results. In this research we have used simple random sampling. Perhaps using more advanced sampling methods (e.g. stratifying buildings based on different characteristics) would lead to a more effective training dataset.

## 6 Potential applications and large-scale experiments

3D city models derived from heights inferred from non-elevation sources are not as accurate as those derived from direct measurements such as lidar. Nevertheless, they can generally indicate the urban form that is useful in various urban applications (Ratti and Richens, 2004; Biljecki et al., 2015b), and may be of use for various purposes where high accuracy is not crucial. For instance, they may be used for visualisation purposes (e.g. for navigation), and their appearance may be

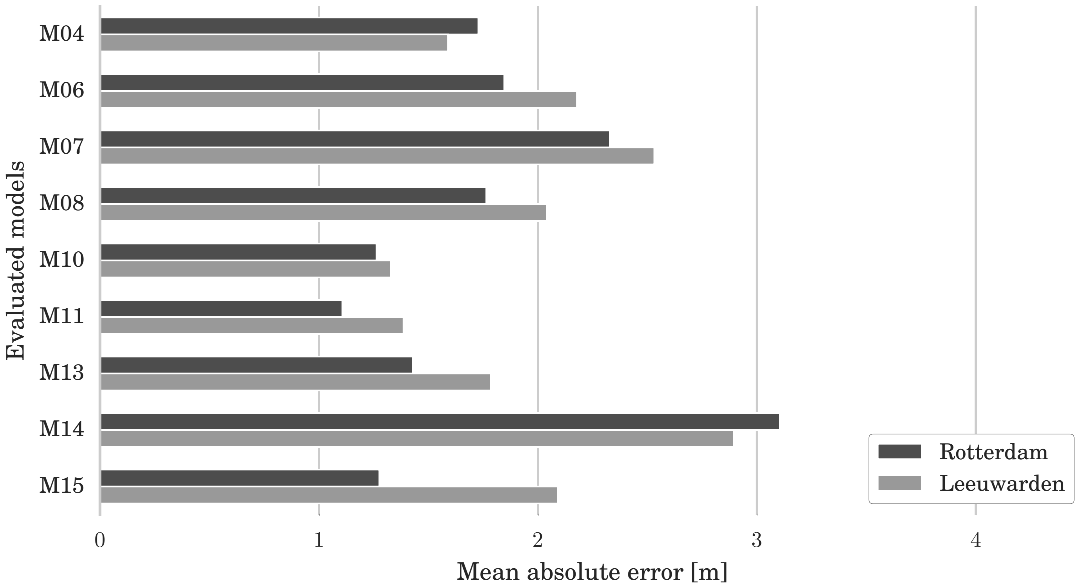



Figure 15: The performance of inferring heights far from the area where the predictive models were developed. Some predictive models fare even better than in the original context where they have been developed.

enhanced with procedural modelling techniques (Müller Arisona et al., 2013; Rautenbach et al., 2016).

This reasoning is also evident from Section 2.2 where we review several papers using 3D models generated from the number of storeys. In addition, these applications may include determining the urban heat island effect (van der Hoeven and Wandl, 2015), computing the building roughness indicator (Helbich et al., 2016), analysing the vertical growth of a city (Koziatek et al., 2016), seismic vulnerability assessment (Pittore and Wieland, 2012; Wieland et al., 2012), noise pollution predictions (Stoter et al., 2008), waste management (Mastrucci et al., 2016), estimating air pollution (Eeftens et al., 2013), storm surge vulnerability assessment (Liu et al., 2016), and analysing urban density (Taubenbock et al., 2016). It is our observation that most of these papers used crude data, hence our assumption is that the applications are not very demanding when it comes to accuracy of the underlying 3D models (it should also not be ignored that if such 3D models are constructed from very accurate footprints such as in our case, the planar accuracy of the 3D model still remains high).

Furthermore, some spatial analyses require aggregated data of buildings at a neighbourhood level. Such applications are calculating the volume of buildings in the neighbourhood, e.g. for energy demand estimation and thermal simulations (Amado et al., 2016; Zucker et al., 2016), population estimation (Xie et al., 2015), and estimating the material stock (Schebek et al., 2016). In fact, Rotterdam was already a subject of similar analyses (Nouvel et al., 2015) in which aggregated data on the energy demand of neighbourhoods have been estimated.

Calculating and presenting the volume of each building individually would not be very accurate, but our hypothesis is that on a larger area such as neighbourhoods, the computations would not be that far from the true value.

