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The effect of acquisition error and level of detail on the accuracy of spatial analyses

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ABSTRACT
There has been a great deal of research about errors in geographic information and how they affect spatial analyses. A typical GIS process introduces various types of errors at different stages, and such errors usually propagate into errors in the result of a spatial analysis. However, most studies consider only a single error type thus preventing the understanding of the interaction and relative contributions of different types of errors. We focus on the level of detail (LOD) and positional error, and perform a multiple error propagation analysis combining both types of error. We experiment with three spatial analyses (computing gross volume, envelope area, and solar irradiation of buildings) performed with procedurally generated 3D city models to decouple and demonstrate the magnitude of the two types of error, and to show how they individually and jointly propagate to the output of the employed spatial analysis. The most notable result is that in the considered spatial analyses the positional error has a much higher impact than the LOD. As a consequence, we suggest that it is pointless to acquire geoinformation of a fine LOD if the acquisition method is not accurate, and instead we advise focusing on the accuracy of the data.

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Introduction

Geographical data are produced in many different flavors and combinations: at different levels of detail (LODs) and at different accuracies depending on the nature of the data, spatial scale, acquisition technique, and available funds. These different qualities affect spatial analyses in distinct ways, and investigating the propagation of a specific type of error (e.g. thematic error) has been extensively researched in geographical information science. However, mixed error propagation studies, which analyze the joint propagation of multiple error types, are scarce. Error propagation analyses commonly focus on one type of error and on one spatial analysis, and they are never carried out at multiple scales. This prevents the understanding of the relation, magnitude and relative contribution of each type of error.

In this paper we focus on the errors induced by (i) different LODs and by (ii) positional errors incurred by the acquisition. We run experiments to isolate and quantify them, and to investigate whether the benefit provided by spatial data of finer LOD is still valid in cases of significant acquisition errors.

Understanding the relation between detail and acquisition error is important for stakeholders in GIScience in order to put the two quality characteristics into perspective. For example, the presented approach provides practitioners and scientists a way of determining whether it is worth increasing the accuracy of the dataset, or rather its LOD, when designing the specification of a dataset to be acquired, so that the produced data will be suitable for a specific purpose (e.g. "What should the minimum accuracy and LOD available in the data be, so that these are usable for accurately calculating the volume of buildings?"). Likewise, it is relevant to set expectations about the capabilities of a certain dataset: this involves determining whether a dataset is adequately detailed and accurate enough to derive sufficiently reliable results in a spatial analysis. For instance, a user can avoid ordering the acquisition of an expensive and overly detailed dataset, which in a certain spatial analysis brings only a minuscule benefit when compared with a less detailed and less costly alternative.

Before proceeding to the core of the paper, it is important to separate the two considered qualities of geographical data – LOD and accuracy, which are unfortunately perennially misapprehended as synonyms. While there is an association between the two (representations at finer scales tend to be of higher quality (Heuvelink, 1998)), these are two independent concepts (Chrisman, 1991).

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For instance, a national government may produce a GIS dataset in which buildings are modeled in a coarse but accurately derived representation, and a municipality may produce a dataset of a city in finer detail but with less accuracy due to an inferior acquisition technique (e.g. automatic reconstruction from lidar instead of terrestrial measurements).

While acquisition induces multiple types of errors (e.g. thematic and positional), in this paper we focus on the positional errors resulting from acquisition. However, the developed work may be applied to investigate other aspects of acquisition as well.

The type of questions that we address in this paper are usual considerations for GIS users:

- Given two distinct datasets covering the same area (from multiple sources), where one is less detailed but more accurate than the other, which is the better choice for a particular spatial analysis?
- At what LOD and at what accuracy should a 3D model be acquired to be usable for a particular spatial analysis? Understanding this aspect would aid data producers in designing a specification that bears in mind the intended use of the data.
- Is it beneficial to acquire a dataset of a fine LOD if the acquisition technique has poor accuracy? Understanding this aspect may prevent wasting effort to produce a dataset that is detailed and it is perhaps visually pleasing, but is ultimately not acceptable for a particular spatial analysis because of poor accuracy. This reasoning was also described by Burrough and McDonnell (1998): "The quality of GIS products is often judged by the visual appearance of the end-product [...]. Uncertainties and errors are intrinsic to spatial data and need to be addressed properly, not swept away under the carpet of fancy graphics displays." (p. 220)

This research is also relevant in regard to the increasing availability of datasets with heterogeneous quality (Goodchild & Li, 2012). An example of such dataset is one based on old but accurate cadastral data, in which newer buildings have been supplemented with other acquisition techniques such as footprints digitized from aerial images. Such approaches may result in data of variable accuracy and differing LODs, a phenomenon inherent to volunteered geoinformation (Camboim, Bravo, & Sluter, 2015; Fan, Zipf, Fu, & Neis, 2014; Senaratne, Mobasheri, Ali, Capineri, & Haklay, 2017; Touya & Brando-Escobar, 2013; Uden & Zipf, 2013). Because such data are becoming increasingly used for spatial analyses (Wendel, Murshed, Sriramulu, & Nichersu, 2016), it is worthwhile to investigate for which portions of the dataset caution should be exercised due to lower reliability than in other parts of the dataset. Figure 1 shows an example of such dataset.

Our experiments help in determining which LOD and accuracy are sufficiently acceptable for particular spatial analyses.

Figure 2 illustrates the goal of this paper: to run the same spatial analysis (estimating wind flow) on two different datasets, where one is less accurate and has a coarser LOD than the other.

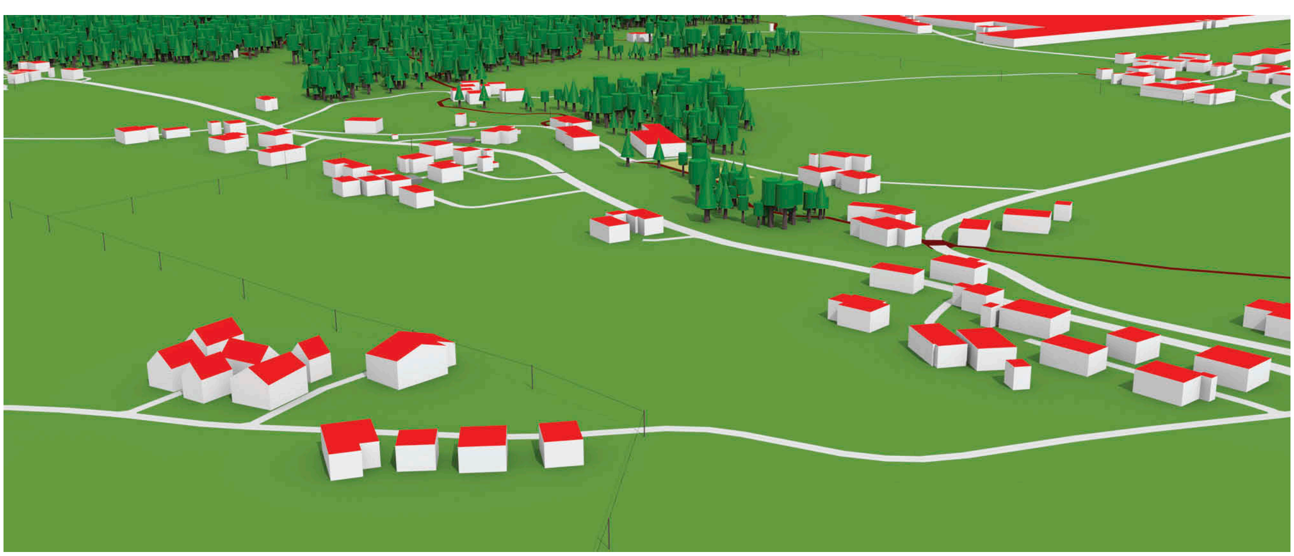

Figure 1. 3D building models of heterogeneous lineage within the same dataset. Example of a 3D model of a village in Austria obtained with crowdsourcing. In reality, almost all buildings in the area have pitched roofs, however, they are modeled only in a few buildings on the left. The rest of the buildings are represented by simple block models. Data courtesy of OpenStreetMap and OSM2World.

