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How does data accuracy influence the reliability of digital viewshed models? A case study with wind turbines

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A B S T R A C T

Viewshed analysis is a GIS tool commonly used in a number of research and practical spatial analyses. Input data and their spatial uncertainty are important aspects affecting analysis reliability. Given that inappropriately selected input geodata can produce imprecise visibility models and as a result cause incorrect spatial decisions, quantifying the effect of this uncertainty on resulting visibility models is important for the models' subsequent use. The objective of our study was to evaluate the suitability of digital surface models with varying levels of detail (a LiDAR-based model and models based upon vector data at differing scales) for simple (binary) viewshed analysis of wind turbines (three wind parks each containing 3–6 turbines). Visibility models based upon this input data were compared with actual visibility from 150 control points at random locations. The study results confirmed the prediction that the viewshed model based on more precise input data corresponded more closely to reality. Moreover, our study is the first to demonstrate that only the number of false positives (where the model predicts that an object is visible while in reality it is not) depended on input data precision, while input data did not affect the false negatives. In addition, all vector-based models had far more false positives than false negatives, while the opposite was true for the LiDAR-based model.

When we considered the same number of modeled and actually visible wind turbines as a model's matching of reality, there were matches at 83.6–93.7% of control points (95% confidence interval) for the LiDAR-based model. For models based upon vector maps of various scales, the intervals were 68.4–82.2% (1:10,000), 59.1–74.2% (1:25,000), and 48.1–63.9% (1:500,000). We recorded false positives in 6 cases with the LiDAR-based model and 26, 39, and 59 cases, respectively, for vector-based models.

1. Introduction

Viewshed analysis is a GIS tool in standard use for more than two decades (e.g., Fisher, 1992; Nagy, 1994; Sansoni, 1996) to perform numerous scientific and practical tasks. Such analyses enable detection of surfaces that are or are not visible from one or more observation locations, and, inasmuch as visibility is symmetrical, identification of surfaces from which certain objects on the Earth's surface are visible. The wide range of possibilities for its use include, for example, planning telecommunications tower placement (De Floriani, Marzano, & Puppo, 1994); constructing military structures (Smith & Cochrane, 2011), observation towers, and tourist routes (Chamberlain & Meitner, 2013; Lu, Zhang, Lv, & Fan, 2008); selecting sites for new photovoltaic power plants (Fernandez-Jimenez et al., 2015); applications in archaeological research (e.g., Paliou, 2011) and landscape planning (De Montis & Caschili, 2012); and tagging landscape photographs in combination with volunteer geographic information (Brabyn & Mark, 2011). Throughout the time that visibility analyses have been used, their limitations and inaccuracies have been discussed. Fisher (1992) noted two mistaken assumptions in visibility analysis: first, that the input digital elevation model is accurate, and second, that viewsheds constitute a Boolean phenomenon. This author (Fisher, 1992, 1993, 1994, 1995, 1996) as well as a number of later studies (e.g., Chamberlain & Meitner, 2013; Fernandez-Jimenez et al., 2015; Ogburn, 2006) dealt with the possibilities and algorithms of fuzzy viewshed modeling and visual magnitude, the result of which is a raster giving the probability of visibility or degree of visibility, respectively, and not merely binary visible/nonvisible values. Such algorithms enable incorporation of the studied object's distance from the observer, the observation's solid angle, perspective, and so

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forth. Recent studies have suggested further procedures for individualizing the viewshed that take into account such aspects as solid angle, defined by Domingo-Santos, de Villarán, Rapp-Arrarás, and de Provens (2011) as the surface area of the observer's retina covered by a given object, and the vertical dimension of terrain, which combines the slope of the visible surface, difference in elevation between the observer and the visible terrain, and relative aspect of the terrain in relation to the observer into a new Vertical Visibility Index (Nutsford, Reitsma, Pearson, & Kingham, 2015). One field with particularly apparent efforts to bring visibility analyses closer to reality and human perception is that of assessing the visual impact of wind turbines (WTs). Here, in addition to the aforementioned improvements in GIS algorithms and creation of specialized software (Manchado et al., 2013), we encounter a number of other evaluation techniques. These include verbal questionnaires, photo-based questionnaires, questionnaires based on computer simulation, and questionnaires completed while viewing actual landscapes (for a review of these methods' use, see Molnarova et al., 2012). Research designed in this way (e.g., Betakova, Vojar, & Sklenicka, 2015; Bishop & Miller, 2007) conveys information on distances from the observer at which WTs have the greatest visual impact, frequently in combination with such other parameters as the number of WTs, rotor movement, and the landscape's scenic beauty. These results provide a solid foundation for planning studies focused on GIS viewshed analysis quality and selecting specific parameters (landscape character, number of WTs in the study area, viewshed distance, and so on).

