A critical evaluation of visibility analysis approaches for visual impact assessment (VIA) in the context of environmental impact assessment (EIA)

Cilliers, D. [1*], Cloete, M. [1] , Bond, A.[2], Retief, F. [1], Alberts, R. [1], Roos, C. [1]

[1] Unit for Environmental Sciences and Management, North-West University, South Africa

[*] Corresponding author

[2] School of Environmental Sciences, University of East Anglia, Norwich Research Park, Norwich, NR4 7TJ, UK

A critical evaluation of visibility analysis approaches for visual impact assessment (VIA) in the context of environmental impact assessment (EIA)

Abstract

Visual impact assessment (VIA) concerns the identification and evaluation of the potential impacts that a proposed activity might have on the visual quality of a landscape and makes an important contribution to decision making in the environmental impact assessment (EIA) context. Visibility analysis is often used to assist in determining these impacts through a variety of approaches employing different techniques and data inputs. This paper identifies the visibility analysis approaches often used in VIA practice by reviewing a sample of VIA reports representing eleven (11) countries. The identified approaches were then evaluated for accuracy across differing landscapes through a total of 72 simulations. Analysis of variance was used to determine the sensitivity of the identified approaches to different variables within different landscape contexts. The type of digital elevation model (DEM) used was found to be the most significant variable affecting accuracy across all landscapes, while the technique used had some significance and resolution little significance.

Keywords

Visual impact assessment, VIA, EIA, Visibility analysis, Zone of theoretical visibility, Viewshed, Line of sight.

Highlights:

- Type of digital elevation model (DEM) used has a significant impact on the accuracy of visibility analysis results across all landscapes.
- The choice of DEM further has a significant effect on accuracy with digital surface models (DSM) resulting in the most accurate results across all landscapes.
- The technique used showed some significance while resolution had no significant impact on accuracy.

1. Introduction and aim

Anticipating and pro-actively managing possible harmful impacts associated with development proposals is an important objective of environmental impact assessment (EIA) (IAIA, 1999). Impacts should be identified and considered prior to decision making to ensure that adverse effects are avoided. These include not only impacts related to the biophysical and socio-economic environment, but also impacts affecting the aesthetic value of a landscape. Approaches for dealing with the assessment of the latter have been applied since at least the early 1970s (Smardon, 2016) and were formalised into what has become known as visual impact assessment (VIA) in the 1980s (Palmer, 2019). VIA is now commonly applied as an important specialist input to EIA and is often also referred to as landscape and visual impact assessment (LVIA) and can be defined as the process of determining the possible impacts of a proposed development or activity on the visual quality of a landscape (Feimer *et al*., 1979; Knight & Therivel, 2017).

Many regulators and institutions have drafted VIA guidelines (e.g., Landscape Institute, 2013; Oberholzer, 2005; AILA, 2018; HKEPD, 2019) describing techniques and approaches for use in VIA. One approach often mentioned in VIA Guidelines is the delineation of a so-called zone of theoretical visibility (ZTV) to support the impact assessment process. The ZTV, which can also be referred to as the zone of visual influence or the visual influence map (Knight & Therivel, 2017), represents the extent of the area from where a development proposal will potentially be observable. Delineating the ZTV is important because it is a necessary precursor to an evaluation of the impacts of a proposed development from specific viewpoints (Wood, 2000) that might be particularly important (e.g., from a popular footpath in a protected area, or looking towards a protected area). For some development types, where visual impacts are the major impact (*e.g.*, power lines), accurate delineation of the ZTV would be essential for developing an optimal routing strategy (Marshall & Baxter, 2002).

Different visibility analysis techniques can be used to determine a ZTV depending on factors such as landscape characteristics (Pardo García & Mérida Rodríguez, 2015) and availability of data (Bartie *et al.*, 2010; Nutsford *et al.*, 2015). Examples of such techniques are viewshed analysis, cumulative viewshed analysis, fuzzy viewshed analysis and line of sight analysis (Chamberlain & Meitner, 2013; Garnero & Fabrizio, 2015; Nutsford *et al*., 2015; Murphy *et al*., 2018). One commonality between all visibility analysis techniques is that they rely on a computer-generated digital elevation model (Bartie *et al*., 2010; Qiang *et al*., 2019) that represents the topographical characteristics of an area, to simulate theoretical visibility and determine a ZTV (Klouček *et al*., 2015; Kantner & Hobgood, 2016). Digital elevation models (DEMs) can be divided into two categories, namely, digital terrain models (DTMs), representing only the bare surface of the terrain, and digital surface models (DSMs), where surface features such as trees and buildings form part of the representation (Robert, 2018; Qiang *et al*., 2019). The type of DEM used directly influences the visibility analysis result, *e.g.*, theoretical visibility tends to be overestimated when based on a DTM which excludes surface features and their potential screening effects (Danese *et al*., 2011; Sullivan & Meyer, 2014; Verutes *et al*., 2014). Whilst this suggests that DSM should routinely be used in preference to DTM, the data are not always available to develop a DSM a high resolution, and there remains uncertainty over the extent to which a DSM can accurately portray screening effects due to assumptions needing to be made about the heights of different land cover elements. In addition to the type of DEM, the algorithm used to generate the DEM and the resolution at which this is done will affect the DEM's accuracy (Anile *et al*., 2003; Fisher & Tate, 2006) and the visibility analysis result. Finally, the terrain complexity, which concerns the relief and rugosity of the area being studied (Huaxing, 2008; Zhou *et al*., 2006), will also affect the creation of a DEM (Fisher & Tate, 2006) and subsequently the visibility analysis results. The use of visibility analysis to determine a ZTV is, therefore, affected by a multitude of factors. Although a great deal of work has been done on viewshed analysis methods and approaches (e.g. Klouček *et al*., 2015; Zhao *et al.*, 2013; Kim *et al.,* 2004), as well as different aspects of VIA (e.g. Palmer, 2019; Corry, 2012; Landenburg *et al.,* 2013; Takacs & Golden, 2019), apart from the work by Wood (2000), very little has been done on the use of visibility analysis within the context of VIA specifically. Although Wood (2000) evaluated the accuracy of some approaches through case studies, details on the types of visibility analysis approaches often used in VIA and the suitability of approaches across different landscape contexts remains vague. An understanding of how a variety of variables influence overall accuracy across different landscapes can help in the identification of the most effective approach for undertaking a visibility analysis, taking into account the availability of, or access to, different data sets. This paper therefore aims to provide recommendations for the approach to visibility analysis that practitioners should take in different contexts of landscape complexity and data availability. To do this, we build on the work by Wood (2000) by identifying and evaluating the approaches often used in VIA.