In order to test this hypothesis we compute the volume of buildings per neighbourhood, and compare it to the value obtained from lidar. For the experiments we have chosen the model 15, which performed moderately well in our analysis, and it does not require attributes of buildings. Using the estimated data, the error in the computation of volume of individual buildings is 20.2%, however, when summing the volumes per neighbourhood the error drops to 13.8%. The volume on the scale of Rotterdam was computed with an error of 3.8%. Predictive models with a higher accuracy have further yielded better results in computing the building stock volume of neighbourhoods (e.g. 8.4% for model 9).

With this section we also fulfill our third quality requirement stated in Section 3.4, as these results suggest that in absence of very accurate 3D city models, those obtained without elevation data are worth considering for certain spatial analyses.

# 7 Conclusion

We have shown that 3D city models can be generated automatically without elevation data, namely for three reasons:

- Several attributes available solely from 2D data can hint at a building's height. The method works also with attributes other than the number of storeys, so 3D models can be generated outside areas with the availability of this convenient but not omnipresent attribute.
- The achieved accuracy is comparable to many other instances used in research and practice. In fact, in many of the predictive models, the majority of the heights was predicted with an error below 1 m, which fares better than a number of instances of 3D models acquired with traditional direct techniques.
- The experiments and the discussion show that these models could be useful in a number of spatial analyses.

Despite advancements in remote sensing, elevation data required to generate 3D city models will still not be available for many areas around the world for some time. In fact, many developed countries still lack national coverage of elevation data suitable for producing 3D city models (Hartmann et al., 2016). In the meantime, the insights presented in our paper can serve to quickly obtain 3D models in LOD1 in such places where there are no elevation measurements available, but are rich with footprints from governments and volunteered geoinformation. Depending on the purpose, these 3D models obtained with approximate heights can be a reasonable provisional solution until elevation measurements become available, or if they are outdated—before they are refreshed.

While we have not invented the extrusion of footprints based on the number of storeys, no study has critically evaluated this method so researchers have used such models without the awareness of the quality. Furthermore, no research has been done on using machine learning techniques and whether there are other attributes that can be used to predict the height of a building, which is important especially because the information on the number of storeys still suffers from completeness issues. Our comprehensive study bridges these gaps: we investigate 9 other attributes, and perform experiments in 17 predictive models obtaining a thorough quality insight in what are the possibilities to generate 3D city models with non-elevation attributes. While the number of storeys remains the most useful attribute, including other predictors improves the predictive accuracy.

For future work we plan to investigate whether it is possible to infer the roof type, possibly leading to the generation of LOD2 models without elevation data. The papers of Allani-Bouhoula and Perrin (2008) and of Henn et al. (2013) suggest that this idea is not unrealistic. For example, in the latter, in automatic mapping of buildings from point clouds researchers use attributes of buildings to improve the quality of the reconstruction of roofs. Perhaps the characteristics of buildings alone can give a reliable indication of the roof type.

In addition, it might be beneficial to further analyse the surrounding context of a building, which is readily available from volunteered geoinformation. For example, Bakillah et al. (2014) analysed amenities around buildings to map population. Following a similar logic (taller buildings host more people, which results in more demand into supermarkets and other facilities) might result in improved predictions.


## Acknowledgements

We gratefully acknowledge the reviewers for their comments, and the City of Rotterdam, Kadaster, Statistics Netherlands, and AHN for providing the data. Additionally, we would like to thank Jonas Teuwen, Tom Commandeur, Peter Groeneveld, Christian Wisse, Michiel Boelhouwer, and Kian Wee Chen for their valuable help.

This research is supported by the Dutch Technology Foundation STW, which is part of the Netherlands Organisation for Scientific Research (NWO), and which is partly funded by the Ministry of Economic Affairs (project code: 11300).


## References


Agugiaro, G., 2016a. Energy planning tools and CityGML-based 3D virtual city models: experiences from Trento (Italy). Applied Geomatics 8, 41–56.

Agugiaro, G., 2016b. First steps towards an integrated CityGML-based 3D model of Vienna. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. III-4, 139–146.

Ahmed, F.C., Sekar, S.P., 2015. Using Three-Dimensional Volumetric Analysis in Everyday Urban Planning Processes. Applied Spatial Analysis and Policy 8, 393–408.

Al Amouri, A., Kolbe, T.H., 2009. Quality assessment of historical Baalbek's 3D city model. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XXXVIII-2/W11, 5.

Alahmadi, M., Atkinson, P., Martin, D., 2013. Estimating the spatial distribution of the population of Riyadh, Saudi Arabia using remotely sensed built land cover and height data. Computers, Environment and Urban Systems 41, 167–176.