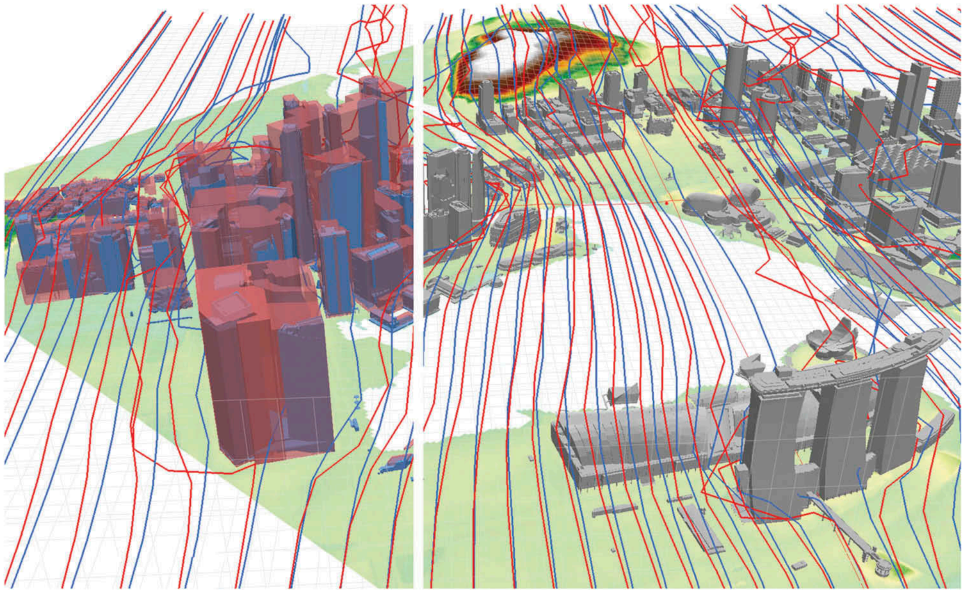

Figure 2. The results of two wind flow analyses of the Singapore central business district: one carried out on an accurate and detailed 3D city model shown here (flow lines in blue), and another one with a crude block model (flow lines in red). The left panel shows both LODs in corresponding colors, while the right panel reveals only the data in the finer LOD for clarity. Data, analysis, and image (c) Singapore Land Authority.

While the difference between the two LODs is obvious, it cannot be determined whether the difference in the results should be attributed primarily to the progression of the LOD or to the increase in the accuracy of the data. Furthermore, due to the absence of ground truth data, it is not clear whether the improvement that a more detailed dataset brings is still advantageous, as it may still deviate considerably from the real-world. A minor caveat here is that due to the absence of ground truth data we do not have proof that in this case the dataset of the finer LOD and higher accuracy brings more accurate results. However, it is reasonable to assume that such comparative differences bring more accurate results (or at least equally accurate) in comparison to analyses using their coarser and less accurate counterparts.

In Section Background we introduce a theoretical framework and an overview of related work. Section Data and method presents the design of a method to decompose and quantify the two types of errors under consideration. We select three spatial analyses (estimating the area of the building envelope, gross volume of a building, and solar irradiation of roofs) in order to investigate their different behaviors. We investigate whether these spatial analyses are more sensitive to positional error or to the reduction in the LOD. The results are presented in Section Results and discussion.

Background: decomposition of errors and related work

Decoupling errors

We decompose the errors induced in a typical GIS process into multiple components. Figure 3 illustrates our standpoint: error is induced before any acquisition has even taken place because a specification is designed to capture a certain subset of reality at a certain LOD. For instance, a data producer may decide to model buildings with simple roof shapes, without openings and finer details; such LOD induces an error which we call *representation-induced error*.

The second step in the process is to *realize* the specification with data acquisition techniques. Due to the imperfection of measurements, several types of errors are induced in the process and the results of a spatial analysis are further degraded. When such errors propagate through a spatial analysis, we call this as *acquisition-induced error*. Here we focus on the positional error, as it is one of the most prominent types of errors in many context and application (Ariza-López & Rodríguez-Avi, 2015b; Drummond, 1995) and subject to intensive research (e.g. Biljecki, Heuvelink, Ledoux, & Stoter, 2015; Cheung & Shi, 2004; Chow, Dede-Bamfo, & Dahal, 2016; Jacquez, 2012; McKenzie, Hegarty, Barrett, & Goodchild, 2016; Ruiz-Lendínez, Ariza- López, & Ureña-Cámara, 2016).

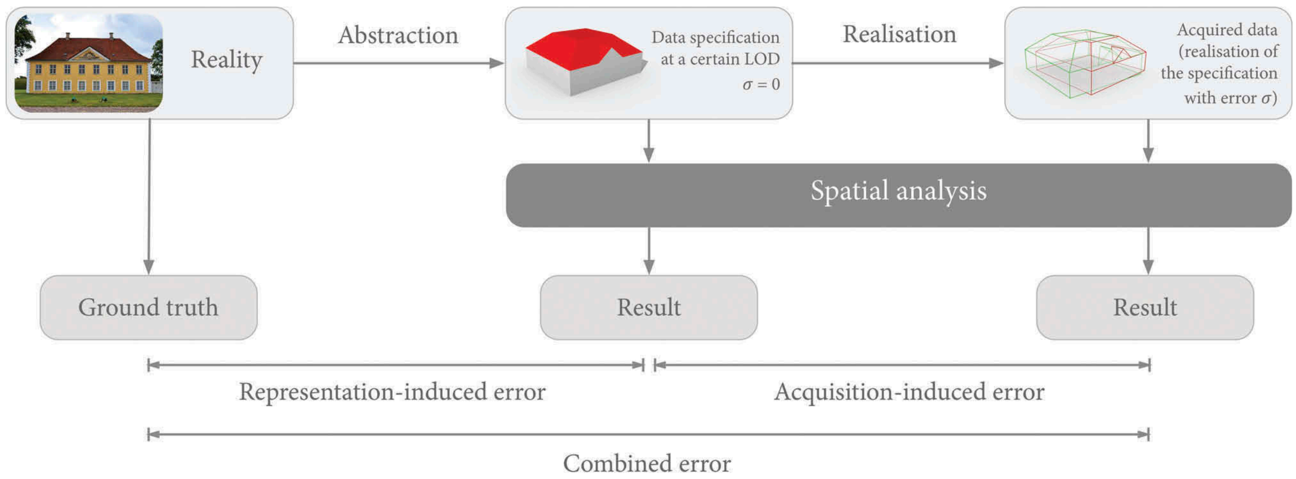

Figure 3. Longitudinal error decomposition as discussed in this paper: errors are induced at different stages of a typical GIS process, most prominently errors induced by abstraction and by realization of the data. In reality it would include additional errors; see the overview of Lunetta et al. (1991).

We term the combination of the acquisition-induced and positional errors as *combined error*, and describe them in further detail in the next subsections.

Representation-induced error

Depending on the purpose and scale of measurement, real-world phenomena may be modeled in different ways – different LODs.

In appropriate scale ranges (Mackaness, 2007), data modeled in finer detail are inherently believed to benefit spatial analyses, at the expense of an increased cost of acquisition, storage complexity and maintenance, and hindering the speed of spatial analyses. Hence, the benefit may not always justify the investment.

Experiments that we present in this paper are relevant for understanding how different LODs affect the accuracy of a spatial analysis. This has a twofold meaning. First, as modeling data at finer LODs comes at a higher cost, a relevant question is whether a certain spatial analysis can take advantage of this finer detail. Second, the problem may be approached from the generalization perspective; 3D geoinformation at fine LODs may in fact be too complex for certain spatial analyses. Hence, the data are occasionally generalized to reduce complexity while attempting to preserve usability (Deng & Cheng, 2015). Insights into the performance of the LODs may help to achieve that balance: by generalizing the models to a point at which their complexity is sufficiently reduced but at the same time their usability is not compromised by the reduced LOD.

There has been a considerable amount of research on the influence of different representations in cartography and remote sensing across multiple scales (Hillsman & Rhoda, 1978). For instance, Veregin (2000) and Cheung and Shi (2004) study the effect of the simplification of lines (e.g. roads) in maps and their propagation to positional displacement.

Usery et al. (2004), Booij (2005), Chaubey, Cotter, Costello, and Soerens (2005), Ling, Ehlers, Usery, and Madden (2008), and Pogson and Smith (2015) investigated the effects of input rasters using different resolutions and found a significant difference in the outcome of a spatial analysis. For example, the study of Chaubey et al. (2005) indicates that the resolution of digital elevation models affects the output of a hydrologic spatial analysis.

In another relevant study, Ruiz Arias, Tovar Pescador, Pozo Vázquez, and Alsamamra (2009) estimated the solar irradiation of several locations with digital elevation models of different resolutions (100 m vs. 20 m grid). A strong point of Ruiz Arias et al. (2009) is that predictions were evaluated against independent, accurate measurements from meteorological stations, essentially obtaining the difference against true data. The results showed that the improvement of the resolution of the Digital Elevation Models (DEMs) was minuscule in comparison to the error induced by the spatial analysis.