The following objectives inform the aim of the research:

- Objective 1: Identify visibility analysis approaches often used in the VIA component of EIA.
- Objective 2: Evaluate the accuracy of identified approaches and their sensitivity to key variables across different landscapes.
- Objective 3: Provide recommendations to practitioners on the appropriate visibility analysis approaches to use based in different landscape contexts and data availability circumstances.

To achieve this aim, the next section introduces key concepts pertaining to visibility analysis and its role in VIA, followed by a description of the method in section 3. The results of the research are presented in section 4, followed by recommendations is section 5 and finally, the conclusions in section 6.

2. The role of visibility analysis in VIA

VIA entails the part of the EIA process concerned with the assessments of landscape and visual impacts (Wilson, 2002) by considering and evaluating possible changes in the visual attributes of a landscape brought about by a proposed project (Manchado *et al*., 2014; Depellegrin, 2016). Once evaluated, the VIA can inform the EIA process to help avoid or minimise the potential negative effects of a development and, where appropriate, propose opportunities for landscape enhancement (Wilson, 2002). As mentioned, the VIA process is often supported by computer-based tools for conducting visibility analysis (Chamberlain & Meitner, 2013; Manchado *et al.,* 2014; Kim *et al*., 2004; Zhou *et al*., 2006), which, according to Manchado *et al*. (2014) is one of the most important analyses informing the VIA process.

2.1. *Defining visibility analysis*

Visibility analysis applies the principle of intervisibility (Manchado *et al.,* 2014) and, therefore, determines visibility through the principle of line-of-sight (LOS). For example, a straight line is generated between two points, and if at any point the line is obstructed, either by a landscape form or a surface feature, the target point is deemed not visible (Feng *et al*., 2015; Verutes *et al*., 2014; Zhao *et al*., 2013). One point represents an observer, while the other represents a target object for which visibility is determined (Verutes *et al*., 2014). During visibility analysis, the process described above is repeated numerous times for different observation and target points. Results are combined to generate what can be referred to as a viewshed or ZTV, that represents the areal extent from which a certain object will theoretically be visible (Feng *et al.,* 2015; Qiang *et al.,* 2019). Over the years, different visibility analysis techniques have been developed and although these techniques generally all rely on the LOS principle, they differ in the way visibility is presented (Llobera, 2007; Bartie *et al*., 2010; Domingo-Santos *et al.*, 2011; Chamberlain & Meitner, 2013; Nutsford *et al.,* 2015). Techniques and approaches relevant to this research are briefly discussed below.

2.2. *Selected approaches to visibility analysis that can be applied in ZTV determination*

2.2.1. *Line of sight analysis*

Although the LOS principle underlies most visibility analysis techniques, it can also be employed as a standalone method. The biggest difference between LOS analysis and approaches such as viewshed analysis is that it does not result in a ZTV, but rather determines visibility along a line that is connecting two points (Feng *et al.,* 2015; Verutes *et al.,* 2014). The line is presented as obstructed and non-obstructed sections, *i.e.*, sections from where a target will not be visible and sections from where it will be visible.

2.2.2. *Viewshed analysis*

Viewshed analysis is one of the most popular techniques used in visibility analysis (Nutsford *et al.*, 2015) and essentially identifies the cells in an input DEM from where an object will be observable. This is achieved by generating lines between target objects and the cells contained in a DEM. The line-of-sight principle is applied to determine whether a cell will form part of the ZTV or not (Pardo García & Mérida Rodríguez, 2015). The technique is often used in VIA (Möller, 2006; Miller *et al.,* 2011) and has been applied for various types of projects, *e.g.*, photovoltaic power plants (Fernandez-Jimenez *et al*., 2015), light pollution analysis (Verutes *et al.,* 2014), and land and marine-based wind park developments (Depellegrin, 2016; Klouček *et al.,* 2015).

2.2.3. *Cumulative viewshed analysis*

Cumulative viewshed analysis is based on the same principles as viewshed analysis but differs in that cumulative viewshed analysis combines the results from numerous individual viewsheds (Depellegrin, 2016), *i.e.*, it can be defined as the sum of individual viewsheds. When combined the resultant cumulative viewshed indicates the number of target objects that will be observable from a specific cell and not only whether the cell will be part of the ZTV or not (Llobera, 2003; Danese *et al*., 2011; Wheatley & Gillings, 2013). The areal extent of the ZTV generated through viewshed analysis will, therefore, be the same as that generated through cumulative viewshed analysis, with the difference being that the ZTV generated through a cumulative viewshed approach will reflect different levels of visibility. The technique is also frequently used in VIA, especially where the analysis involves multiple target objects (Depellegrin, 2016).