Allani-Bouhoula, N., Perrin, J.P., 2008. Architectural rules for three-dimensional reconstruction, in: CGIM '08 Proceedings of the Tenth IASTED International Conference on Computer Graphics and Imaging, Innsbruck, Austria. pp. 237–242.

Amado, M., Poggi, F., Amado, A.R., 2016. Energy efficient city: A model for urban planning. Sustainable Cities and Society 26, 476–485.

Angel, S., Parent, J., Civco, D.L., 2010. Ten compactness properties of circles: measuring shape in geography. The Canadian Geographer 54, 441–461.

Aringer, K., Roschlaub, R., 2014. Bavarian 3D Building Model and Update Concept Based on LiDAR, Image Matching and Cadastre Information, in: Innovations in 3D Geo-Information Sciences. Springer International Publishing, pp. 143–157.

Bahu, J.M., Koch, A., Kremers, E., Murshed, S.M., 2015. Towards a 3D Spatial Urban Energy Modelling Approach. International Journal of 3-D Information Modeling 3, 1–16.

Bakillah, M., Liang, S., Mobasheri, A., Jokar Arsanjani, J., Zipf, A., 2014. Fine-resolution population mapping using OpenStreetMap points-of-interest. International Journal of Geographical Information Science 28, 1940–1963.

Basiouka, S., Potsiou, C., Bakogiannis, E., 2015. OpenStreetMap for cadastral purposes: an application using VGI for official processes in urban areas. Survey Review 47, 333–341.

Bast, H., Storandt, S., Weidner, S., 2015. Fine-grained population estimation, in: Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems, ACM, New York, New York, USA. pp. 17–10.

Belgiu, M., Tomljenovic, I., Lampoltshammer, T., Blaschke, T., Höfle, B., 2014. Ontology-Based Classification of Building Types Detected from Airborne Laser Scanning Data. Remote Sensing 6, 1347–1366.

Bertaud, A., Brueckner, J.K., 2005. Analyzing building-height restrictions: predicted impacts and welfare costs. Regional Science and Urban Economics 35, 109–125.

Biljecki, F., Arroyo Ohori, K., Ledoux, H., Peters, R., Stoter, J., 2016a. Population Estimation Using a 3D City Model: A Multi-Scale Country-Wide Study in the Netherlands. PLOS ONE 11, e0156808.

Biljecki, F., Heuvelink, G.B.M., Ledoux, H., Stoter, J., 2015a. Propagation of positional error in 3D GIS: estimation of the solar irradiation of building roofs. International Journal of Geographical Information Science 29, 2269–2294.

Biljecki, F., Ledoux, H., Stoter, J., 2016b. An improved LOD specification for 3D building models. Computers, Environment and Urban Systems 59, 25–37.

Biljecki, F., Ledoux, H., Stoter, J., Vosselman, G., 2016c. The variants of an LOD of a 3D building model and their influence on spatial analyses. ISPRS Journal of Photogrammetry and Remote Sensing 116, 42–54.

Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., Çöltekin, A., 2015b. Applications of 3D City Models: State of the Art Review. ISPRS International Journal of Geo-Information 4, 2842–2889.

Boeters, R., Arroyo Ohori, K., Biljecki, F., Zlatanova, S., 2015. Automatically enhancing CityGML LOD2 models with a corresponding indoor geometry. International Journal of Geographical Information Science 29, 2248–2268.

Brasebin, M., Perret, J., Haëck, C., 2012. Towards a 3D geographic information system for the exploration of urban rules, in: Urban and Regional Data Management. CRC Press, pp. 37–49.

Brasebin, M., Perret, J., Mustiere, S., Weber, C., 2016. A Generic Model to Exploit Urban Regulation Knowledge. ISPRS International Journal of Geo-Information 5, 14.

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32.

Buhur, S., Ross, L., Büyüksalih, G., Baz, I., 2009. 3D City Modelling for Planning Activities, Case Study: Haydarpasa Train Station, Haydarpasa Port and Surrounding Backside Zones, Istanbul. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XXXVIII-1-4-7/W5, 1–6.

Chai, T., Draxler, R.R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. Geoscientific Model Development 7, 1247–1250.

Chau, K.W., Wong, S.K., Yau, Y., Yeung, A.K.C., 2007. Determining Optimal Building Height. Urban Studies 44, 591–607.