In 3D geoinformation, the influence of different representations has mostly been evaluated in urban planning and related domains in which the visual impression is the main decisive factor (Ellul & Altenbuchner, 2013; Hannibal, Brown, & Knight, 2005; Herbert & Chen, 2015; Kibria, Zlatanova, Itard, & Dorst, 2009; Rautenbach, Çöltekin, & Coetzee, 2015).

There are related analyses comparing the results of a spatial analysis utilizing data of the same area modeled at different LODs (Besuievsky, Barroso, Beckers, & Patow, 2014; Biljecki, Ledoux, & Stoter, 2017; Billger, Thuvander, & Wästberg, 2016; Brasebin, Perret, Mustière, & Weber, 2012; Deng, Cheng, & Anumba, 2016; Ellul, Adjrad, & Groves, 2016; Fai & Rafeiro, 2014; Neto, 2006; Peronato, Bonjour, Stoeckli, Rey, & Andersen, 2016; Strzalka, Monien, Koukofikis, & Eicker, 2015). In general, research has demonstrated that in certain spatial analyses the benefit of a finer LOD may be overestimated and even detrimental, as the potential small benefit may be countervailed by cost and complexity. A shortcoming of such analyses is that most of these are performed on only two LODs, and on real-world data, thus preventing the focus on the representation-induced error alone. Moreover, some of the datasets used, are generated from different sources, containing different magnitudes of errors. Furthermore, the analyses do not put the derived error into perspective – the error induced by the LOD may seem significant, but if other errors are added to the equation, it could turn out to be irrelevant.

An aspect that cannot be ignored is how the spatial detail is modeled, as there are multiple valid representations of a feature that are of the same detail and scale. For instance, on a coarse scale a city may be represented as a point. The placement of the point (e.g. centroid vs. a point placed at the most populous area of the city) may affect the calculation of the distance between two cities. Such examinations have been the subject of many research papers (Cromley, Lin, & Merwin, 2012; Hillsman & Rhoda, 1978; Miller, 1996; Murray & O'Kelly, 2002). In this research, we do not separate the two, but instead we use the most common modeling approaches (e.g. median height of the roof structure is selected as the elevation of the top surface of LOD1 models), based on the conclusions of Biljecki, Ledoux, Stoter, and Vosselman (2016).

Acquisition-induced error

The realization of the specification intrinsically introduces errors. Several different types of errors can be introduced during the acquisition, which propagate through a spatial analysis in different ways, depending on the context. For instance, the standard ISO 19157 on geographic data quality defines several types of errors, for example, completeness, topological, positional, thematic (attribute), and temporal errors (ISO, 2013). Most of these have been the focus of various analyses, for example, thematic error (Veregin, 1995).

In this paper we focus on positional error, which has been the subject of several error propagation analyses (Beekhuizen et al., 2014; de Bruin, Heuvelink, & Brown, 2008; Heuvelink, Burrough, & Stein, 1989). For example, Goulden, Hopkinson, Jamieson, and Sterling (2016) investigate the propagation of positional error in point clouds to the calculation of various topographic attributes, such as slope, aspect, and watershed area. Griffith, Millones, Vincent, Johnson, and Hunt (2007) and Zandbergen, Hart, Lenzer, and Camponovo (2012) observe the influence of positional error in geocoded addresses on various administrative use cases such as the assignment of houses to census blocks, and allocation of students to their nearest public schools. Hartzell, Gadomski, Glennie, Finnegan, and Deems (2015) estimate the propagation of positional error from terrestrial laser scanning to the measurement of snow volume.

Positional errors are omnipresent in GIS and they have been much discussed in the literature, hence they do not require a lengthier introduction.

Multiple error propagation analyses

Virtually all error propagation analyses focus on one type of error. In contrast, our analysis considers two types of errors. To the extent of our knowledge, we are aware of only a few analyses that investigate multiple types of errors, that is, multiple error propagation analyses. Moreover, not all of these investigate the error propagation simultaneously, that is, in most cases a separate analysis is made for each type of error.

Shi, Ehlers, and Tempfli (1999), Couturier et al. (2009), and Tayyebi, Tayyebi, and Khanna (2013) investigate the combined effect of positional and thematic error in land cover maps. Rios and Renschler (2016) mix probabilistic and fuzzy positional error models to expose the error in the detection of the contamination of groundwater. Lee, Chun, and Griffith (2015) examine the propagation of error in blood lead-level measurements of children and the locations of their residential addresses. Their analysis exposes the error in the aggregated results per census block.

An effort that is to some extent related to ours is the recent paper of Leao (2016) which examines the tradeoff between spatial resolution and the quality of climate data. The analysis is performed on 2D raster data. A characteristic of the data is that due to interpolation the relationship between resolution and quality is not consistent, and the paper seeks to find the balance between the two.

Analysis-induced error

A spatial analysis per se is not faultless: no matter how accurate and detailed a dataset we have at our disposal, there will usually be error induced by the imperfection of the empirical models and other factors behind a spatial analysis. Usually these differences are due to external factors that are not influenced by geographic information. Here we do not focus on such error, but we deem that this type of error has been overlooked in related work, and it is important to acknowledge its presence by dedicating a few paragraphs to it. A few examples follow:

(1) Geographic information may be used to predict the energy demand of households based on the morphology of a building, among other factors (Bruse, Nouvel, Wate, Kraut, & Coors, 2015; Nouvel et al., 2015; Swan & Ugursal, 2009). However, such predictions are sensitive to building occupation, energy consumption habits and lifestyles of occupants, and differences in insulations of homes; which are regularly not included in the modeling (Guerra-Santin & Itard, 2010; Ioannou & Itard, 2015; Majcen, Itard, & Visscher, 2013).

(2) 3D city models are frequently used to estimate the solar irradiation of building rooftops for determining the suitability of installing photovoltaic panels (Bremer, Mayr, Wichmann, Schmidtner, & Rutzinger, 2016; Lukač, Seme, Dežan, Žalik, & Štumberger, 2016). However, estimation models are empirically derived, and use other data which are prone to errors (e.g. cloud cover data). Besides the imperfection of the empirical models, each year is subject to different atmospheric conditions. All of these factors are beyond the scope of the quality of geographic information and are typically ignored in a GIS analysis.

(3) Based on the distribution of building stock, population estimation can be conducted. However, different factors such as vacant buildings and variable apartment densities due to socioeconomic aspects affect the accuracy estimates. Again, these factors are typically not included in an analysis and hence invoke an analysis-induced error.

While spatial analyses have been extensively researched, surprisingly they are rarely validated using true data, most likely due to a variety of reasons. Foremost, the true value of a specific phenomena is frequently absent as the exact value is typically unobservable (Heuvelink & Brown, 2016), or it is not feasible to acquire it, as large-scale validation utilizing more accurate data is expensive and laborious. For instance, in order to validate the analysis-induced error of solar potential estimates it would be required to gauge the output of a myriad of solar panels or to place instruments (e.g. pyranometers) on many roofs (Erdélyi, Wang, Guo, Hanna, & Colantuono, 2014; Jakubiec & Reinhart, 2013; Lukač, Seme, Žlaus, Štumberger, & Žalik, 2014). Hence, when such scarce studies are available, they are limited to small sample sizes.

Another reason for the infrequency of such studies is that the output of a spatial analysis using real-world data already contains different types of errors (see again Figure 3). Determining the analysis-induced error is difficult because it may not be possible to isolate other errors from the error budget. For instance, Freitas, Cristóvão, Amaro e Silva, and Brito (2016) assess the performance of using lidar data to predict the sky view factor, by comparing measurements with estimates derived with other methods. Here it is not possible to deduce whether the performance improves if the density of the point cloud (akin to scale or LOD) is augmented. Furthermore, there is no proof that the measurements that represent the ground truth are of an order of magnitude more accurate to warrant their role. Researchers working on other spatial analyses such as estimating the residential stock also cite this problem (Boeters, Arroyo Ohori, Biljecki, & Zlatanova, 2015).

This topic is important to keep in mind when assessing the propagation of positional and LOD errors.

Data and method

Experiments

The method used in this research is straightforward: a 3D building model in multiple LODs is intentionally degraded with simulated acquisition errors in repeated iterations (Monte Carlo simulation; an approach widely used in tasks such as this one (Xue et al., 2016)), and is used in multiple spatial analyses. The Monte Carlo method was used because of its convenience when spatial analyses are too complex to trace the uncertainty propagation analytically (Yeh & Li, 2006).