Based on the number of articles published, we can state that the study of those phenomena affecting visibility in terms of humans' subjective perception and improvements to GIS viewshed algorithms constitute a rather frequent topic of research (e.g., Bishop & Miller, 2007; De Montis & Caschili, 2012; Domingo-Santos et al., 2011; Germino, Reiners, Blasko, McLeod, & Bastian, 2001; Kim, Rana, & Wise, 2004; Manchado et al., 2013). Very few papers, however, have dealt with the effect of the spatial precision of input geodata on the reliability of results from visibility analyses, even though some authors had previously noted a potential effect (Fisher, 1992; Huss & Pumar, 1997) and input geodata's influence on the results of spatial analyses has been demonstrated many times in other fields. For example, a potentially analogous situation can be seen in ecology, where geodata's spatial uncertainty is an established concept and its effect on analytical results is a known fact (for review see, e.g., Barry & Elith, 2006; Moudrý & Šímová, 2012). In the case of visibility modeling, the accuracy of the resulting model, whether based on a basic viewshed algorithm or its more advanced variants, potentially depends on the precision of the input digital surface model (DSM), which combines the accuracy of a digital terrain model with the correct elevation and spatial determination of objects within the model, particularly vegetation and structures. Examples of rare studies dealing with input data precision were presented by Lake, Lovett, Bateman, and Day (2000) and Sander and Manson (2007), who focused upon modeling structures as vertical obstacles to visibility. In order to create a DSM, data at differing spatial scales are generally used and are based upon both remote sensing and ground mapping. Probably the most precise inputs are LiDAR-based surface models (see Castro, García-Espona, & Iglesias, 2015; Lake et al., 2000; Murgoitio, Shrestha, Glenn, & Spaete, 2014). At the same time, LiDAR data is also the most expensive as well as the most demanding in terms of processing the original point cloud into a raster or triangulated surface (a triangulated irregular network). Moreover, it frequently is unavailable for a given study location. A question thus arises as to the degree to which LiDAR-based surfaces can be replaced within visibility analysis by surfaces created through such approaches as using contour lines with elevation values and objects with expertly assigned height, such as polygons of forests boundaries and structure footprints, as well as a question as to the effect that the scale of the data used has on the reliability of visibility analysis.

Evaluating whether a viewshed model has identified visibility in accordance with reality, and therefore whether the tested algorithm and/or input data used are appropriate for the modeling purpose, requires comparison with a control model, a control simulation, or a control dataset. Various methods are used for model verification, including to compare the visible area with a reference visibility model (Lake et al., 2000; Sander & Manson, 2007), photographic documentation, or 3D visualization (Germino et al., 2001; Maloy & Dean, 2001). A rarely used approach is direct comparison of modeled visibility with actual visibility in the field using visual control from predefined locations, as seen in the work of Meek, Goulding, and Priestnall (2013). Even though other authors have used direct determination of visibility in the field (Lang, Opaluch, & Sfinarolakis, 2014), they did not use it to compare a model with reality, but rather as the primary method to determine visibility. This was due presumably to their having insufficiently accurate input data for the purpose of their study. Maloy and Dean (2001) used viewpoints to obtain comparison photographs and not for direct visibility control.

The visual impact of WTs is a frequently discussed topic in connection with visibility analyses. Given that, to the best of our knowledge, the effect of input data on the reliability of such analyses has not been resolved, we directed our attention to this issue. The objectives of our study were to evaluate the suitability of DSMs with various levels of detail (a LiDAR-based DSM and DSMs based on vector data at differing scales) for simple binary visibility analyses of WTs at three wind parks and to quantify the extent to which visibility models based on these inputs matched reality. We focused on both the overall extent to which the visibility models matched actual visibility in the field and the structure of those errors occurring, i.e., the occurrence of false positives (where the model predicts that an object is visible while in reality it is not) and false negatives (where the model predicts that an object is not visible while in reality it is). We hypothesized that (i) the extent to which a digital visibility model matched reality would depend on the detail of input DSMs, with more-detailed DSMs recording higher match rates, and (ii) the probability of false positives and false negatives would not be equal in visibility models based upon surface models differing in precision.

2. Material and methods

2.1. Study area and input data

The study analyzed the visibility of WTs in the north of the Czech Republic (50°56′ N, 15°08′ E). The study area covering 300 km^2 is characterized by a wide range of elevations (200–1120 m a.s.l.) and closely related substantial heterogeneity of land cover. Homogenous spruce monocultures predominate at higher elevations and the percentage of forest stands diminishes with decreasing elevation in favor of agriculturally cultivated areas. The selected area therefore combines several landscape types which differ in terms of their conditions for visibility analysis. Within this broader study area, the evaluation focused on visibility in the surroundings of WTs at three wind parks, defined as a buffer with a radius of 5 km around each WT (see Fig. 1). These parts of the study area are characterized by undulating terrain with elevation varying between 211 and 723 m a.s.l. (see Fig. 2). Mean elevations and their standard deviations within individual wind parks are as follow: (1) 266 ± 36, (2) 436 ± 79, (3) 421 ± 50). Wind parks with more than one WT (3–6 per park) and the evaluation distance were selected in view of the findings by Betakova et al. (2015).