Chen, K.W., Norford, L., 2016. Workflow for Generating 3D Urban Models from Open City Data for Performance-Based Urban Design, in: Proceedings of the Asim 2016 IBPSA Asia Conference, Jeju, Korea.

Cheng, F., Thiel, K.H., 1995. Delimiting the building heights in a city from the shadow in a panchromatic SPOT-image—Part 1. Test of forty-two buildings. Remote Sensing 16, 409–415.

Commandeur, T., 2012. Footprint decomposition combined with point cloud segmentation for producing valid 3D models. Master's thesis. Delft University of Technology.

Conedera, M., Tonini, M., Oleggini, L., Vega Orozco, C., Leuenberger, M., Pezzatti, G.B., 2015. Geospatial approach for defining the Wildland-Urban Interface in the Alpine environment. Computers, Environment and Urban Systems 52, 10–20.

Coors, V., 2003. 3D-GIS in networking environments. Computers, Environment and Urban Systems 27, 345–357.

Coors, V., Hünlich, K., On, G., 2009. Constraint-based Generation and Visualization of 3D City Models, in: 3D Geo-Information Sciences. Springer Berlin Heidelberg, pp. 365–378.

Dalmau, F., Garcia-Almirall, P., Domínguez, E., Escudero, D., 2014. From Raw Data to Meaningful Information: A Representational Approach to Cadastral Databases in Relation to Urban Planning. Future Internet 6, 612–639.

Deakin, M., Campbell, F., Reid, A., Orsinger, J., 2014. The Urban Context, in: The Mass Retrofitting of an Energy Efficient—Low Carbon Zone. Springer London, London, pp. 23–38.

Dehbi, Y., Gröger, G., Plümer, L., 2016. Identification and Modelling of Translational and Axial Symmetries and their Hierarchical Structures in Building Footprints by Formal Grammars. Transactions in GIS 20, 645–663.

Duan, L., Lafarge, F., 2016. Towards Large-Scale City Reconstruction from Satellites, in: Spatial Information Theory. Cognitive and Computational Foundations of Geographic Information Science. Springer International Publishing, Cham, pp. 89–104.

Eeftens, M., Beekhuizen, J., Beelen, R., Wang, M., Vermeulen, R., Brunekreef, B., Huss, A., Hoek, G., 2013. Quantifying urban street configuration for improvements in air pollution models. Atmospheric Environment 72, 1–9.

Ellul, C., Adjrad, M., Groves, P., 2016. The impact of 3D data quality on improving GNSS performance using city models initial simulations. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. IV-2-W1, 171–178.

Fan, H., Zipf, A., 2016. Modelling the world in 3D from VGI/ Crowdsourced data, in: Capineri, C., Haklay, M., Huang, H., Antoniou, V., Kettunen, J., Ostermann, F., Purves, R. (Eds.), European Handbook of Crowdsourced Geographic Information. Ubiquity Press, London, pp. 435–446.

Fan, H., Zipf, A., Fu, Q., Neis, P., 2014. Quality assessment for building footprints data on OpenStreetMap. International Journal of Geographical Information Science 28, 700–719.

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., Alsdorf, D., 2007. The Shuttle Radar Topography Mission. Reviews of Geophysics 45, RG2004.

Figueiredo, R., Martina, M., 2016. Using open building data in the development of exposure data sets for catastrophe risk modelling. Natural Hazards and Earth System Sciences 16, 417–429.

Goetz, M., 2013. Towards generating highly detailed 3D CityGML models from OpenStreetMap. International Journal of Geographical Information Science 27, 845–865.

Goetz, M., Zipf, A., 2012. OpenStreetMap in 3D – Detailed insights on the current situation in Germany, in: Proceedings of the AGILE'2012 International Conference on Geographic Information Science, Avignon, April. pp. 288–292.

Gröger, G., Plümer, L., 2012. CityGML – Interoperable semantic 3D city models. ISPRS Journal of Photogrammetry and Remote Sensing 71, 12–33.

Grömping, U., 2009. Variable Importance Assessment in Regression: Linear Regression versus Random Forest. The American Statistician 63, 308–319.

Guney, C., Akdag Girginkaya, S., Cagdas, G., Yavuz, S., 2012. Tailoring a geomodel for analyzing an urban skyline. Landscape and Urban Planning 105, 160–173.

Gupta, K., Bhardwaj, A., Kumar, P., Pushpalata, P., 2015. Procedural rule based 3D city modeling and visualization using high resolution satellite data. International Journal of Advancement in Remote Sensing, GIS and Geography 3, 16–25.