2.2.4. *Fuzzy viewshed analysis*

Fuzzy viewshed analysis includes a distance decay function to account for the loss of visibility over distance (Murphy *et al.*, 2018). It essentially goes one step beyond viewshed and cumulative viewshed analysis by indicating the probability that a cell falls inside a ZTV when considering distance decay (Loots, 1999). This inclusion of a distance decay function or a limit on visibility provides a more realistic representation of visibility, especially for observation points further away (Fisher, 1992; Murphy *et al.*, 2018).

3. Method

A mixed-methods design was employed to achieve the research aim and objectives as described below.

3.1. *Identify visibility analysis approaches often used in the VIA component of EIA (Objective 1)*

To determine which visibility analysis techniques are often used in practice, a sample of VIA reports were reviewed. A purposeful sampling approach was used, and an attempt made to access as many VIA reports as possible. VIA reports were sourced by searching keywords such as "Visual impact assessment", "Visual impact statement" and "Landscape and visual impact assessment" using the Google search engine. Regional settings were changed throughout in attempts to obtain reports from different countries, *e.g.*, the region was set to Australia and the keywords searched, then changed to Brazil and the keywords searched again. Where applicable, keywords were also translated into other languages, e.g., French for France, to find more reports. Only reports in which a ZTV was determined as part of the VIA and where details pertaining to the approach used were discussed, were considered for review. A total of 48 VIA reports from eleven countries, representing North America, South America, Europe, Africa, and Oceania were subsequently considered. The countries included were Argentina, Australia, Brazil, Canada, Chile, France, Ireland, South Africa, Spain, the UK, and the USA. The aim of the review was, however, not to do a country comparison, but to identify the approaches often used in practice to determine the ZTV, which were to inform Objective 2. These reports were not reviewed for quality, *i.e.*, no attempt to determine the quality of the analysis and assessment was made. The documents were reviewed for a description of the visibility analysis technique used, the type of elevation model used, and the manner and extent to which the screening effects caused by surface features were considered. Findings from the review were tabulated and analysed to identify the approaches often used in VIA.

3.2. *Evaluate the sensitivity of identified visibility analysis approaches to key variables across different landscapes. (Objective 2)*

The visibility analysis approaches often used in VIA studies were tested and evaluated across different landscape contexts. It was recognised that terrain models will be more accurate at higher spatial resolutions, but different resolutions were tested also to examine the sensitivity of the approaches to this aspect; this provides important understanding for the credibility of the method where high resolution (*e.g.* 5m) data sets do not exist. The different approaches were, therefore, tested across different landscape types and using different input datasets.

3.2.1. *Study areas representing different landscape types*

The analysis was conducted in South Africa as control points had to be captured and, therefore, the study areas had to be accessible to the researchers. To conduct the evaluation across different types of landscapes, three study areas with different landscape characteristics and varying levels of terrain complexity were identified. One prerequisite was that the three study areas had to contain similar features that could be used as observation objects during the analysis. Possible observation objects were identified based on the following criteria: (1) must be an existing object suitable for use in visibility analysis; (2) must be a significant feature in the landscape offering a visual presence due to its overall height and size; (3) must be a common object present in many landscapes; and (4) must be accessible. Based on these criteria, grain silos were decided on as suitable objects for use in the study. Silos (typically used to store grains like maize or wheat) were treated as the midpoints for the study areas and 20 km buffers were used to demarcate study area boundaries (Murphy *et al*., 2018). A combination of a topographic position index (TPI) and a compound terrain complexity index (CTCI) was used to characterise and identify three study areas offering varying degrees of overall terrain complexity summarised in Table 1. TPI is the difference between the elevation of a cell and the average elevation of the surrounding cells (De Reu *et al*., 2013; Nair *et al.,* 2018; Vinod, 2017) and classifies an area into different TPI classes which are valleys, lower slopes, flat slopes, middle slopes, upper slopes and ridges. For each study area the percentage coverage of each class was calculated. CTCI is a method that utilizes four terrain complexity indices to create a statistical representation of terrain complexity (Huaxing, 2008; Véga *et al.*, 2015). These are elevation range, elevation standard deviation, rugosity and curvature. Each index was calculated for the three study areas with higher values representing more complex terrain. The three areas showed significant variation in landscape complexity as seen in Table 1.

Table 1. Study areas

	TPI Slope classifications		CTCI	
Study area	*Slope position*	*Percentage of area (%)*	*Indices*	*Mean value*
Grootpan	Valley	6.18	Elevation range	0.21
	Lower slopes	9.00	Elevation standard deviation	0.07
	Flat slopes	70.85	Rugosity	1.00
	Middle slopes	0.29	Curvature	0.03
	Upper slopes	7.50	CTCI	0.01
	Ridge	6.19		
Syferbult	Valley	8.25	Elevation range	0.77
	Lower slopes	7.96	Elevation standard deviation	0.25
	Flat slopes	63.30	Rugosity	1.01
	Middle slopes	5.82	Curvature	0.14
	Upper slopes	6.94	CTCI	0.02

	Ridge	7.73		
Swartruggens	Valley	10.83	Elevation range	1.12
	Lower slopes	10.78	Elevation standard deviation	0.36
	Flat slopes	46.66	Rugosity	1.01
	Middle slopes	10.88	Curvature	0.22
	Upper slopes	10.07	CTCI	0.03
	Ridge	10.78		

3.2.2. *Data*

Four key datasets were used during analysis and included both secondary and primary data. The four datasets were (1) elevation data, (2) land cover data, (3) reference points, and (4) silo dimensions.