The results of the spatial analyses using the erroneous models are compared with the results of their error-free counterparts.

However, each of these steps is hampered by several barriers, primarily lack of data and lack of suitable spatial analyses. Besides technical details, in this section we present solutions to these challenges.

Representations

The concept of LOD in 3D GIS is somewhat different from the one in cartography and imagery (Biljecki, Ledoux, Stoter, & Zhao, 2014). In rasters, detail is simply quantified as the size of pixels (spatial resolution). Hence it is straightforward to line up different representations (e.g. orthophotos with pixel sizes of 10, 20, and 50 cm). In maps, the LOD is tied to scale: each scale series (e.g. 1:10k, 1:20k, and 1:50k) contains a certain amount of detail that ought to be mapped. However, in 3D city modeling the distinction is not as straightforward, due to the digital environment and involvement of different features, which results in different understandings of measuring detail.

In this paper we focus on the most prominent LOD categorization, the one found in the OGC CityGML standard (Gröger & Plümer, 2012). The standard defines LODs that progress in geometric detail and semantic information: LOD1 is a block model, LOD2 is a generalized model containing basic roof shapes, and LOD3 is an architecturally detailed model containing openings and facade detail (Kolbe, Gröger, & Plümer, 2005).

These LODs roughly reflect the different outcomes of different acquisition techniques (Biljecki, Ledoux, & Stoter, 2016b). For instance, LOD1 is usually produced by extruding footprints (Ledoux & Meijers, 2011), LOD2 can be acquired automatically from lidar data (Kada & McKinley, 2009), while LOD3 usually involves substantial manual work or is obtained after conversion from architectural sources (Donkers, Ledoux, Zhao, & Stoter, 2016). Examples of buildings modeled in these LODs will be exhibited in the next sections (Figures 4 and 5).

LOD3 marks the boundary of 3D GIS, as data of finer detail are considered to belong to the Building Information Modeling arena. Moreover, LOD3 models are rarely used in spatial analyses and we are not aware of any LOD3 model produced on a large spatial scale due to excessive costs of acquisition. Hence LOD3 is a good choice as ground truth reference data.

Selection of the spatial analyses

3D city models may be used for a variety of purposes, for instance, estimating the noise pollution at a location (Stoter, de Kluijver, & Kurakula, 2008), assessing visibility (Koltsova, Tunçer, & Schmitt, 2013), and analyzing thermal comfort (Nichol & Wong, 2005). However, not all of the outcomes of these analyses result in a quantifiable result, which is a prerequisite for error propagation analyses as it provides a measure to

Figure 4. Two datasets of different LODs overlaid on an orthophoto (LOD1 – blue and LOD2 – yellow) of the same area but of different accuracy. The models are produced in separate campaigns, resulting in different positional accuracies and varying completeness. Data (c) Swiss Federal Office of Topography.

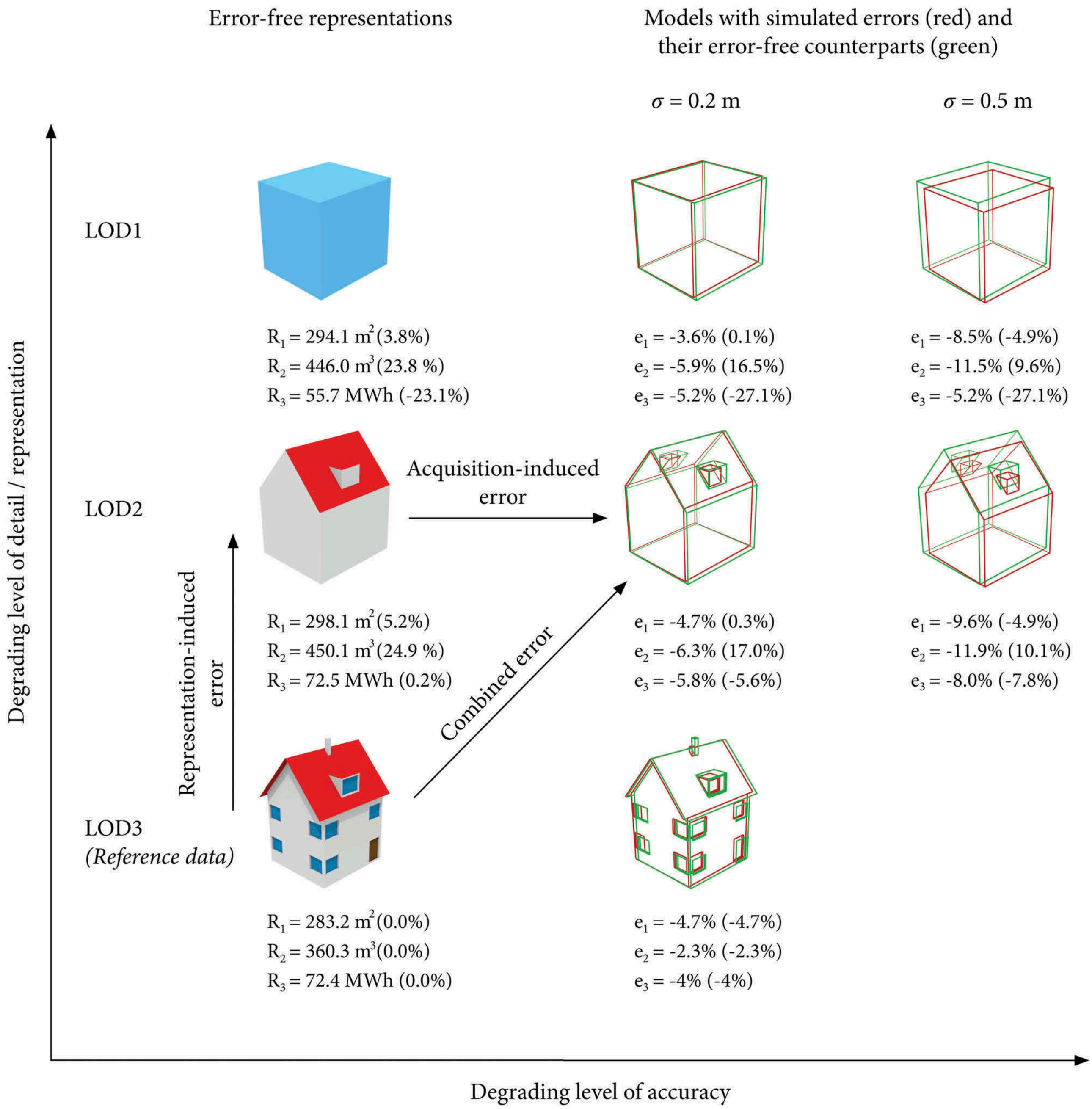

Figure 5. Illustration of a subset of the experiments and results of one simulation on a sample of one 3D building model disturbed according to two different levels of accuracy ($\sigma_{x,y,z} = 0.2$ and 0.5 m). The results from the three considered spatial analyses are listed in the figure, and two types of errors are given for each case: the acquisition-induced error, and the combined error (in parentheses). This particular case is interesting because in the first two spatial analyses the LOD1 model inherently results in less inaccurate results than the LOD2 model.

compare results. Several spatial analyses appear to derive ambiguous results, notwithstanding the challenges of how to quantify them. For instance, 3D city models may be used for different kinds of visibility analyses, and therefore quantified in different ways: binary (a point in space is visible or not), distance (range) of visibility, the area or volume visible from a point, number of buildings that have visual access to a feature, and population that has visual access to a point (Cervilla, Tabik, Vías, Mérida, & Romero, 2016; Grassi & Klein, 2016; Wrózyński, Sojka, & Pyszny, 2016; Yu et al., 2016). Each one has different error propagation behavior (Biljecki et al., 2017).

The error propagation task is further impeded by the fact that capabilities of existing software are limited. In analyses such as this several building models are disturbed in hundreds of simulations, resulting in a large abundance of datasets that have to be analyzed. Thus the capability to automatically and repeatedly load the data and analyze the results is essential, so studies such as this one entail the creation of custom software. Moreover, the large number of model runs entails an increased computational cost, which can be substantial in some spatial analyses. For example, estimating the wind flow (as in Figure 2) may take a few hours of computational time. Since Monte Carlo simulations involve repeated disturbances of data and re-running spatial analyses for hundreds if not thousands of simulations, this can result in substantial simulation time. Hence, it is important to select spatial analyses that are feasible for Monte Carlo simulations.