Ha, J., Lee, S., Park, C., 2016. Temporal Effects of Environmental Characteristics on Urban Air Temperature: The Influence of the Sky View Factor. Sustainability 8, 895.

Hamilton, S.E., Morgan, A., 2010. Integrating lidar, GIS and hedonic price modeling to measure amenity values in urban beach residential property markets. Computers, Environment and Urban Systems 34, 133–141.

Hartmann, A., Meinel, G., Hecht, R., Behnisch, M., 2016. A Workflow for Automatic Quantification of Structure and Dynamic of the German Building Stock Using Official Spatial Data. ISPRS International Journal of Geo-Information 5, 142.

Hecht, R., Kunze, C., Hahmann, S., 2013. Measuring Completeness of Building Footprints in OpenStreetMap over Space and Time. ISPRS International Journal of Geo-Information 2, 1066–1091.

Hecht, R., Meinel, G., Buchroithner, M., 2015. Automatic identification of building types based on topographic databases – a comparison of different data sources. International Journal of Cartography 1, 18–31.

Helbich, M., van Emmichoven, M.J.Z., Dijst, M.J., Kwan, M.P., Pierik, F.H., de Vries, S.I., 2016. Natural and built environmental exposures on children's active school travel: A Dutch global positioning system-based cross-sectional study. Health & Place 39, 101–109.

Henn, A., Gröger, G., Stroh, V., Plümer, L., 2013. Model driven reconstruction of roofs from sparse LIDAR point clouds. ISPRS Journal of Photogrammetry and Remote Sensing 76, 17–29.

Henn, A., Römer, C., Gröger, G., Plümer, L., 2012. Automatic classification of building types in 3D city models. Geoinformatica 16, 281–306.

Hermosilla, T., Ruiz, L.A., Recio, J.A., Cambra-López, M., 2012. Assessing contextual descriptive features for plot-based classification of urban areas. Landscape and Urban Planning 106, 124–137.

Hintze, J.L., Nelson, R.D., 1998. Violin Plots: A Box Plot-Density Trace Synergism. The American Statistician 52, 181–184.

van der Hoeven, F., Wandl, A., 2015. Amsterwarm: Mapping the landuse, health and energy-efficiency implications of the Amsterdam urban heat island. Building Services Engineering Research and Technology 36, 67–88.

Irvin, R.B., McKeown, D.M., 1989. Methods for Exploiting the Relationship Between Buildings and Their Shadows in Aerial Imagery, in: Barrett, E.B., Pearson, J.J. (Eds.), Proceedings of SPIE 1076 - Image Understanding and the Man-Machine Interface II, International Society for Optics and Photonics. pp. 156–164.

Jaugsch, F., Löwner, M.O., 2016. Estimation of solar energy on vertical 3D building walls on city quarter scale. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2-W2, 135–143.

Joshi, K.K., Kono, T., 2009. Optimization of floor area ratio regulation in a growing city. Regional Science and Urban Economics 39, 502–511.

Jurelionis, A., Bouris, D., 2016. Impact of Urban Morphology on Infiltration-Induced Building Energy Consumption. Energies 9, 177.

Kada, M., McKinley, L., 2009. 3D building reconstruction from LiDAR based on a cell decomposition approach. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XXXVIII-3/W4, 47–52.

Kolbe, T.H., 2009. Representing and exchanging 3D city models with CityGML, in: Zlatanova, S., Lee, J. (Eds.), 3D Geo-Information Sciences. Springer Berlin Heidelberg, pp. 15–31.

Kolbe, T.H., Burger, B., Cantzler, B., 2015. CityGML goes to Broadway, in: Photogrammetric Week '15, Stuttgart, Germany. pp. 343–356.

Koziatek, O., Dragicevic, S., Li, S., 2016. Geospatial modelling approach for 3D urban densification developments. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLI-B2, 349–352.

Kunze, C., Hecht, R., 2015. Semantic enrichment of building data with volunteered geographic information to improve mappings of dwelling units and population. Computers, Environment and Urban Systems 53, 4–18.

Kurakula, V., Kuffer, M., 2008. 3D noise modeling for urban environmental planning and management, in: Schrenk, M., Popovich, V., Engelke, D., Elisei, P. (Eds.), 13th International Conference on Urban Planning in Information and Knowledge Society (REAL CORP 2008), Vienna, Austria. pp. 517–523.

Ledoux, H., Meijers, M., 2011. Topologically consistent 3D city models obtained by extrusion. International Journal of Geographical Information Science 25, 557–574.