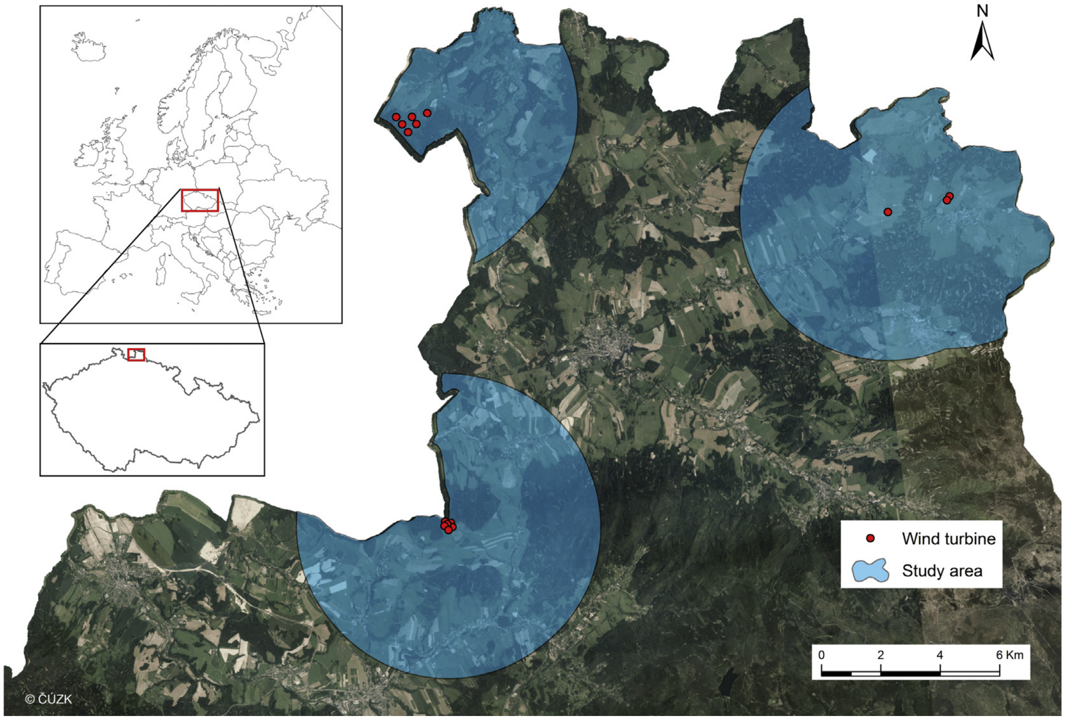

Fig. 1. Study area: 5 km buffers around WTs, north Czech Republic.

The study area also has available geodata that differ not only by the method of their acquisition but also in scale and accuracy. Thus, they represent a cross section of products available in the Czech Republic potentially usable for visibility analysis (see Table 1 for details). We used four input datasets, which can be divided into two categories: LiDAR-based and vector-based. The most modern and most accurate is the 1st Generation LiDAR-based DSM of the Czech Republic (LSM), acquired progressively across the entire Czech