We select the following three spatial analyses that we have found to be appropriate for our research:

(1) *Area of the building envelope*. 3D city models are suitable to calculate the area of the exposed building shell. This information is useful in planning energy-efficient retrofitting, estimating indoor thermal comfort and energy consumption, analyzing the urban heat island effect, and further similar applications (Chwieduk, 2009; Deakin, Campbell, Reid, & Orsinger, 2014; Eicker, Nouvel, Duminil, & Coors, 2014; Maragkogiannis, Kolokotsa, Maravelakis, & Konstantaras, 2014; Nouvel, Schulte, Eicker, Pietruschka, & Coors, 2013; Perez, Kämpf, & Scartezzini, 2013; Previtali et al., 2014; van der Hoeven & Wandl, 2015).

(2) *Gross volume of a building*. Estimation of the volume of buildings is useful in various analyses, such as urban planning (Ahmed & Sekar, 2015), estimating the stock of materials in the building sector (Schebek et al., 2016), waste management (Mastrucci, Marvuglia, Popovici, Leopold, & Benetto, 2016), population estimation (Lwin & Murayama, 2009), quantifying development densities (Meinel, Hecht, & Herold, 2009), energy estimation (Eicker et al., 2014; Nouvel et al., 2013), and predicting thermal comfort (Chwieduk, 2009; Perez et al., 2013).

(3) *Solar irradiation of rooftops*. Estimating the insolation (solar exposure) of buildings is one of the most prominent spatial analyses using 3D city models. The solar irradiation of rooftops is calculated based on the orientation and inclination of roofs, among other factors, which involve spatial operations that are all prone to errors. This application has wide applicability, for example, assessing the suitability of installing solar panels (Szabó et al., 2016), preventing overheating (Nichol & Wong, 2005), and predicting house prices (Helbich, Jochem, Mücke, & Höfle, 2013). Typically the annual exposure to sun is estimated and quantified in kWh/m^2 (Nault, Peronato, Rey, & Andersen, 2015). We take into account solar irradiation because it is an interesting use case, where the coarsest LOD considered performs poorly because it only has flat roofs, hence it is subject to large systematic error. Due to computationally quite intensive estimations we do not take shadowing into account. However, the work of Biljecki et al. (2017) demonstrates that the LOD does not have a significant influence on shadow estimation.

A particularity of our spatial analyses is that they are prone to positional errors that affect *deformable* objects (whose relative position can vary under uncertainty – for example, the width of the modeled building may be smaller than it is in reality). However, the analyses considered here is not affected by errors related to positional error in *rigid* objects (e.g. displacement of a building by 20 m due to processing errors does not alter its volume). For more on this topic the reader is referred to Heuvelink, Brown, and van Loon (2007).

Procedural generation of the data

While it is reasonable to assume that using real-world data in the analyses is the best option, it is important to be aware that real-world data are also burdened by acquisition errors. As a result, there is a risk of varying levels of quality and inconsistencies in the realization of the specification. For instance, the LOD may not be consistent across the dataset. In addition, real-world data have several other shortcomings making their use implausible. First, real-world 3D datasets are hard to perturb due to complex geometries, and they usually contain topological errors, not only preventing spatial analyses but also making the simulations more difficult and prone to inconsistencies. Second, multi-LOD datasets are rare (data producers usually produce data in one representation), and when they are available, they are usually sourced from a different lineage; such integration may induce additional errors or other types of errors (and is therefore not comparable) (Figure 4). Third, an alternative to producing data in multiple LODs would be to take a fine LOD and obtain coarser counterparts with generalization. However, data modeled in a fine LOD are seldom available, and when available these are usually restricted to a small area, insufficiently large and diverse for experiments. Moreover, while research in 3D generalization is plentiful (Xie & Feng, 2016), there is no implementation we are aware of. The absence of data in fine LODs would make experiments less interesting and would result in lack of a reference to gauge the results.

All of the above shortcomings can be solved by the use of procedurally generated data as procedural modeling offers a sterile and controllable environment suited for this problem. Procedural modeling involves generating geographical data based on a set of customized rules to represent a specific setting (Müller, Wonka, Haegler, Ulmer, & van Gool, 2006). Their importance in GIS is growing (Tsiliakou, Labropoulos, & Dimopoulou, 2014), for instance, to enhance existing data (Müller Arisona, Zhong, Huang, & Qin, 2013). In general, synthetic data have already been in use in GIS when experimenting with error and spatial analyses (Besuievsky et al., 2014; Burnicki, Brown, & Goovaerts, 2007; Erdélyi et al., 2014), and were proven powerful in testing diverse configurations.

An advantage of procedural models is that they can be generated in a straightforward manner and for a large area, and such an approach minimizes inconsistencies. Furthermore, the nature of procedural modeling warrants that the models are produced according to a strict specification which introduces no additional errors.

In this paper, we use a procedural modeling engine developed by Biljecki, Ledoux, and Stoter (2016a), which generates 3D diverse building models, and can generate a fine representation in LOD3, which we use as reference data. The engine generates a diverse configuration of buildings (from small sheds to tall buildings), warranting a variation of the input dataset.

Perturbation and grades of accuracy

3D city models may be derived with different approaches involving diverse technologies, each with different capabilities when it comes to the accuracy. Hence, it is important to investigate different magnitudes of positional error (standard deviation σ).

In our approach, we simulate positional error by degrading the geometry of a 3D city model with values sampled from a normal probability distribution function with standard deviation σ, which is in line with related work (Ben-Haim, Dalyot, & Doytsher, 2015; Brown & Heuvelink, 2007; Xue et al., 2016). The vertices of the 3D model are disturbed while retaining right angles to mimic common acquisition approaches of the data, such as photogrammetric mapping.

Our approach assumes that there is no correlation in the errors in different dimensions. We follow the assumption of uncorrelated errors in coordinates. 3D city models are often acquired in different acquisition campaigns (e.g. footprints are acquired with a geodetic survey, while the elevation of the building is acquired with airborne laser scanning). However, we acknowledge that correlated errors may influence the outcome of the analysis, as demonstrated by Navratil and Achatschitz (2004).

With the exception of satellite platforms (Duan & Lafarge, 2016; Toth & Jóźków, 2016), researchers regularly report submeter accuracy of 3D acquisition techniques (Jarząbek-Rychard & Borkowski, 2016; Kabolizade, Ebadi, & Mohammadzadeh, 2012; Mårtensson & Reshetyuk, 2016; Rottensteiner et al., 2014; Wang, Kutterer, & Fang, 2016). Hence, we consider positional accuracy in the range of 0–1 m in 10 cm increments resulting in 11 error classes. Taking into consideration multiple accuracy classes also helps in understanding the impact that increasing the error of the input has on the error of the output.

Because of the integration of data from different sources and the nature of acquisition methods, another point that we consider is the varying level of accuracy in the planar and vertical coordinates ($\sigma_{x,y} \neq \sigma_z$). While this is an inherent property of 3D acquisition techniques such as laser scanning (Gil de la Vega, Ariza-López, & Mozas-Calvache, 2016; Goulden et al., 2016; McClune, Mills, Miller, & Holland, 2016), the varying accuracies are especially emphasized in cases such where building footprints and heights were derived in separate measurements, for example, footprints from ground measurements and heights guessed from the number of storeys or with another method of incomparable accuracy. In such cases the difference between planar and vertical accuracies may be substantial, so for each of $\sigma_{x,y}$ and σ_z we combine 11 classes resulting in 121 independent accuracy classes. LOD3 is an exception as the perturbations were carried out up to $\sigma = 0.3$ m, as in reality the error is not larger than that.

Implementation

We generated a dataset of 100 3D building models in CityGML and perturbed these in 1000 iterations using Monte Carlo simulation, according to 121 accuracy classes resulting in 12.1 million cases to be analyzed. The methodology is described in Biljecki et al. (2015).

An example of a part of the simulations is shown in Figure 5. The simulations and the spatial analyses took several weeks. During the simulations, there were some occasions with excessive acquisition-induced errors, causing the realization of data containing topological errors. Our implementation includes a built-in validator according to international standards in GIS (Ledoux, 2013), therefore simulations that had topological errors were discarded to avoid the introduction of inconsistencies other than positional errors.

Results and discussion

Due to the large number of results we specifically focus on the most important findings. We present the results graphically in plots and tables, and describe them in the text. Furthermore, in order for a direct comparison of results between different spatial analyses, we present the errors in percentages of the true value.