Lee, T., Kim, T., 2013. Automatic building height extraction by volumetric shadow analysis of monoscopic imagery. International Journal of Remote Sensing 34, 5834–5850.

Liasis, G., Stavrou, S., 2016. Satellite images analysis for shadow detection and building height estimation. ISPRS Journal of Photogrammetry and Remote Sensing 119, 437–450.

Lin, C., Huertas, A., Nevatia, R., 1994. Detection of buildings using perceptual grouping and shadows, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, IEEE, Seattle, WA. pp. 62–69.

Liu, J., Gong, J.H., Liang, J.M., Li, Y., Kang, L.C., Song, L.L., Shi, S.X., 2016. A quantitative method for storm surge vulnerability assessment – a case study of Weihai city. International Journal of Digital Earth , 1–21.

Lwin, K., Murayama, Y., 2009. A GIS Approach to Estimation of Building Population for Micro-spatial Analysis. Transactions in GIS 13, 401–414.

Lwin, K.K., Sugiura, K., Zettsu, K., 2016. Space–time multiple regression model for grid-based population estimation in urban areas. International Journal of Geographical Information Science 30, 1579–1593.

Macay Moreia, J.M., Nex, F., Agugiaro, G., Remondino, F., Lim, N.J., 2013. From DSM to 3D building models: a quantitative evaluation. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XL-1/W1, 213–219.

Mastrucci, A., Marvuglia, A., Popovici, E., Leopold, U., Benetto, E., 2016. Geospatial characterization of building material stocks for the life cycle assessment of end-of-life scenarios at the urban scale. Resources, Conservation & Recycling .

Meinel, G., Hecht, R., Herold, H., 2009. Analyzing building stock using topographic maps and GIS. Building Research & Information 37, 468–482.

Müller Arisona, S., Zhong, C., Huang, X., Qin, H., 2013. Increasing detail of 3D models through combined photogrammetric and procedural modelling. Geo-spatial Information Science 16, 45–53.

Mutanga, O., Adam, E., Cho, M.A., 2012. High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. International Journal of Applied Earth Observation and Geoinformation 18, 399–406.

Neidhart, H., Sester, M., 2004. Identifying building types and building clusters using 3-D laser scanning and GIS-data. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XXXV/B4, 715–720.

NEN, 2007. Nederlandse norm NEN 2580:2007 — Oppervlakten en inhouden van gebouwen - Termen, definities en bepalingsmethoden (Netherlands standard on Areas and volumes of buildings - Terms, definitions and methods of determination).

Nevatia, R., Lin, C., Huertas, A., 1997. A System for Building Detection from Aerial Images, in: Automatic Extraction of Man-Made Objects from Aerial and Space Images (II). Birkhäuser Basel, Basel, pp. 77–86.

Nichol, J., Wong, M.S., 2005. Modeling urban environmental quality in a tropical city. Landscape and Urban Planning 73, 49–58.

Noskov, A., Doytsher, Y., 2013. Hierarchical Quarters Model Approach toward 3D Raster Based Generalization of Urban Environments. International Journal On Advances in Software 6, 343–353.

Nouvel, R., Mastrucci, A., Leopold, U., Baume, O., Coors, V., Eicker, U., 2015. Combining GIS-based statistical and engineering urban heat consumption models: Towards a new framework for multi-scale policy support. Energy and Buildings 107, 204–212.

OGC, 2012. OGC City Geography Markup Language (CityGML) Encoding Standard 2.0.0. Technical Report. Open Geospatial Consortium.

Olivares García, J.M., Virgós Soriano, L.I., Velasco Martín-Varés, A., 2011. 3D Modeling and Representation of the Spanish Cadastral Cartography, in: Proceedings of the 2nd International Workshop on 3D Cadastres, Delft, the Netherlands. pp. 209–222.

Over, M., Schilling, A., Neubauer, S., Zipf, A., 2010. Generating web-based 3D City Models from OpenStreetMap: The current situation in Germany. Computers, Environment and Urban Systems 34, 496–507.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12, 2825–2830.

Peeters, A., 2016. A GIS-based method for modeling urban-climate parameters using automated recognition of shadows cast by buildings. Computers, Environment and Urban Systems 59, 107–115.

Peeters, A., Etzion, Y., 2012. Automated recognition of urban objects for morphological urban analysis. Computers, Environment and Urban Systems 36, 573–582.

Perez, D., Kämpf, J.H., Scartezzini, J.L., 2013. Urban Area Energy Flow Microsimulation for Planning Support: a Calibration and Verification Study. International Journal On Advances in Systems and Measurements 6, 260–271.