Elevation data used for deriving digital elevation models

Elevation data was sourced from the Chief Directorate: National Geo-spatial Information (NGI) national mapping agency of South Africa. Point heights and 5 m contour data were sourced for each of the three study areas. Point heights represented locations for which vertical height was surveyed by the South African Surveyor General's office and numbered 6,045 points for Grootpan, 1,513 points for Syferbult and 3,277 points for Swartruggens. Contours reflected the landscape at 5 m vertical intervals and was also surveyed by the South African Surveyor General's office. The point and contour datasets were projected into the WGS 1984 UTM Zone 35 S projected coordinate system and clipped to the applicable study area extent.

Land cover data

The South African National Land-Cover 2018 (SANLC 2018) dataset was obtained from the South African Department of Environment, Forestry and Fisheries (DEFF) for use in the study. The dataset contains 73 land-cover classes at a 20 m spatial resolution and has a reported accuracy of 90.14 % based on 6, 570 reference points (Thompson, 2019). The dataset was the most recent land-cover dataset available for the three areas. It was projected to the WGS 1984 UTM Zone 35 S projected coordinate system and clipped to each study area boundary. Fieldwork was conducted to determine the relative height of different features represented by land cover classes (Table 2). This information was later used to create DSMs representing not only elevation but also surface features. Relative height values were determined using a range finder and the Pythagorean theorem. A Nikon 550 rangefinder was used to determine the distance between the researcher and the bottom of a feature; additionally, the same procedure was repeated to measure the distance to the top of the feature. The researcher stood at a fixed location during both measurements, while maintaining a 90-degree angle between the observer and feature for the bottom distance measurement. The method presents some difficulty in certain areas, as the base of trees were not always visible as they would sometimes be screened by grass coverage. In the areas where these factors influenced measurements or the distance between the base and top measurement were insignificant, the average height values were estimated. Measurements for similar features were averaged to determine relative height values for each land cover class (Table 2).

Table 2. Relative land cover heights

Land cover classes	Relative heights allocated
Natural rivers, Natural pans, Artificial dams, Artificial flooded mine pits, Temporary unplanted (clear-felled) plantation forest, Herbaceous wetlands (currently mapped), Herbaceous wetlands (previously mapped), Natural rock surfaces, Dry pans, Eroded lands, Bare riverbed material, Other bare, Fallow land & old fields (bare), Residential formal (bare), Residential informal (low veg / grass), Residential informal (bare), Village scattered (bare & low veg/ grass combo), Village dense (bare & low veg / grass combo), Smallholdings (low veg / grass), Smallholdings (bare), Urban recreational fields (grass), Urban recreational fields (bare), Industrial Roads & rails (major linear), Mines: surface infrastructure, Mines: extraction pits, quarries, Fallow land & old fields (wetlands)	0 m
Low shrubland (other), Sparsely wooded grassland, Natural grassland, Fallow land & old fields (grass), Fallow land & old fields (low shrub)	1 m
Cultivated commercial permanent orchards, Commercial annual crops pivot irrigated, Commercial annual crops non-pivot irrigated, Commercial annual crops rain-fed / dryland, Subsistence / small-scale annual crops, Fallow land & old fields (bush), Residential formal (bush), Residential informal (bush), Smallholdings (bush), Urban recreational fields (bush)	2 m
Commercial	4 m
Contiguous low forest & thicket, Fallow land & old fields (trees), Residential formal (tree), Residential informal (tree), Smallholdings (tree), Urban recreational fields (tree)	5 m
Open woodland	8 m
Dense forest & woodland	10 m
Contiguous (indigenous) forest	12 m
Contiguous & dense plantation forest, Open & sparse plantation forest, Mine: tailings and resource dumps	15 m

Reference points for determining the accuracy of visibility analysis results

Reference points were collected to evaluate the accuracy of the different visibility analysis simulations. A total of 40 reference points from where an observer (eye level at 1.8m) faced the direction of the silo and the visibility of the silo was ascertained were collected for each study area. The 40 reference points for each study area were divided into three groups based on the following visibility and screening criteria:

- Fifteen (15) reference points from where the silo was fully visible;
- Fifteen (15) reference points from where the silo was not visible and screened because of the landscape form; and

- Ten (10) reference points from where the silo was not visible and screened by surface features also present in the land cover dataset.

The reference points were captured on a Garmin eTrex Venture GPS, with a positional accuracy of 3 m (Vari, 2002). All points were mapped in the World Geodetic System (WGS) 1984 Geographic Coordinate System and later projected to the WGS 1984 UTM Zone 35 S projected coordinate system.

Silo dimensions

The silo dimensions were obtained from the general manager of each silo. This ensured the correct height and diameter values were incorporated into simulations. Boundary points were determined for each silo complex based on the number of silos and their diameters as illustrated in Figure 1 (blue dots).

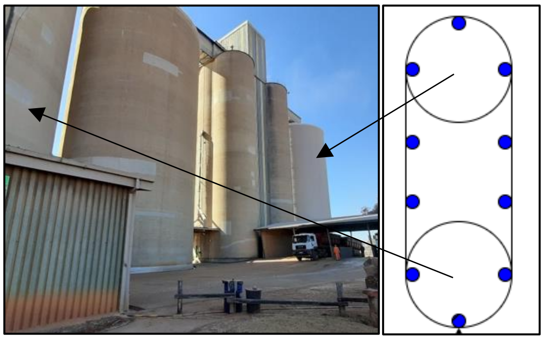

Figure 1: Examples of boundary points.