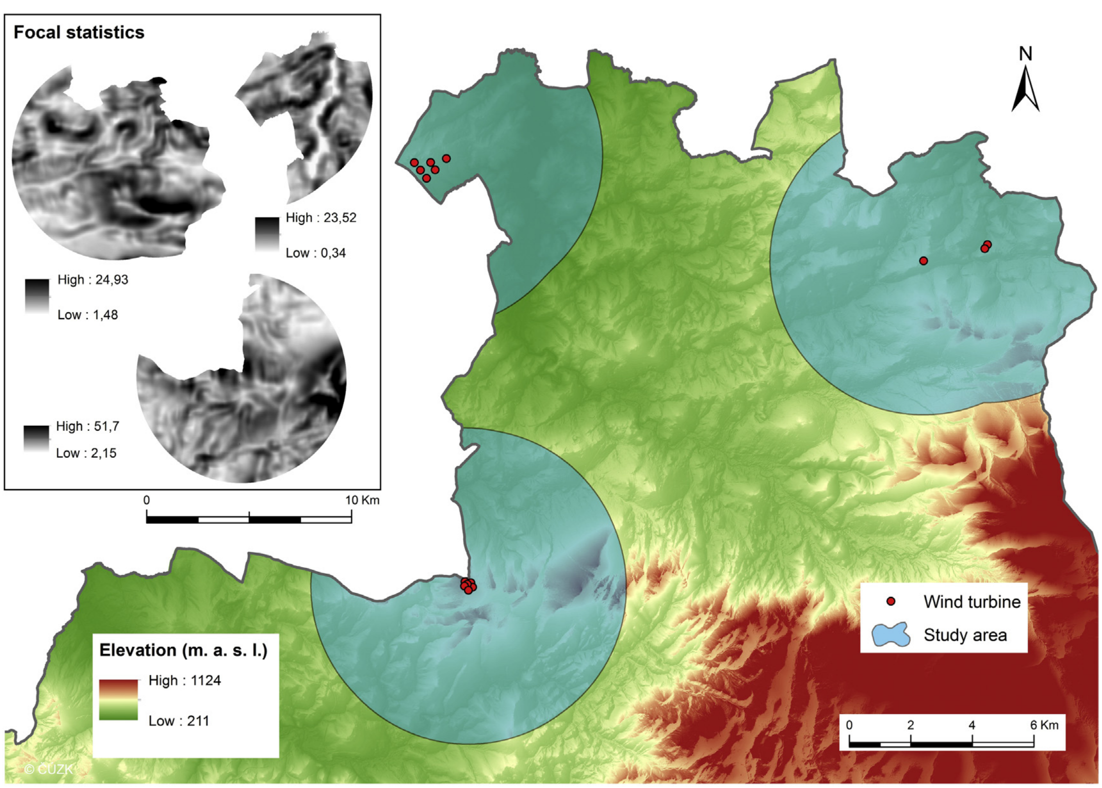

Fig. 2. Character of terrain within the study area. Focal statistics box describes terrain heterogeneity as standard deviation of elevation within 100 × 100 m moving window.

Table 1
Description of input datasets.

	Acronym within study	Czech acronym	Scale	Year of last update	Elevation accuracy	Planimetric accuracy	Contour interval	Data description
LiDAR-based dataset	LSM	DMP 1G	Density of elevation point cloud is 1–2 point/m^2	2010	0.4–0.7 m	0.4–0.7 m	No contour	Digital surface model represented by elevation point cloud from data acquired by aerial LiDAR covering part of the Czech Republic
Vector-based datasets	Map10	ZABAGED	1:10,000	2011	0.7–5 m	0.5–1 m	1 m 2 m 5 m[a]	Small-scale vector database covering the entire Czech Republic
	Map25	DMU 25	1:25,000	1998	5–10 m	0.5–20 m	5 m	Medium-scale vector database covering the entire Czech Republic
	Map500	ArcCR 500	1:500,000	2014	25–50 m	up to 200 m	50 m	Large-scale vector database covering the entire Czech Republic

[a] The interval depends on the character of the terrain.

Republic using airborne laser scanning. Vector-based datasets, within which we include standard, commonly used vector topographic maps, were represented within the study at various scales. Small-scale datasets are represented by a basic national map at a scale of 1:10,000 (Map10). Medium-scale datasets are represented by a vector topographical map called Digital Model of Area 1:25,000 (Map25). Large-scale datasets are represented by a vector geodatabase of the Czech Republic at a scale of 1:500,000 (Map500). In all vector-based datasets, elevation is displayed by contour lines and topography by polygons representing the footprints of individual objects on the ground.

2.2. GIS data processing

All GIS analyses were conducted using ArcGIS 10.2 software (ESRI, CA, USA). Inasmuch as it already has been known for nearly two decades (see, e.g., Dean, 1997) that use of DSMs yields more accurate results for the viewsheds than does use of DTMs, we created four DSMs as inputs for visibility analyses based on input geodata. For vector-based datasets, the DSMs were always calculated as a sum of rasters comprising the terrain (a digital terrain model [DTM]) and objects on the terrain (a digital object model [DOM]). For details, see Table 2. DTMs were calculated by interpolating contour lines using the Topo to Raster method. To create DOMs, we added the estimated elevation of objects on the ground to individual polygons representing said objects and rasterized the polygons. Inasmuch as the study area contains only rural structures mainly comprising houses, we selected the height of 8 m for structures. We assigned the height of 20 m to forest stands as an estimate of the dominant height of forest stands in the area based on data from forest management. Where other woody vegetation types, such as young forests and orchards, were distinguished in the datasets' attributes, we assigned them the height of 5 m, which on the basis of our experience is a typical average height for these features in the study area. The DSM from the LSM was created by resampling the triangulated irregular network supplied by the State Administration of Land Surveying and Cadastre into a regular raster. All DSMs were created at 5 m resolution.

We assigned the height of hubs (center of blade rotation) to points representing individual WTs according to the wind parks' technical documentation at 40–95 m (OFFSETA parameter) and observer height at 1.8 m (OFFSETB parameter). The Observer Points tool was employed for all visibility analyses. This tool identifies how many and which analyzed objects are visible from each raster location, and so the resulting rasters' pixel values include the number of WTs visible from a given location. Each wind park was analyzed independently and the resulting layers were clipped by the 5 km buffer zones. As it is reasonable to assume that observers in the forest or among structures cannot see anything, we set the value for all forests and built-up zones to zero. The final visibility analysis output is four digital visibility models: a) a LiDAR-based visibility model, b) a vector-based visibility model at 1:10,000, c) a vector-based visibility model at 1:25,000, and d) a vector-based visibility model at 1:500,000 (see Fig. 3 for an example).

2.3. Field data collection

The aim of the field data collection and subsequent analysis was to evaluate and compare how digital visibility models matched actual visibility in the field. Prior to the fieldwork, we designated 50 random control points for each wind park (i.e., 150 in total). To avoid spatial autocorrelation of visibility conditions, the minimum distance between control points was set at 200 m. Due to minimal visibility from forest and built-up zones, points were generated only in open areas. At the random control points, the visibility of WT hubs was examined by human eye. Field data were collected in April 2014 under constant meteorological conditions. The weather was clear to partly cloudy, temperatures ranged around 15 °C, and wind speeds were under 5 m/s. A portable GPS receiver (Oregon 450t, Garmin) was used to navigate to the coordinates of individual points.