Representation-induced errors

Table 1 shows the magnitude of errors induced by the representation. Not surprisingly, the findings show that LOD2 is a better choice than LOD1 in all three spatial analyses, as it resembles the abstracted phenomena in more detail. However, it is visible that in the first two spatial analyses the difference between the two is relatively small. Hence, it might not be justifiable to acquire a finer model. LOD2 may come at a significantly higher cost but for a marginal improvement.

Table 1. Representation-induced errors in the three considered spatial analyses.

	RMSE in spatial analyses [%]		
Representation	Envelope	Volume	Solar
LOD1	7.9	3.7	14.2
LOD2	7.4	0.0	3.4
LOD3	0.0	0.0	0.0

The results for the computation of volume are interesting: LOD2 conceptually derives the same volume as LOD3, because the details brought by LOD3 (e.g. windows, facade details, awnings, chimneys) do not bring any difference to the computation of volume. Hence,

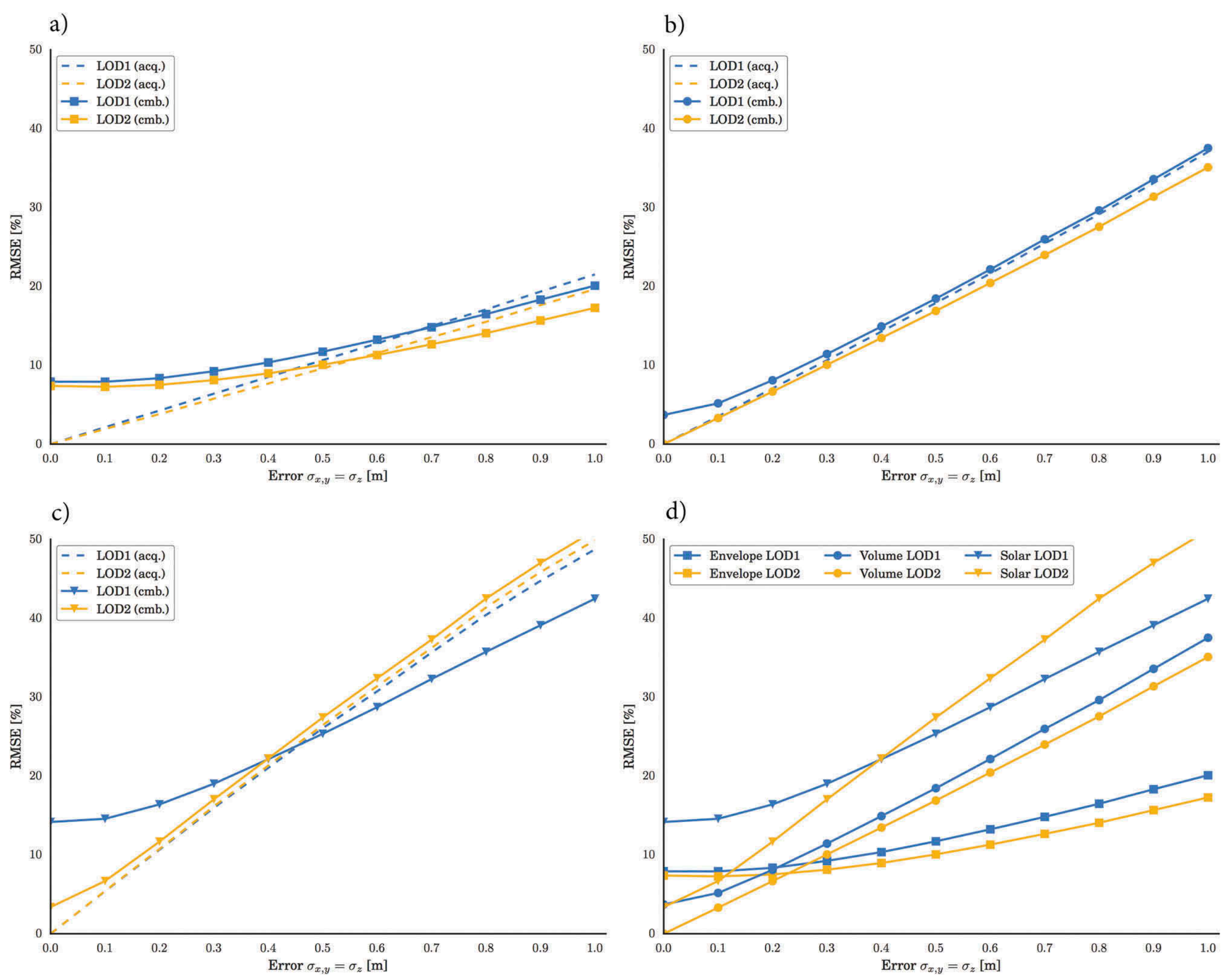

Figure 6. The propagation of varying positional error per each spatial analysis. The results indicate different behavior of each spatial analysis, preventing a generalized conclusion.

Table 2. Comparing errors (%) of two datasets with opposite qualities: a fine detailed (LOD2) model acquired with poor accuracy, and a coarse model (LOD1) acquired with higher accuracy.

	LOD1 $\sigma = 0.2$ m			vs.	LOD2 $\sigma = 0.5$ m		
Spatial analysis	R	A	C		R	A	C
Envelope	7.9	4.3	**8.4**		7.4	9.6	**10.1**
Volume	3.7	7.1	**8.1**		0.0	16.9	**16.9**
Solar	14.2	10.7	**16.4**		3.4	26.6	**27.5**

Key: R–Representation-induced error, A–Acquisition-induced error, C–Combined error.

The solar spatial analysis exhibits a paradox: initially the representation-induced error is very large since most of the roof shapes inherently significantly deviate from the real situation. However, due to the simplicity of the representation, the acquisition-induced error is much smaller than with LOD2.

ignoring acquisition errors at this point, it appears that LOD3 does not bring any benefit over LOD2 when it comes to the computation of gross volume.

Acquisition-induced errors

The results shown in Section Representation-induced errors indicate the magnitude of error if the models were (theoretically) acquired without acquisition errors. This section first considers the effect of positional errors in isolation. These effects are visualized in the dashed lines of Figure 6, for each spatial analysis separately.

The results indicate that the error propagates linearly in all three analyses, but that it has a different impact on the final result. For instance, the error induced by acquisition scenario $\sigma_{x,y} = 0.4$ m/$\sigma_z = 0.2$ m for the three analyses is 6.6%, 12.6%, and 20.8%, respectively.

The propagation of positional error is similar between LODs in all three spatial analyses. However, notice that in the first experiment the error for LOD1 (dashed blue line) is larger than that of LOD2 (dashed yellow line), which is not the case for the third spatial analysis, while in the second experiment they coincide. This result suggests that positional error affects different LODs in different spatial analyses in different ways.

Two errors in combination

Figure 6 shows the combination of the two errors as solid lines. In addition, the plot in the bottom right shows the combined errors jointly for the three spatial analyses for comparison. The representation-induced error is also provided in the plots: this is the case where $\sigma = 0$.

The results suggest that the combined effect of the two error sources is not additive but is much more complex than that. The reason has to be studied in further research. The results also indicate that LOD2 is in most cases better than LOD1 by a thin margin, which means that despite the added positional error, the finer LOD2 still offers a slight benefit over the coarser LOD1.

However, the propagation of error in the third experiment gives unexpected results. LOD1 has an unfavorable starting point (the representation induces gross errors owing to flat rooftops), but eventually at $\sigma = 0.5$ m it surpasses the accuracy of the analysis with LOD2, probably owing to the more complex geometry of LOD2. A second unexpected result occurs in the first experiment (envelope area): the acquisition error (dashed line) is larger than the combined error (solid line), for both LOD1 and LOD2. These results indicate the presence of a systematic error.

Recall the dilemma discussed in the introduction in regard to using a dataset of a finer LOD but of lesser accuracy in contrast to the inverse situation. In our experiments an LOD1 acquired with $\sigma = 0.2$ m is a much better choice than the finer LOD2 acquired with poorer accuracy ($\sigma = 0.5$ m); see Table 2 for comparison of all three considered spatial analyses.

Influence of differing planar and vertical error

To retain the simplicity of the presentation, the errors so far have been considered with equal magnitudes ($\sigma_{x,y} = \sigma_z$). This section analyses the propagation of varying error magnitudes in the planar and vertical coordinates.

The behavior for all three experiments is similar, both for LOD1 and LOD2. We therefore only present plots for the combined error in LOD2: see Figure 7.