3.2.3. *Visibility analysis*

Digital elevation models

Both DTMs and DSMs were derived for the three study areas. The elevation point data for each study area were randomly divided at an 80/20 ratio to create training and testing datasets. The training datasets (80 %) were used (along with contours) to generate digital terrain models (DTMs), while the testing datasets (20 %) were used to evaluate the accuracy of the DTMs using root means square error (RMSE) calculations. RMSE is a standard measurement of accuracy (Fisher & Tate, 2006) and is aimed at providing a statistical measurement of vertical accuracy (Razak *et al*., 2013):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(zDEM - zRef)^2}{n}}$$

Where ZDEM = the elevation value predicted by the DEM, and ZRef = the surveyed elevation value, i.e. the values from the 20 % of surveyed elevation points that was not considered in the creation of the

DEM. The lower the RMSE score the closer the predicted and observed values and the more accurate the DEM.

DTMs were generated in ArcMap 10.7 using the *Topo to Raster* tool which is based on an interpolation algorithm developed to specifically create hydrologically correct surfaces (Razak *et al*., 2013). Four DTMs were generated for each study area at four different resolutions (5 m, 10 m, 25 m and 50 m) to allow for testing sensitivity to resolution. RMSE scores were calculated for each of the twelve DTMs (Table 3). The Grootpan study area (lowest landscape complexity) had the lowest variation in RMSE scores across the different resolutions, while Syferbult (medium landscape complexity) and Swartruggens (highest landscape complexity) both showed larger variability. DTM accuracy increased as resolution increased, as expected, while intensity of elevation change and the frequency of elevation change further also affected accuracy values, especially at lower resolutions. Most DTMs showed acceptable RMSE scores except for the Syferbult 25 m, Syferbult 50 m, and Swartruggens 50 m DTMs. All DTMs were, however, used during visibility analysis simulations to determine the relationship between DTM accuracy and visibility analysis simulation accuracy.

The method used to create DSMs for each study area were based on studies undertaken by Garnero and Fabrizio (2015) and Klouček *et al*. (2015). The method utilizes an existing DTM and adds land cover elevation values to the DTM through height values assigned to each land cover class (Table 2). The land cover dataset was resampled at 50 m, 25 m, 10 m and 5 m and combined with the relevant DTMs to generate the DSMs.

Table 3. RMSE scores for DTMs

Study area	RMSE scores			
	DTM 5 m	DTM 10 m	DTM 25 m	DTM 50 m
Grootpan (low complexity)	1.32	1.32	1.52	2.00
Syferbult (medium complexity)	2.36	3.17	13.16	48.94
Swartruggens (high complexity)	1.83	1.95	3.68	10.88

Visibility analysis

The visibility analysis techniques identified through the review were tested for the three study areas across different resolutions and DEMs. The three techniques often used in VIA were viewshed analysis, cumulative viewshed analysis and line of sight (LOS) analysis. A total of 72 simulations were conducted. Observer height was set at 1.8 m as this height conforms to the height value used to collect the reference points. All analysis was conducted in the ArcMap 10.7 software suite. As LOS analysis does not generate ZTVs by default, as in the case of viewshed and cumulative viewshed, but can be configured to do so. The study area boundary was converted into points at 10 m intervals. The distance of 10 m between points was decided on as it presents a close enough distance between points to generate enough sightlines to present visibility, and allowed for the results to be converted to a raster surface at a suitable resolution. The same was done for the silo boundaries after which both sets of points were converted to 3D point features based on the applicable DTM and then connected with sight lines. These sight lines, which subsequently covered the entire study area were used to conduct the LOS analysis and the results converted to raster format for display purposes.

3.2.4. *Accuracy assessment*

The accuracy of the 72 simulations was assessed through cross-validation conducted between the visibility results and the reference points (40 points per site) collected during the field visit as suggested by Sullivan and Meyer (2014). The *Extract multi values to points* tool in ArcMap 10.7 was used to extract the visibility results for each of the reference points across the 72 simulations*, i.e.*, for each of the 40 reference points the prediction (visible or not visible) was extracted for all 72 simulations. The extracted values were exported to Microsoft Excel where the predicted visibility for each point could be compared to the observed visibility and an accuracy percentage for each simulation determined expressed as a percentage:

$$Accuracy \ = \ (p/n) * 100$$

where p = the number of correctly predicted reference points (could be visible or not visible) and n = the total number of referenced points in the sample. For example, a score of 80 % would indicate that the viewshed had an 80 % accuracy as it predicted 80 % of the 40 reference points correctly. Analysis of variance (ANOVA) was used to determine if different techniques, DEMs and resolutions had any significant effect on accuracy. ANOVA determines if there is a statistically significant difference between the means of two or more groups of data (*e.g*. results from different terrain models). The ANOVA analysis were conducted in Microsoft Excel with the significance level set to 0.05.

3.2.5. *Determine sensitivity to key variables across different landscape types*

To determine the sensitivity of the tested approaches to key variables across different landscape types, multivariate analysis of variance (MANOVA) was applied to the accuracy results. MANOVA is an extension of ANOVA and allows for the simultaneous assessment of the effect of multiple explanatory variables. MANOVA was conducted for different terrain types treating accuracy as the dependant variable and DEM, resolution, and technique as explanatory variables. The MANOVA analysis was conducted using the XLSTAT plugin in Microsoft Excel with the significance level also set to 0.05.

3.3. *Provide recommendations to practitioners on the appropriate visibility analysis approaches to use based on different landscape contexts and data availability circumstances (Objective 3)*

Based on the findings of the analyses, the extent to which different variables are essential to deliver accurate results can be evaluated. Recommendations are provided on the importance of variables to ensure accuracy. This then acts as the basis for practitioners to make choices about the visibility analysis approaches based on their study area, data availability and cost.