2.4. Statistical analysis and evaluation of visibility models' reliability

To evaluate the accuracy of individual digital visibility models, we used as input data the values acquired by comparing visibility modeled at each control point and visibility determined at those

Table 2
Creation of four digital surface models (DSMs) from input datasets.

DSM		DTM – source elevation data		DOM – source planimetric data
LiDAR-based surface model	=	elevation point cloud		elevation point cloud
Vector-based surface model, 1:10,000	=	MAP10 (contour lines)	+	Map10: forest (20 m), orchard (5 m), built-up area (8 m)
Vector-based surface model, 1:25,000	=	MAP25 (contour lines)	+	Map25: forest (20 m), orchard (5 m), built-up area (8 m)
Vector-based surface model, 1:500,000	=	MAP500 (contour lines)	+	MAP500: forest (20 m), built-up area (8 m)

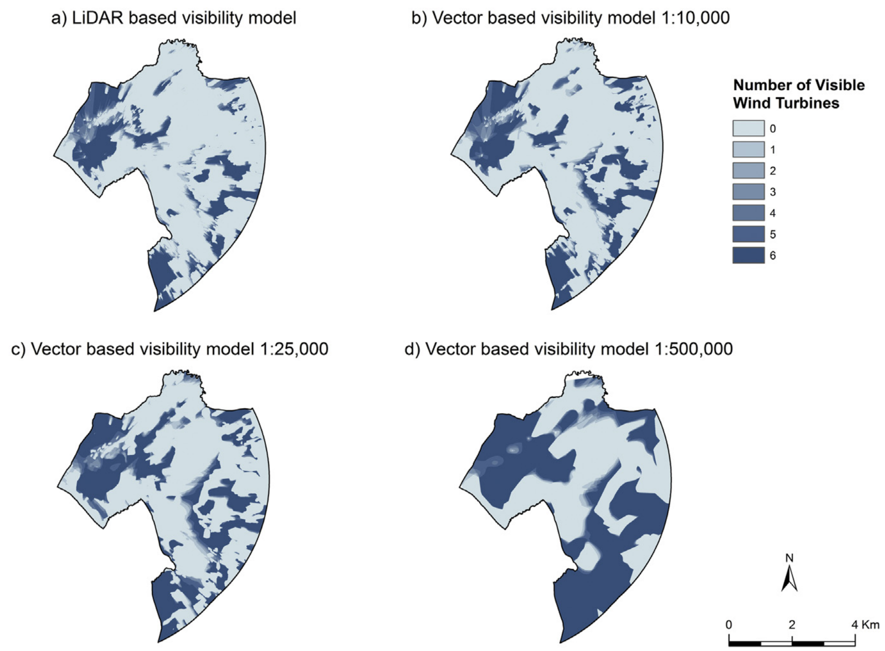

Fig. 3. Example of digital visibility models created from different DSMs (5 km buffer): (a) LiDAR-based visibility model, (b) vector-based visibility model at 1:10,000, (c) vector-based visibility model at 1:25,000, (d) vector-based visibility model at 1:500,000.

points by field examination. We predicted that the LSM-based model would best correspond to reality, followed (in order) by the models based on MAP10, MAP25, and MAP500. We worked in two ways with the research hypothesis that the rate-modeled visibility's match of reality would depend on input DSM precision. First (Section 3.1.), we focused on differences in the number of WTs visible at each control point in the model and in reality. We tested whether these differences between datasets were significant always for two "neighboring" datasets, that is to say for the LSM-based model with the MAP10-based model, the MAP10-based model with the MAP25-based model, and the MAP25-based model with the MAP500-based model. As the distribution of the tested values apparently differed from the normal distribution, we used the nonparametric Wilcoxon one-tail paired test. To compensate for multiple comparisons, we adjusted the significance level for the three tests from $p < 0.05$ to $p < 0.0167$ using Bonferroni correction.

The second way of comparing visibility models simulated situations when the absolute difference between modeled counts and actually visible counts of objects is not important for a landscape planning task and it is only important whether or not the model agrees with reality in a given way. These binary true and false values were defined in two ways. The first (Analysis 2a, Section 3.2.) worked with absolute accuracy, i.e., for the value to be true the same number of WTs must be visible from the control point as were given by the model. In the second case (Analysis 2b, Section 3.3.), the true value was defined less strictly, simulating such cases as when the visibility of even one WT would be considered as decreasing landscape beauty. For the value to be true, it was therefore enough for the model to determine that some (one or more) WTs were visible from the given location and for some actually to be seen or, alternatively, for no WTs to be visible in both the model and reality. In both cases, we used a test for homogeneity with a binomial distribution to test whether the probability of success (i.e., achieving a value of true) was identical for visibility models based on various datasets. We compared each set with all others using Holm's p-value adjustment method to compensate for multiple comparisons. All statistical analyses were done using R software (R Development Core Team., 2015).