It appears that the varying levels of planar and vertical accuracies have different impacts on the considered spatial analyses. The insights into the impact of planar and vertical accuracies, as shown in Figure 7, may guide choosing the proper acquisition approach that warrants that the obtained 3D city model yields results with an error lower than a certain threshold.

For all analyses, planar error has a larger effect than error in the vertical coordinates. However, the degree of such influence differs, and this behavior is mostly exhibited in the estimation of solar irradiation.

Influence of the building form

We noticed that errors (both in relative and absolute terms) substantially depend on the morphology of buildings. We therefore divided the buildings into four quartiles based on their volume. Figure 8 shows the behavior of errors for each quartile in each spatial analysis and different type of error.

These plots clearly show that when it comes to relative errors, they are larger in smaller buildings. However, in absolute terms the behavior of errors is opposite: the errors increase with the increase in the building size. The small

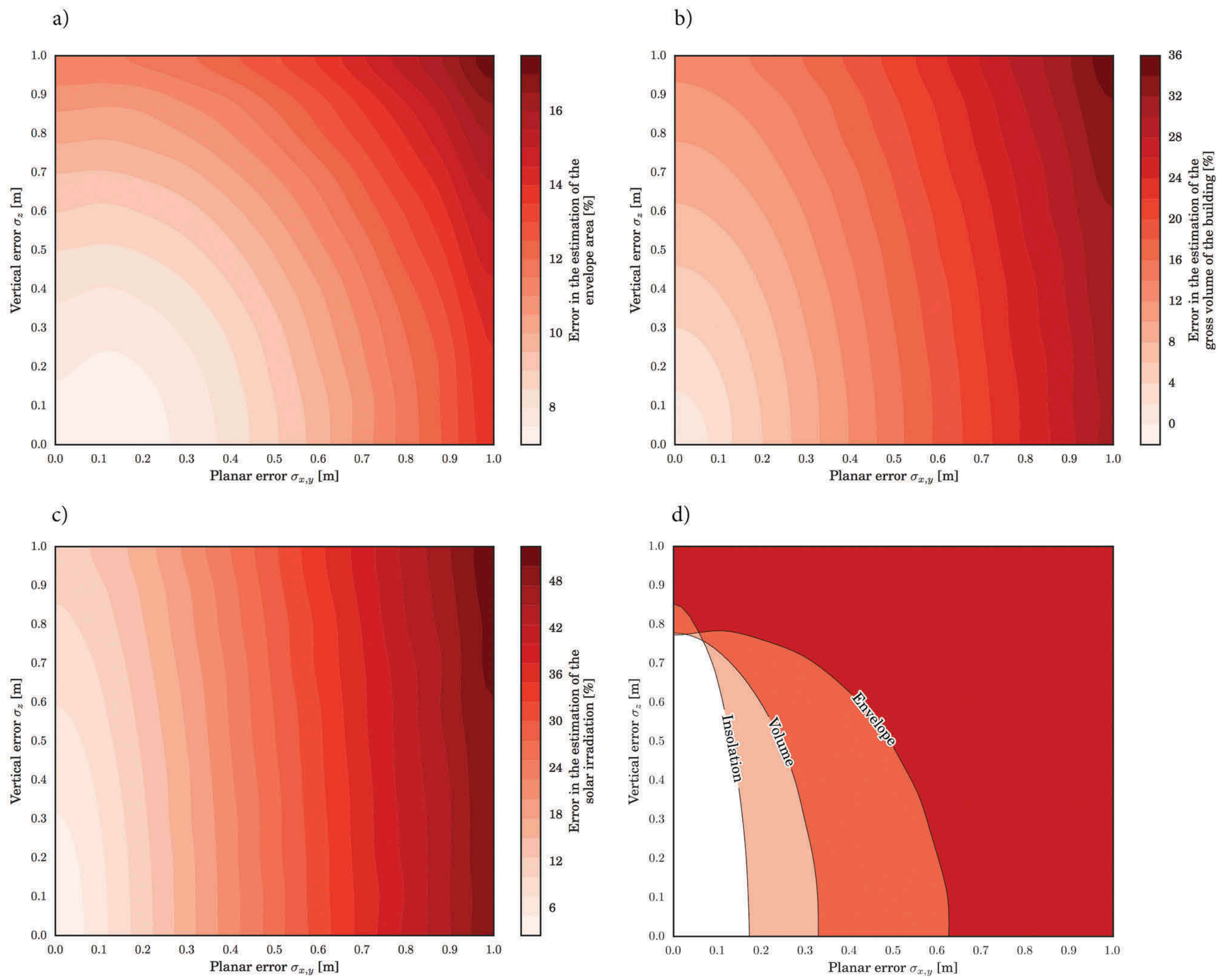

Figure 7. Contour plots showing the influence of variable accuracy levels onto the error of the three spatial analyses for LOD2. Note that the color ranges vary among plots. The bottom right plot exposes the differences in error propagation by showing the sensitivity of the spatial analyses at a certain threshold (value of 10% RMSE).

exception in the third experiment (right plot in the bottom row; showing different order for Q3 and Q4) is caused by the varying degrees of insolation of roof surfaces. That is, rooftops with smaller areas may have a higher amount of solar irradiation than larger rooftops, so that rooftops of smaller buildings may have a larger absolute error in solar irradiation than rooftops of larger buildings.

These results imply that the outcome of analyses such as these also depend on the base dataset that is used, primarily because these are driven by the morphology of the buildings. In 2D this topic has been investigated by Berk and Ferlan (2016), pointing out that the size and the shape of a parcel may characterize the propagation of error when calculating its area.

General discussion and key findings

A major finding of this paper is that taking care of the accuracy of the data is more important than striving to produce data of a finer LOD, at least in the spatial analyses that we considered.

LOD1 and LOD2 are significantly different models – they are acquired with different approaches with the latter being more complex to produce. Despite such distinction, when used in the first two spatial analyses (envelope area and gross volume) the difference in the performance of LOD1 and LOD2 is so small that it appears that in many cases it is not worth acquiring an LOD2. For instance, when an LOD1 is used in the estimation of envelope area the RMSE is 7.9%, and LOD2 shaves off the error to 7.4%, which is practically negligible. In such cases it may be more favorable to use the coarser LOD1–they are simpler to acquire, they have a smaller storage footprint, and they are faster to process. Hence the increased costs for obtaining the finer LOD2 may not always be justified.

The leap between LOD2 and LOD3 is much larger than between LOD1 and LOD2. Hence it would be