4. Results

4.1. *Common approaches to visibility analysis in VIA*

The VIA reports reviewed included a wide variety of activities, including renewable energy projects, residential developments, and commercial developments. From the VIA reports reviewed, viewshed analysis was by far the most frequently used technique for determining the ZTV (72.9 %). The second and third most used techniques were cumulative and line of sight analysis (14.6 % and 12.5 % respectively). In terms of the digital elevation models used, digital terrain models were used most often (77.1 %), followed by digital surface models (14.6 %). A few reports did not reveal the type of model used (8.3 %). Very few VIA reports reported considering land cover screening during the ZTV phase, which was considered in only seven reports (18.8 %). Viewshed analysis based on a DTM without the consideration of screening effects was the approach most often used in the VIAs reviewed (Table 4). This was followed by cumulative viewshed analysis based on the same inputs.

Table 4: Visibility analysis approaches used in VIA

DEM and screening	Techniques: Viewshed	Cumulative viewshed	Line of sight (LOS)
DTM with land cover screening	0 %	0 %	4.2 %
DTM without land cover screening	58.3 %	10.4 %	4.2 %
DSM with land cover screening	3 %	4.2 %	4.2 %
DSM without land cover screening	0 %	0 %	0 %

4.2. Accuracy results

Both the DEM type and the visual analysis technique used had a significant ($p < 0.05$) effect on the accuracy of the analysis with scores of 0.000 and 0.028 respectively. The DEM type that produced more accurate results was the DSM while LOS proved to be the more accurate technique to use. Resolution did not have a significant effect on accuracy results.

Table 5: Summary of accuracy results

Variable		Average accuracy score	Significance (p)
DEM Type	*DSM*	72.8 %	0.000
	DTM	60.6 %	
Resolution	*5m*	69.0 %	0.190
	10m	68.5 %	
	25m	66.4 %	
	50m	63.1 %	
Technique	*VS*	65.9 %	0.028
	CVS	65.9 %	
	LOS	70.4 %	

4.3. Sensitivity of identified visibility analysis approaches to key variables across different landscapes

Table 6 contains the results for the MANOVA analysis and shows the effect of different variables on the accuracy of the visibility analysis for different landscape types. The type of DEM used has the most significant effect ($p < 0.05$) on the accuracy of the visibility analysis. When considered against the accuracy results, this confirms that a DSM will result in a more accurate result across all landscape types. The significance decreases slightly, however, as landscape complexity increases. The selection of technique only had a significant impact on the accuracy of results in areas of medium complexity. This might be ascribed to the fact that different visibility analysis techniques all rely on the same underlying principle of line-of-sight analysis. When considered against accuracy results, however, the LOS analysis approach as applied in the study generally resulted in more accurate results than viewshed and cumulative viewshed analysis. Although higher resolution results in more accurate DEMs, the analysis did not find resolution to have a significant impact on accuracy results for any of the landscape contexts. Its contribution to accuracy did however seem to decrease with increased terrain complexity.

Table 6: MANOVA results

Variable | Terrain:	*Low complexity*	*Medium complexity*	*High complexity*
DEM Type	0.0004	0.0003	0.010
Resolution	0.121	0.455	0.581
Technique	0.149	0.001	0.131

5. Recommendations

The determination of a ZTV is a critical input to VIA processes. The results suggest that, although often used in visual impact assessment, viewshed analysis and cumulative viewshed analysis are not the optimal and most accurate approaches for the determination of the ZTV, but rather an optimised LOS analysis. The accuracy achieved through the latter is further substantially higher than the accuracy scores obtained in similar studies, *e.g.* Maloy and Dean (2001) that reported accuracy scores in the mid 50 % range, Berry and Kidner (2005) in the mid 60% range, and Wood (2000) in the lower 60 % range. The type of DEM should further be a key consideration across all landscape types. Practitioners should prioritise the use of DSM's, something which the review results suggest is not currently the case. Where resolutions higher than readily available DSMs such as the 30m SRTM are needed, landcover datasets can be used to derive a DSM, especially where budget for more sophisticated datasets such as LiDAR is not available. It is, therefore, recommended that LOS analysis applied as a study area wide analysis, *i.e.*, sightlines covering the full extent of the study area, and based on a DSM should be considered by practitioners to obtain the most accurate results across all study area types. Although resolution did not prove to have a significant impact on accuracy, higher resolutions should be considered, especially in areas of lower terrain complexity where changes is the landscape is more subtle and might 'get lost' at courser resolutions.

6. Conclusion

The research aimed to identify and evaluate visibility analysis approaches often used in VIA and provide recommendations for the approach to visibility analysis that practitioners should take in different contexts of landscape complexity and data availability. Approaches were identified and evaluated across varying landscapes and using different input variables. The main conclusions drawn from the results are:

- The type of DEM used has a significant impact on the accuracy of the visibility analysis results across all landscapes.
- DSMs resulted in the most accurate results across all landscapes.

- The technique used has some significance, while LOS analysis provides more accurate results than viewshed or cumulative viewshed, which are currently the favoured approaches in VIA practice.
- DEM resolution had no significant impact on the accuracy of results; however, the findings suggests that resolution becomes increasingly important at lower resolutions.

With this research we hope to contribute to VIA best practice, especially as it relates to the best approaches to ZTV determination. However, going forward we would also recommend similar research into the less often used approaches such as fuzzy viewshed analysis and probability viewshed analysis, but also research into the quality of VIA reports and more specifically the viewshed analysis component. It is only by applying and continually evaluating different approaches that the practice of VIA can be improved towards better decision making.

7. References

Anile, M.A., Furno, P., Gallo, G., & Massolo, A. 2003. A fuzzy approach to visibility maps creation over digital terrains. Fuzzy Sets Syst. 135:63–80.