Peronato, G., Bonjour, S., Stoeckli, J., Rey, E., Andersen, M., 2016. Sensitivity of calculated solar irradiation to the level of detail: insights from the simulation of four sample buildings in urban areas, in: PLEA, Los Angeles, CA, United States. pp. 1–6.

Petrescu, F., Aldea, M., Luca, O., Iacoboaea, C., Gaman, F., Parlow, E., 2016. 3D geo-information in urban climate studies. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2-W2, 51–55.

Pittore, M., Wieland, M., 2012. Toward a rapid probabilistic seismic vulnerability assessment using satellite and ground-based remote sensing. Natural Hazards 68, 115–145.

Ratti, C., Richens, P., 2004. Raster Analysis of Urban Form. Environment and Planning B: Planning and Design 31, 297–309.

Rautenbach, V., Coetzee, S., Çöltekin, A., 2016. Investigating the use of 3D geovisualizations for urban design in informal settlement upgrading in South Africa. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLI-B2, 425–431.

Roschlaub, R., Batscheider, J., 2016. An INSPIRE-konform 3D building model of Bavaria using cadastre information, lidar and image matching. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLI-B4, 747–754.

Salimzadeh, N., Sharif, S.A., Hammad, A., 2016. Visualizing and Analyzing Urban Energy Consumption: A Critical Review and Case Study, in: Construction Research Congress 2016, American Society of Civil Engineers, Reston, VA. pp. 1323–1331.

Santana, J.M., Wendel, J., Trujillo, A., Suárez, J.P., Simons, A., Koch, A., 2017. Multimodal Location Based Services—Semantic 3D City Data as Virtual and Augmented Reality, in: Progress in Location-Based Services 2016. Springer International Publishing, Cham, pp. 329–353.

Sathish Kumar, D., Arya, D.S., Vojinovic, Z., 2013. Modeling of urban growth dynamics and its impact on surface runoff characteristics. Computers, Environment and Urban Systems 41, 124–135.

Schebek, L., Schnitzer, B., Blesinger, D., Köhn, A., Miekley, B., Linke, H.J., Lohmann, A., Motzko, C., Seemann, A., 2016. Material stocks of the non-residential building sector: the case of the Rhine-Main area. Resources, Conservation & Recycling , 1–13.

Schläpfer, M., Lee, J., Bettencourt, L.M., 2016. Urban Skylines: Building Heights and Shapes as Measures of City Size , 1–22.

Şengül, A., 2010. Extracting Semantic Building Models From Aerial Stereo Images and Conversion to CityGML. Master's thesis. Istanbul Technical University and Technical University Berlin. Istanbul, Turkey.

Shao, Y., Taff, G.N., Walsh, S.J., 2011. Shadow detection and building-height estimation using IKONOS data. International Journal of Remote Sensing 32, 6929–6944.

Shiravi, S., Zhong, M., Beykaei, S.A., Hunt, J.D., Abraham, J.E., 2015. An assessment of the utility of LiDAR data in extracting base-year floorspace and a comparison with the census-based approach. Environment and Planning B: Planning and Design 42, 708–729.

Sırmaçek, B., Ünsalan, C., 2008. Building detection from aerial images using invariant color features and shadow information, in: 23rd International Symposium on Computer and Information Sciences (ISCIS), IEEE, Istanbul, Turkey. pp. 1–5.

Stoter, J., de Kluijver, H., Kurakula, V., 2008. 3D noise mapping in urban areas. International Journal of Geographical Information Science 22, 907–924.

Stoter, J., Roensdorf, C., Home, R., Capstick, D., Streilein, A., Kellenberger, T., Bayers, E., Kane, P., Dorsch, J., Woźniak, P., Lysell, G., Lithen, T., Bucher, B., Paparoditis, N., Ilves, R., 2015. 3D Modelling with National Coverage: Bridging the Gap Between Research and Practice, in: Advances in 3D Geo-Information Sciences. Springer International Publishing, Cham, pp. 207–225.

Strzalka, A., Alam, N., Duminil, E., Coors, V., Eicker, U., 2012. Large scale integration of photovoltaics in cities. Applied Energy 93, 413–421.

Sugihara, K., Shen, Z., 2016. Automatic generation of 3D house models with solar photovoltaic generation for smart city, in: 3rd MEC International Conference on Big Data and Smart City (ICBDSC), IEEE, Muscat, Oman. pp. 1–7.