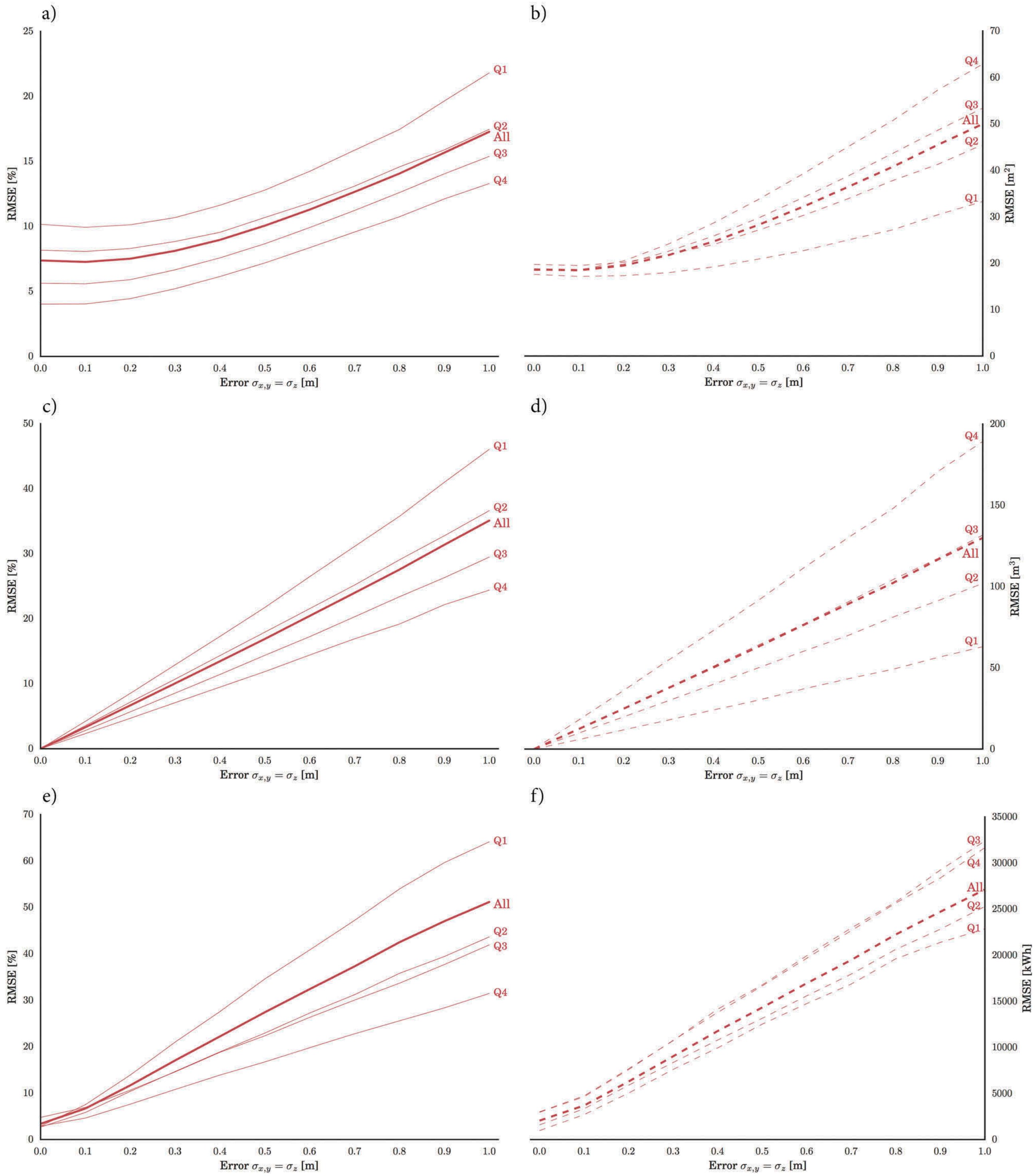

Figure 8. Dissecting the combined errors: building size influences the results. The plots on the left side show the errors in percentages, while the plots on the right express the errors in the units of measurements.

beneficial to strive toward the large-scale production of LOD3. However, such an advancement does not yet appear imminent: while many LOD3 models of limited spatial extent have been produced and used in various analyses, their production will remain expensive and wide coverage will not be feasible for some time.

Taking into account the realization of the 3D models, positional error has a substantial effect on the errors of the quantities estimated in this study (building envelope area, gross volume, and solar irradiation of rooftops). In these cases, positional error dominates over the error induced by a coarse LOD. A fairly small error of 0.2 m outweighs the benefit of a fine LOD, and our results indicate that in two of the three considered spatial analyses, an LOD1 acquired with $\sigma = 0.2$ m is a much better choice than the finer LOD2 acquired with poorer accuracy ($\sigma = 0.5$ m). However, this is not the case for the solar irradiation of rooftops use case, in which LOD1 cannot be used due to its systematic shortcoming of having flat roofs. A paradox in this spatial analysis is that at poorer accuracies the error by LOD1 is smaller, due to the high sensitivity of solar irradiation estimation to positional errors.

The combined error cannot be simply decoupled into representation- and acquisition-induced error because they do not sum up. This is also obvious from the errors given in Figure 5, see for instance the case of LOD1 disturbed with $\sigma = 0.5$ m. Such result indicates that there are interactions between the errors, as they are not additive.

These experiments provide insight into designing specifications of 3D city models while taking into account the intended spatial analyses; the increase of detail does conceptually bring some benefit, but in practice, when models are realized (and hence affected by the imperfection of measurement) the benefit is countervailed by acquisition errors. As a consequence, the representation benefit between LOD1 and LOD2 becomes negligible.

The results also show that each spatial analysis has different behavior. Hence, it is important to consider each spatial analysis separately in experiments. As the work also suggests that spatial analyses have a substantially different behavior when compared to each other, data suitable for one spatial analysis may be of little value for another.

Real-world data offer little room for manoeuvre in experiments such as ours, hence we suggest researchers in related work resorting to procedurally generated models as their benefit in such analyses is underestimated and unparalleled. By using a procedural approach we were able to obtain models that are burdened only with the errors we want (e.g. we did not have to worry that other errors such as completeness could have compromised our analysis), and by inducing specific errors in a simulation we could isolate the influence of different errors. On the other hand, it should be noted that synthetic data might not always properly represent real-world data.

A limitation of our study is that we do not address the inability of software to take advantage of finer LODs. For example, in theory there could be a substantial difference between using LOD1 and LOD2 for estimating noise pollution (e.g. sloped roofs henceforth available in LOD2 may bounce the noise in a different way resulting in substantially different predictions, see Van Renterghem and Botteldooren (2010) which demonstrates that roof shapes are an important factor to consider in noise pollution estimations). However, the software may simply not be capable of taking advantage of the more detailed geometry of the rooftops (e.g. it considers only the bounding box of a building), and will give the same results as for LOD1.

Looking into this matter is certainly our priority for future work, and for this, we plan to follow the approach of Ruiz Arias et al. (2009). In their analysis involving rasters of multiple resolutions, they compare the results from multiple software packages and conclude that some software solutions lead to larger error propagation. In our analysis we have dealt with volume and area computation, which should not differ between different software packages (when we programmed the two we compared the results from another software for validation). However, this is probably not the case for the solar irradiation use case, especially because due to computationally intensive calculations it was not possible to take into account shadowing effects. In the context of this paper, the absence of shadowing is an example of a factor in the analysis-induced error.

Another aspect that we did not address, is that it is not always possible to separate the LOD and positional errors. Sometimes they are *fused*, for example, a complex building footprint may be simplified as a rectangle, and at the same time its geometry may be displaced due to generalization rules. That is, because in coarser scales such a rectangle would encompass the building (e.g. a bounding box) and the vertices would not correspond across multiple LODs (Arroyo Ohori, Ledoux, Biljecki, & Stoter, 2015). In 3D GIS, LOD1 and LOD2 are usually realized using the same footprints (Biljecki et al., 2016b), hence this does not affect much of our work and while we do not contend that we have a solution here, it is certainly important to acknowledge the occasionally blurry distinction between representation and acquisition errors.

Finally, to maintain a reasonable level of simplicity, this study did not take into account potential systematic errors such as projection errors (Chrisman, 2016; Girres, 2011), which may – together with the errors caused by ignoring terrain elevation – affect the building footprint dimensions (Berk & Ferlan, 2016).

Conclusions

LOD and positional accuracy are arguably some of the main ingredients in the metadata of most GIS datasets. In this paper we performed a combined (multiple) error propagation analysis that demonstrates how much error is induced on top of error caused by using different LODs. Our main contribution in the subject of error propagation is that we take into account simultaneously multiple types of errors, and we consider multiple spatial analyses. While errors may be induced at many different points in a typical GIS process (Gahegan & Ehlers, 2000; Lunetta et al., 1991), we deem that acquisition- and representation-induced errors are the most prominent ones, hence we focused on them.

The main conclusions of this paper are: (i) the positional error is in many cases significantly more dominant than representation error; (ii) as a result of this, in a lot of instances there is no need to go for a high representation level (LOD3) because the added value will vanish due to acquisition error; (iii) the two considered errors are not additive; (iv) error propagation is case specific, hence there is no general conclusion that can be drawn for all spatial analyses; and (v) when disturbed with larger positional errors a lower representation may give better results in a spatial analysis than a higher representation disturbed with the error of the same magnitude.

This paper also suggests that LOD in 3D GIS and scale in 2D GIS are related but different concepts. Scale in 2D is mainly associated with accuracy and precision, with less detail on small-scale maps, while for 3D that relation does not always hold. In 3D data of coarse detail at a high precision/accuracy level is common, regardless of the spatial scale.

Plans for future work are to investigate the behavior of the propagated error in other spatial analyses, and to investigate the behavior of correlated errors as these may significantly impact the error propagation (Navratil & Achatschitz, 2004). Correlations between positional errors can be incorporated in a probabilistic model but will require stationarity assumptions to limit the number of model parameters (Heuvelink et al., 2007). Furthermore, we intend to consider other types of acquisition error common in geoinformation, such as completeness, which next to positional accuracy is commonly cited as a principal acquisition-induced error (Ariza-López & Rodríguez-Avi, 2015a; Demir, 2015). Finally, a continuation of the work would be to consider the bigger picture of errors and analyze their consequences by associating them to a meaningful application. For example, the impact of a 10% error in the estimation of volume depends on the intended use of the derived information. If the volume was used to determine property tax, an error of 10% would not be acceptable. However, if it was used to estimate the volumetric building stock of a complete neighborhood for heating demand estimation or for population estimation, on a large scale such error might be less severe as the errors would probably cancel out in the sum.

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