AILA. Australian Institute of Landscape Architects. 2018. Guidance Note for Landscape and Visual Assessment.

Bartie, P., Reitsma, F., Kingham, S., & Mills, S. 2010. Advancing visibility modelling algorithms for urban environments. Comput. Environ. Urban Syst. Elsevier Ltd. 34(6):518–531.

Chamberlain, B.C. & Meitner, M.J. 2013. A route-based visibility analysis for landscape management. Landsc. Urban Plan. Elsevier B.V. 111:13–24.

Corry, R.C., 2011. A case study on visual impact assessment for wind energy development. *Impact Assessment and Project Appraisal*, *29*(4), pp.303-315.

Danese, M., Nolè, G., & Murgante, B. 2011. Identifying viewshed: New approaches to visual impact assessment. Stud. Comput. Intell. 348:73–89.

Depellegrin, D. 2016. Assessing cumulative visual impacts in coastal areas of the Baltic Sea. Ocean Coast. Manag. Elsevier Ltd. 119:184–198.

De Reu, J., Bourgeois, J., Bats, M., Zwertvaegher, A., Gelorini, V., De Smedt, P., Chu, W., Antrop, M., De Maeyer, P., Finke, P., Van Meirvenne, M., Verniers, J., & Crombé, P. 2013. Application of the topographic position index to heterogeneous landscapes. *Geomorphology*. *Elsevier B.V.* 186:39–49.

Domingo-Santos, J.M., de Villarán, R.F., Rapp-Arrarás, Í., & de Provens, E.C.P. 2011. The visual exposure in forest and rural landscapes: An algorithm and a GIS tool. Landsc. Urban Plan. Elsevier B.V. 101(1):52–58.

Feimer, N. R., Craik, K. H., Smardon, R. C., & Sheppard, S. R. 1979. Appraising the reliability of visual impact assessment methods. In In: Elsner, Gary H., and Richard C. Smardon, technical coordinators. 1979. Proceedings of our national landscape: a conference on applied techniques for analysis and management of the visual resource [Incline Village, Nev., April 23-25, 1979]. Gen. Tech. Rep. PSW-GTR-35. Berkeley, CA. Pacific Southwest Forest and Range Exp. Stn., Forest Service, US Department of Agriculture: p. 286-295 (Vol. 35).

Feng, W., Gang, W., Deji, P., Yuan, L., Liuzhong, Y., & Hongbo, W. 2015. A parallel algorithm for viewshed analysis in three-dimensional Digital Earth. Comput. Geosci. Elsevier. 75:57–65.

Fisher, P. F. 1992. First experiments in viewshed uncertainty: simulating fuzzy viewsheds. *Photogrammetric engineering and remote sensing*, *58*, 345-345.

Fisher, P. F. 1995. *An exploration of probable viewsheds in landscape planning. Environment and Planning B: Planning and Design, 22(5), 527–546.*doi:10.1068/b220527

Fisher, P.F. & Tate, N.J. 2006. Causes and consequences of error in digital elevation models. Prog. Phys. Geogr. 30(4):467–489.

Garnero, G. & Fabrizio, E. 2015. Visibility analysis in urban spaces: a raster-based approach and case studies. Environ. Plan. B Plan. Des. 42(4):688–707.

HKEPD. Hong Kong Environmental Protection Department. 1999. Annex 18: Guidelines for Landscape and Visual Impact Assessment.

Huaxing, L.U. 2008. Modelling terrain complexity. , in: Zhou, Q., Lees, B., Tang, G. (Eds.), Advances in Digital Terrain Analysis. Springer Berlin Heidelberg: Berlin. . Springer Berlin Heidelberg: Berlin, pp. 159–176.

IAIA. International Association for Impact Assessment. (1999). Principles of environmental impact assessment best practice. Institute of Environmental Assessment, 1.

Jijelava, D. and F. Vanclay (2017). "Legitimacy, credibility and trust as the key components of a social licence to operate: An analysis of BP's projects in Georgia." Journal of Cleaner Production **140**: 1077-1086.

Kantner, J. & Hobgood, R. 2016. A GIS-based viewshed analysis of Chacoan tower kivas in the US Southwest: were they for seeing or to be seen? Antiquity. 90(353):1302–1317.

Kim, Y.H., Rana, S., & Wise, S. 2004. Exploring multiple viewshed analysis using terrain features and optimisation techniques. Comput. Geosci. 30(9–10):1019–1032.

Klouček, T., Lagner, O., & Šímová, P. 2015. How does data accuracy influence the reliability of digital viewshed models? A case study with wind turbines. Appl. Geogr. 64:46–54.

Knight, R., & Therivel, R. 2017. Landscape and visual. In Methods of Environmental and Social Impact Assessment (pp. 399-431). Routledge

Ladenburg, J., Termansen, M. and Hasler, B., 2013. Assessing acceptability of two onshore wind power development schemes: A test of viewshed effects and the cumulative effects of wind turbines. *Energy*, *54*, pp.45-54.

Landscape Institute. 2013. Guidelines for landscape and visual impact assessment. Version 3.

Llobera, M. 2003. Extending GIS-based visual analysis: The concept of visualscapes. Int. J. Geogr. Inf. Sci. 17(1):25–48.

Llobera, M. 2007. Modeling visibility through vegetation. Int. J. Geogr. Inf. Sci. 21(7):799–810.

Loots, L., Nackaerts, K., & Waelkens, M. 1999. Fuzzy viewshed analysis of the Hellenistic city defence system at Sagalassos, Turkey. *BAR International Series*, *750*, 82-82.