For both definitions of the model's matching reality, we evaluated the character of errors, which is to say whether the studied datasets resulted in more false positives (a model overestimating visibility) or false negatives (a model underestimating visibility). For evaluation in accordance with Analysis 2a, we took into account the numbers of visible WTs. Cases where the model predicted more WTs than were seen in reality were considered false positives, and vice versa. According to error definition 2b, false positives occurred when the model predicted that at least one WT would be visible when none were visible in reality. Differences among datasets in terms of the representation of false positives were tested identically as were the total number of errors (test for homogeneity with a binomial distribution, Holm's p-value adjustment method).

3. Results

3.1. Analysis 1 — difference in the number of visible WTs

A comparison as to the number of visible WTs by which a model based on a given dataset differed from reality confirmed the prediction that visibility models created based on more-detailed input data correspond more closely to actual visibility. The model based on the LSM provided more reliable results than did the model acquired based on vector data at the most-detailed scale tested (i.e., MAP10, at a very strong significance level [$p < 0.0001$]). Pairs of models based on vector data at neighboring scales (i.e., MAP10 vs. MAP25 and MAP25 vs. MAP500) can be differentiated at a level of significance an order of magnitude weaker, although still very strong ($p < 0.001$). According to this comparison, the most precise visibility model was the one created from the LSM. Vector-based models' reliability was in accordance with the scale of the input data and the tested datasets yielded significantly different results.

3.2. Analysis 2a — model matches reality only when the number of visible WTs is the same in the model and in reality

As seen in Table 3, the number of true values (i.e., the number of control points at which the model agreed with reality according to definition 2a) diminished with decreasing precision of input data. In the case of the LSM-based model, there was disagreement at 11.3% of control points, while the model based on MAP500 disagreed in almost half of cases (44%). A similar trend results from mutual comparison of the reliability of models based on individual datasets using the test for homogeneity with a binomial distribution. The LSM-based model displayed significantly better results than did all vector-based models (the significance of the difference strengthened with decreasing vector dataset precision, see Table 4) and MAP10 was significantly better than was MAP500. For neighboring vector datasets, however, it cannot be said that the MAP10-based model provided results significantly different from those of the MAP25-based model; similarly, the reliability of the MAP25-based model did not differ significantly from that of the MAP500-based model.

3.3. *Analysis 2b — model matches reality if at least one WT is visible in the model and in reality or none are visible in the model and in reality*

The numbers of control points at which the model agreed with reality according to definition 2b are given in Table 5. The number of true values recorded follows the same trend as in the previous case, as a more-detailed input data scale corresponded to increased matching between modeled visibility and actual visibility. The LSM-based model failed to match reality at only 3.3% of control points, whereas the MAP500-based model disagreed in almost one-third of cases (28%). As seen in Table 6, mutual comparison of model reliability shows that some model pairs were not significantly different. For match definition 2b, where the model agrees with reality in more cases than it does for the stricter match definition 2a, the LSM-based model was not significantly more accurate than was the MAP10-based model. The MAP10-based model, however, yielded better results than did the models created using MAP25 and MAP500. We can therefore say that for this very loose definition of matching between reality and model it is apparently possible to replace LiDAR-based data with vector data at a similar scale (1:10,000). There nevertheless was still a clear trend that visibility analysis using more-detailed data provided more reliable results.

3.4. *Character of errors*

For both cases of model error definition (false values according to 2a and 2b), it is apparent at first sight that the number of false negatives recorded did not depend on input data precision (see Table 7). Regardless of how we defined true and false values for this study, the datasets used differed in the extent to which they overestimated visibility (false positives), with visibility overestimated more by models based on less-detailed data. All vector-based models, in addition, had more false positives than false negatives, while the opposite was true for the LSM-based model. The occurrence of false positives in individual models mostly differed significantly between neighboring models, although, as in the evaluation of the total number of true and false values, there were cases where differences in the reliability of models versus neighboring datasets were not significant (see Table 8 for *p*-values).

Table 4
Mutual comparison of reliability of visibility models according to match definition 2a (*p*-value of the test for homogeneity with a binomial distribution, Holm's *p*-value adjustment). Significant values are in bold.