Tack, F., Buyuksalih, G., Goossens, R., 2012. 3D building reconstruction based on given ground plan information and surface models extracted from spaceborne imagery. ISPRS Journal of Photogrammetry and Remote Sensing 67, 52–64.

Taubenbock, H., Standfuß, I., Klotz, M., Wurm, M., 2016. The Physical Density of the City—Deconstruction of the Delusive Density Measure with Evidence from Two European Megacities. ISPRS International Journal of Geo-Information 5, 206.

Teo, T.A., Cho, K.H., 2016. BIM-oriented indoor network model for indoor and outdoor combined route planning. Advanced Engineering Informatics 30, 268–282.

Tong, X., Lin, X., Feng, T., Xie, H., Liu, S., Hong, Z., Chen, P., 2013. Use of shadows for detection of earthquake-induced collapsed buildings in high-resolution satellite imagery. ISPRS Journal of Photogrammetry and Remote Sensing 79, 53–67.

Tu, J., Sui, H., Feng, W., Song, Z., 2016. Automatic building damage detection method using high-resolution remote sensing images and 3D GIS model. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. III-8, 43–50.

Uden, M., Zipf, A., 2013. Open Building Models: Towards a Platform for Crowdsourcing Virtual 3D Cities, in: Progress and New Trends in 3D Geoinformation Sciences. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 299–314.

Ural, S., Hussain, E., Shan, J., 2011. Building population mapping with aerial imagery and GIS data. International Journal of Applied Earth Observation and Geoinformation 13, 841–852.

Varduhn, V., Mundani, R.P., Rank, E., 2015. Multi-resolution Models: Recent Progress in Coupling 3D Geometry to Environmental Numerical Simulation, in: 3D Geoinformation Science. Springer International Publishing, pp. 55–69.

Varga, M., Bašić, T., 2015. Accuracy validation and comparison of global digital elevation models over Croatia. International Journal of Remote Sensing 36, 170–189.

Vartanian, O., Navarrete, G., Chatterjee, A., Fich, L.B., Gonzalez-Mora, J.L., Leder, H., Modroño, C., Nadal, M., Rostrup, N., Skov, M., 2015. Architectural design and the brain: Effects of ceiling height and perceived enclosure on beauty judgments and approach-avoidance decisions. Journal of Environmental Psychology 41, 10–18.

Vermeulen, T., Knopf-Lenoir, C., Villon, P., Beckers, B., 2015. Urban layout optimization framework to maximize direct solar irradiation. Computers, Environment and Urban Systems 51, 1–12.

Wendel, J., Murshed, S.M., Sriramulu, A., Nichersu, A., 2016. Development of a Web-Browser Based Interface for 3D Data—A Case Study of a Plug-in Free Approach for Visualizing Energy Modelling Results, in: Progress in Cartography. Springer International Publishing, Cham, pp. 185–205.

Wieland, M., Pittore, M., Parolai, S., Zschau, J., Moldobekov, B., Begaliev, U., 2012. Estimating building inventory for rapid seismic vulnerability assessment: Towards an integrated approach based on multi-source imaging. Soil Dynamics and Earthquake Engineering 36, 70–83.

Wróżyński, R., Sojka, M., Pyszny, K., 2016. The application of GIS and 3D graphic software to visual impact assessment of wind turbines. Renewable Energy 96, 625–635.

Xie, Y., Weng, A., Weng, Q., 2015. Population Estimation of Urban Residential Communities Using Remotely Sensed Morphologic Data. IEEE Geoscience and Remote Sensing Letters 12, 1111–1115.

Xiong, B., Oude Elberink, S., Vosselman, G., 2016. Footprint map partitioning using airborne laser scanning data. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. III-3, 241–247.

Yu, S.M., Han, S.S., Chai, C.H., 2007. Modeling the value of view in high-rise apartments: a 3D GIS approach. Environment and Planning B: Planning and Design 34, 139–153.

Zandbergen, P.A., 2008. Positional Accuracy of Spatial Data: Non-Normal Distributions and a Critique of the National Standard for Spatial Data Accuracy. Transactions in GIS 12, 103–130.

Zhou, X., Yu, W., Sullivan, W.C., 2016. Making pervasive sensing possible: Effective travel mode sensing based on smartphones. Computers, Environment and Urban Systems 58, 52–59.

Zucker, G., Judex, F., Blöchle, M., Köstl, M., Widl, E., Hauer, S., Bres, A., Zeilinger, J., 2016. A new method for optimizing operation of large neighborhoods of buildings using thermal simulation. Energy and Buildings 125, 153–160.