Manchado, C., Gomez-Jauregui, V., Manero, G., Carrasco, C., & Otero, C. 2014. Teaching visual impact assessment at a master level. *Computer Applications in Engineering Education*, *23*(5), 703-714.

Marshall, R. and R. Baxter (2002). "Strategic Routeing and Environmental Impact Assessment for Overhead Electrical Transmission Lines." Journal of Environmental Planning and Management **45**(5): 747-764.

Miller, M.L., Carstensen, L.W., Campbell, J.B., & Thomas, V. 2011. Analysis of viewshed accuracy with variable resolution LIDAR digital surface models and photogrammetrically- Derived digital elevation models masters of science in geography. Virginia State University.

Möller, B. 2006. Changing wind-power landscapes: Regional assessment of visual impact on land use and population in Northern Jutland, Denmark. Appl. Energy. 83(5):477–494.

Murphy, K.M., Gittings, B., & Crow, J. 2018. Visibility analysis of the Roman communication network in southern Scotland. J. Archaeol. Sci. Reports. Elsevier. 17(October 2017):111–124.

Nair, H.C., Joseph, A., & Padmakumari Gopinathan, V. 2018. GIS Based landform classification using digital elevation model: a case study from two river basins of Southern Western Ghats, Kerala, India. *Model. Earth Syst. Environ. Springer International Publishing*. 4(4):1355–1363

Nutsford, D., Reitsma, F., Pearson, A. L., & Kingham, S. 2015. Personalising the viewshed: Visibility analysis from the human perspective. *Applied Geography*, *62*, 1-7.

Oberholzer, B. 2005. Guideline for involving visual & aesthetic specialists in EIA processes: Edition 1. CSIR Report No ENV-S-C 2005 053 F. Republic of South Africa, Provincial Government of the Western Cape, Department of Environmental Affairs & Development Planning, Cape Town.

Palmer, J. F. 2019. The contribution of a GIS-based landscape assessment model to a scientifically rigorous approach to visual impact assessment. Landscape and Urban Planning, 189, 80-90.

Pardo García, S. & Mérida Rodríguez, M. (2015). A geospatial indicator for assessing urban panoramic views. Comput. Environ. Urban Syst. 49:42–53

Qiang, Y., Shen, S., & Chen, Q. 2019. Visibility analysis of oceanic blue space using digital elevation models. Landsc. Urban Plan. Elsevier. 181:92–102.

Rášová, A. 2014. Fuzzy viewshed, probable viewshed, and their use in the analysis of prehistoric monuments placement in Western Slovakia. In: Huerta, Schade, Granell (Eds): Connecting a Digital Europe through Location and Place. Proceedings of the AGILE'2014 International Conference on Geographic Information Science, Castellón, June, 3-6, 2014. ISBN: 978-90-816960-4-3.

Razak, K.A., Santangelo, M., Van Westen, C.J., Straatsma, M.W., & de Jong, S.M. 2013. Generating an optimal DTM from airborne laser scanning data for landslide mapping in a tropical forest environment. *Geomorphology*. *Elsevier B.V.* 190:112–125.

Robert, S. 2018. Assessing the visual landscape potential of coastal territories for spatial planning: A case study in the French Mediterranean. Land use policy. Elsevier. 72(December 2017):138–151.

Smardon, R. C. 2016. Visual Impact Assessment: Where have we come from and where are we going?. Journal of Environmental Protection, 7(10), 1333.

Sullivan, R. & Meyer, M. 2014. Guide to evaluating visual impact assessments for renewable energy projects. Natural Re ed. National Park Service: Ft. Collins, Colorado.

Takacs, B. and Goulden, M.C., 2019. Accuracy of wind farm visualisations: The effect of focal length on perceived accuracy. *Environmental Impact Assessment Review*, *76*, pp.1-9.

Thompson, M. 2019. South African National Land-Cover 2018 Report & Accuracy Assessment. Pretoria.

Vari, A. 2002. Garmin eTrex Venture personal navigator owner’s manual and reference guide. Garmin.

Véga, C., Vepakomma, U., Morel, J., Bader, J.L., Rajashekar, G., Jha, C.S., Ferêt, J., Proisy, C., Pélissier, R., & Dadhwal, V.K. 2015. Aboveground-biomass estimation of a complex tropical forest in India using lidar. *Remote Sens.* 7(8):10607–10625.

Verutes, G.M., Huang, C., Estrella, R.R., & Loyd, K. 2014. Exploring scenarios of light pollution from coastal development reaching sea turtle nesting beaches near Cabo Pulmo, Mexico. Glob. Ecol. Conserv. Elsevier B.V. 2:170–180.

Vinod, P.G. 2017. Development of topographic position index based on Jenness algorithm for precision agriculture at Kerala, India. *Spat. Inf. Res. Korean Spatial Information Society*. 25(3):381–388.

Wheatley, D., & Gillings, M. 2013. *Spatial technology and archaeology: the archaeological applications of GIS*. CRC Press.

Wilson, S. 2002. Guidelines for landscape and visual impact assessment. Taylor & Francis.

Wood, G. (2000). Is what you see what you get?: Post-development auditing of methods used for predicting the zone of visual influence in EIA. Environmental Impact Assessment Review, 20(5), 537-556.

Zhao, Y., Padmanabhan, A., & Wang, S. 2013. A parallel computing approach to viewshed analysis of large terrain data using graphics processing units. Int. J. Geogr. Inf. Sci. 27(2):363–384.

Zhou, Q., Liu, X., & Sun, Y. 2006. Terrain complexity and uncertainties in grid-based digital terrain analysis. Int. J. Geogr. Inf. Sci. 20(10):1137–1147.