	LSM	MAP10	MAP25
MAP10	0.0129		
MAP25	**<0.0001**	0.1507	
MAP500	**<0.00000001**	**0.0027**	0.1507

4. Discussion

The results indicate that the reliability of visibility models depended on the scale (level of detail) of input data. This trend was particularly clear when we calculated how the number of objects modeled as visible differed from the number actually visible (Section 3.1.). In controlling at 150 random points, the visibility models created based on the tested datasets differed with very strong significance. Therefore, if the purpose is to carry out a GIS viewshed analysis in such a manner as to minimize the difference between the number of objects visible in the model and in reality, then it is possible unequivocally to recommend using the most precise input data possible. Visual impact of WTs provides a good example of when large differences in modeled and actual numbers could be important, because, as demonstrated by Betakova et al. (2015), human perceptions of WTs depend on the number of objects seen. In the cases of some evaluation purposes for which GIS viewsheds are modeled, however, it may be more important to achieve a different type of match between model and reality. In our study, we worked with a scenario wherein the purpose of the analysis was not to minimize the difference in numbers, but rather to achieve the best possible match between the number of visible WTs in the model and in reality (2a), which is to say for the model to predict the correct number of visible objects. In contrast, the second scenario (2b) simulated a situation wherein matching numbers would not matter and the visibility of a single tall structure from the given location would be unacceptable (e.g., for a WT) or sufficient (e.g., for a radio mast). In both scenarios, therefore, match (true) and disagreement (false) between the model and reality were defined as binary. Such evaluation is more forgiving (in the case of Analysis 2b versus 2a) of model imprecision. In certain cases, therefore, the difference between neighboring datasets was not significant (e.g., based on the evaluation used in Analysis 2b, a LiDAR-based model can be replaced with a small-scale vector-based model without losing precision). However, the results still clearly indicate a trend that a more precise input surface model leads to a more reliable visibility model. Moreover, it is possible that significant differences between neighboring datasets would have been achieved by increasing the number of control points (i.e., by boosting the test's power). Therefore, the percentage of cases in which the model matched reality may be more interesting than is the significance of

Table 3
Relative reliability of visibility models as the number and percentage of cases where the model matched reality. Match definition 2a (the number of visible WTs must agree), number of control points $n = 150$.

Digital visibility model	True	False	Relative accuracy (%)	95% Confidence interval
LiDAR-based visibility model	133	17	88.7	83.6–93.7
Vector-based visibility model, 1:10,000	113	37	75.3	68.4–82.2
Vector-based visibility model, 1:25,000	100	50	66.7	59.1–74.2
Vector-based visibility model, 1:500,000	84	66	56.0	48.1–63.9

Table 5
Relative reliability of visibility models as the number and percentage of cases where the model matched reality. Match definition 2b, number of control points $n = 150$.

Digital viewshed model	True	False	Relative accuracy (%)	95% confidence interval
LiDAR-based visibility model	145	5	96.7	93.8–99.5
Vector-based visibility model, 1:10,000	138	12	92.0	87.7–96.3
Vector-based visibility model, 1:25,000	121	29	80.7	74.3–87.0
Vector-based visibility model, 1:500,000	108	42	72.0	64.8–79.2

Table 6
Comparison of reliability of visibility models according to match definition 2b (p-value of the test for homogeneity with a binomial distribution, Holm's p-value adjustment). Significant values are in bold.

	LSM	MAP10	MAP25
LSM			
MAP10	0.2062		
MAP25	**<0.001**	**0.0215**	
MAP500	**<0.00000001**	**<0.00001**	0.2062

the differences. Tables 3 and 5 indicate that this relative accuracy depended on both the dataset used and the specific definition of a match between the model and reality, although the trend was identical for both match definitions used. When selecting input data for GIS viewshed analysis, therefore, it is necessary to take into account not only the scale but also the purpose of the analysis and the relative accuracy that suffices for the given purpose in landscape planning or other field. This study together with papers by other authors (e.g., Berry, Fitzell, & Kidner, 2005; Maloy & Dean, 2001) can provide guidance as to the degree of accuracy that can be achieved in a given case. Nevertheless, specific accuracy values can, of course, differ under the effect of such factors as the configuration of the area of interest.

In terms of the distribution and structure of errors of individual models, vector-based models tended to overestimate, to generate false positives (i.e., to predict that an object is visible from more locations than it is in reality). In contrast, the LiDAR-based model predominantly generated false negatives, which is in accordance with the results of Meek et al. (2013). The occurrence of false negatives (i.e., predicting that a WT is not visible when it is visible in reality) was more or less identical for all models, whereas the number of false positives increased with decreasing input data detail (see Table 7). The dependence of the occurrence of false positives on input precision can be explained by a situation that models based on less-detailed datasets overestimate the extent of the total visible area (see Fig. 3). As suggested by Meek et al. (2013), who reported that a visibility model based on a LiDAR-based DSM originally contained predominantly false negatives but that the opposite situation was true after trees were removed, overestimation of visible area may be caused by inaccurate capture of objects on the ground in coarser-scale data, which causes fewer obstacles to visibility. The same effect may be caused by inaccurate capture of the terrain where the DTM is smother and models only large terrain obstacles. As visible area increases, however, nonvisible area within the study area diminishes and so the independence of the number of false negatives on data accuracy remains surprising in this explanation.

Based on the structure of errors, it can be said that, looking at model accuracy in terms of areas from which a tall structure is not visible, the models display no essential differences. In such analyses, LiDAR-based models can be replaced by vector-based models or a detailed vector-based model by a less-detailed one. Therefore, if for landscape planning purposes we are searching for suitable locations to place a tall structure (e.g., a WT) with the requirement that the structure have the least visibility possible, then it is not a serious mistake to use a large-scale model and place the structure in a location designated as nonvisible. However, we must take into account that using models based on less-detailed data may lead us to overlook potentially suitable locations or not find any suitable locations. In contrast, if a visibility analysis is used that focuses on visible areas based on less precise vector-based models, then visibility is substantially overestimated. This can affect preventive assessment of structure placement in relation to its visibility as well as scenic beauty, where a structure is evaluated as visible from a location with a high aesthetic value and so as having a negative effect even though it would not be visible in reality. Another example of inaccurate modeling of visible areas having an economic impact is the placement of radio masts.

A number of studies mention LiDAR as a theoretically suitable data source for modeling visibility (e.g., Lake et al., 2000; Sander & Manson, 2007) and attention is currently dedicated to quantifying the accuracy of LiDAR-based visibility models (Castro et al., 2015; Murgoitio et al., 2014). In general, we can say that our study confirmed the prediction that LiDAR-based datasets are the most suitable input data for visibility analyses in terms of accuracy and that their accuracy exceeds that of vector-based datasets commonly used in practice. This view is supported in particular by Analysis 1. If LiDAR data is not available for the study area, it is best to use DSMs created using vector data at the most-detailed scale possible. In contrast to vector-based models, the accuracy of LiDAR-based models does not depend primarily on input data scale but rather on the density of the elevation point cloud and the resolution of the DSM created from it (Castro et al., 2015; Murgoitio et al., 2014). The provider of the data product used in this study stated a point cloud density greater than 1 point/m^2 and the resolution of the DSM created was 5 m. The precision of our LiDAR-based model (88.7%) matches that of the model created by Berry et al. (2005) with a resolution of 1 m (88.5%). It is probable that if we were to decrease the pixel size of the DSM we would obtain an even more accurate visibility model, although this would increase computation time demands.

Table 7
Structure (number of cases) of false positives and false negatives in models based on individual datasets. 2a false positive: the model predicts more WTs to be visible than are in reality. 2b false positive: the model predicts at least one WT to be visible while in reality none are visible.

Digital viewshed model	False negative (2a)	False negative (2b)	False positive (2a)	False positive (2b)
LiDAR-based visibility model	11	5	6	0
Vector-based visibility model, 1:10,000	11	2	26	10
Vector-based visibility model, 1:25,000	11	5	39	24
Vector-based visibility model, 1:500,000	7	4	59	38

Table 8
Mutual comparison as to occurrence of false positives in models based on individual datasets. 2a false positive: the model predicts more WTs to be visible than are in reality. 2b false positive: the model predicts at least one WT to be visible while in reality none are visible. *p*-values, test for homogeneity with a binomial distribution, Holm's *p*-value adjustment. Significant values are in bold.

	LSM	MAP10	MAP25
2a false positive			
MAP10	0.011		
MAP25	<0.000001	0.036	
MAP500	**<0.0000000001**	**<0.00001**	0.064
2b false positive			
MAP10	**0.001**		
MAP25	**<0.0000001**	0.093	
MAP500	**<0.0000000001**	**0.00017**	**0.039**

The study was conducted in a study area with undulating relief where elevation ranged between 211 and 723 m a.s.l. It is possible that results could be slightly different in flat areas or in mountains with more dramatic relief. It might logically be assumed that merely slightly undulating landforms will require more detailed data to describe all elevation subtleties, while less detailed datasets could be sufficient for visibility in the mountains. To the best of our knowledge, however, such assumption has not yet been definitively proven and its testing would require systematically selecting a set of sample study areas varying in elevation range from flat land to mountains.

5. Conclusions

The results of our study confirmed the prediction that the reliability of GIS visibility analyses depends on the input data's level of detail. This dependence was demonstrated through the example of assessing the visibility of tall structures, specifically WTs. Considering the difference between the number of WTs visible from random control points as predicted by GIS visibility models and the number that are visible in reality, the most suitable data input is unequivocally a LiDAR-based DSM. The suitability of visibility models for which the input was surface models created using vector data (contour lines, woody vegetation, and buildings) can be ranked according to input data scale. A similar trend can be observed in the case of the binary evaluation of match and disagreement between modeled visibility and reality, although in certain cases the differences between individual datasets were not unequivocal and depended on how the model's match with reality was specifically defined.

In terms of the reliability of visibility models, none of the input datasets tested differed in the number of recorded false negatives (i.e., cases where the model underestimated WT visibility as compared to reality). Differences consisted in the numbers of false positives (i.e., overestimation of modeled visibility as compared to reality). For both definitions of true and false values, the LiDAR-based model provided the best results. All models based on vector data significantly overestimated visibility compared to the LiDAR-based model, and this overestimation was greater for data from less-detailed scales.

In conclusion, we can state that (i) as predicted, more-detailed input data led to more reliable visibility analysis results; (ii) the vector-based models used had more false positives, while the LiDAR-based model had more false negatives; (iii) only the number of false positives depended on input data precision, while the occurrence of false negatives was similar for all datasets used; and (iv) the trends determined are therefore valid also for various definitions of the models' matching of reality. Our conclusions are valid for analyses at a detailed evaluation scale.

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