

ASSESSING LANDSCAPE VISIBILITY USING LIDAR, SAR DEM AND GLOBALLY AVAILABLE ELEVATION DATA: THE CASE OF BONGABONG, ORIENTAL MINDORO, PHILIPPINES

Edwin R. Abucay (1,2), Yi-Hsing Tseng (1)

¹ National Cheng Kung University, No.1, University Road, Tainan City 701,
Taiwan (R.O.C)

² University of the Philippines Los Banos, College, Laguna, 4031, Philippines
Email: erabucay@prs.geomatics.ncku.edu.tw; tseng@mail.ncku.edu.tw

KEY WORDS: Landscape visibility, LiDAR, DEM

ABSTRACT: Modeling of landscape visibility using digital data offers an efficient way to assess a geographic area systematically. This approach has been widely used in historical and archeological studies, renewable energy such as solar and wind farm, telecommunications tower assessments, military use, landscape architecture, landscape planning and management, spatial planning, among others. Disaster events such as flooding and landslides as a result weather disturbance has significantly changed our landscapes affecting population and resources. With the availability of Digital Elevation Models (DEMs) of various spatial scales, visibility analyses can be carried out for rapid landscape assessment. This study was done in a 46km² area in Bongabong, Oriental Mindoro, Philippines. Visibility analyses used: 1) Light Detection and Ranging (LiDAR) derived Digital Terrain Model (DTM) and Digital Surface Model (DSM) at 1m spatial resolution; 2) Synthetic Aperture Radar (SAR) DEM at 10m spatial resolution; 3) Advanced Land Observing Satellite (ALOS) DSM at 30m spatial resolution; and 4) Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2). Observer location was randomly established along major roads and compared with the observer location at ecotourism sites. Results showed that LiDAR-derived elevation models offer greater details concerning the visibility of landscapes along the main roads compared to SAR DEM, ALOS DSM, and ASTER GDEM, respectively. On the other hand, regardless of spatial resolution, visible areas of the study area along the main roads using SAR DEM (30.07 km²), ALOS DSM (30.16 km²) and ASTER GDEM (30.18 km²) is comparable to LiDAR-derived DTM (25.77 km²). Computationally, LiDAR DTM took about 28 mins to complete the visibility analysis compared to about 19 sec. for SAR DEM, and about 3 sec. for ALOS DSM and ASTER GDEM, respectively. Further investigation reveals that the visible areas of the landscapes are predominantly agricultural lands, and prone to flooding. High spatial resolution elevation/surface data offer greater detail when it comes to visibility analysis of the landscape. In areas where these data are not available, medium resolution elevation data can be used for landscape assessments.

1. INTRODUCTION

Assessment of the landscape requires the evaluation of its environmental, aesthetic, and perceived values which in most cases, depends upon the individual or observers experiences and psychological perceptions. The value of a landscape as an environmental resource must be considered across spatial scales for sustainable land use planning and landscape management (Ramos & Pastor, 2012). Remote sensing (RS) and Geographic Information Systems (GIS) are increasingly used in studying the human environment and landscape interactions mainly as a tool for efficient planning and management (Ayad, 2005; Crawford, 1994; Fábrega-Álvarez & Parcero-Oubiña, 2019; Franch-Pardo, Cancer-Pomar, & Napoletano, 2017; Hilal, Joly, Roy, & Vuidel, 2018; Sahraoui, Vuidel, Joly, & Foltête, 2018; Wu, Bishop, Hossain, & Sposito, 2006).

Modeling of landscape visibility using digital data offers an efficient way to assess a geographic area systematically. Using digital data such as topographic models and satellite imageries, the visual perception of the physical environment can be quantified using landscape metrics or indicators (Ervin & Steinitz, 2003; O'Sullivan & Turner, 2001; Sahraoui et al., 2018). This approach has been widely used in historical and archeological studies, renewable energy such as solar and wind farm, telecommunications tower assessments, military use, landscape architecture, landscape planning and management, spatial planning, among others (Bishop, 2019; Brown & Brabyn, 2012; Czyńska & Rubinowicz, 2019; Kim, Rana, & Wise, 2004; Lopes, Macedo, Brito, & Furtado, 2019; Manchado et al., 2013; Pinto-Correia & Kristensen, 2013; Poerwoningsih, Antariksa, Leksono, & Hasyim, 2016; Sunak & Madlener, 2016). Renewable energy such as wind farms is a valuable energy resource that is beneficial to the environment but may have a positive or negative impact on property values in terms of visibility (Sunak & Madlener, 2016). The changes in the landscapes and its surroundings are likewise affecting the visibility of important heritage sites (Lopes et al., 2019). Problems associated with this can be assessed and quantified using a variety of computation tool within a GIS system. Disaster events such as flooding and

landslides as a result weather disturbance has also significantly changed our landscapes affecting population and resources. To deal with such challenges, decision-makers must recognize the inherent nature and spatial aspect in landscape planning and management which can be aided with the use of remote sensing and geographic information system tools (Kaku, 2019; Lagmay, Racoma, Aracan, Alconis-Ayco, & Saddi, 2017; Van Western, 2013). For development planning, natural disasters pose challenge in ensuring continued and sustainable development of the communities towards resiliency (Mohammed, 2018; Raza, 2018).

Digital surface data with a moderate spatial resolution are accessible and available to the public with global coverage such as the Advanced Land Observing Satellite (ALOS) Digital Surface Model (DSM), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2). With the availability of these spatial data of various spatial scales, visibility analyses, for example, can be carried out for rapid landscape assessment. These data can also complement country/locally available surface data which can provide relevant information for efficient handling of landscape resources.

This paper attempts to assess landscape visibility using locally and globally available surface data for a case study area in the Philippines. A comparison will be made for locally available LiDAR data with fine spatial resolution and globally available medium spatial resolution surface data. Additionally, initial landscape attributes of visible areas will be identified and quantified.

2. METHODS

The study was done in a 46 km² landscape area in the municipality of Bongabong, Oriental Mindoro, the Philippines dominated by agricultural and trees/shrubs land cover (Fig. 1). Areas close to the river tributary has moderate and high flood susceptibility accounting to about 8.89 km² and 5.25 km², respectively (Fig. 2). The municipality of Bongabong with a total population of 72,073 (2015 Census) is located about 102 km from Calapan City, capital of Oriental Mindoro island province and has a total land area of about 498.20 km². Moreover, it is situated roughly 293 km south of Manila, Philippines.

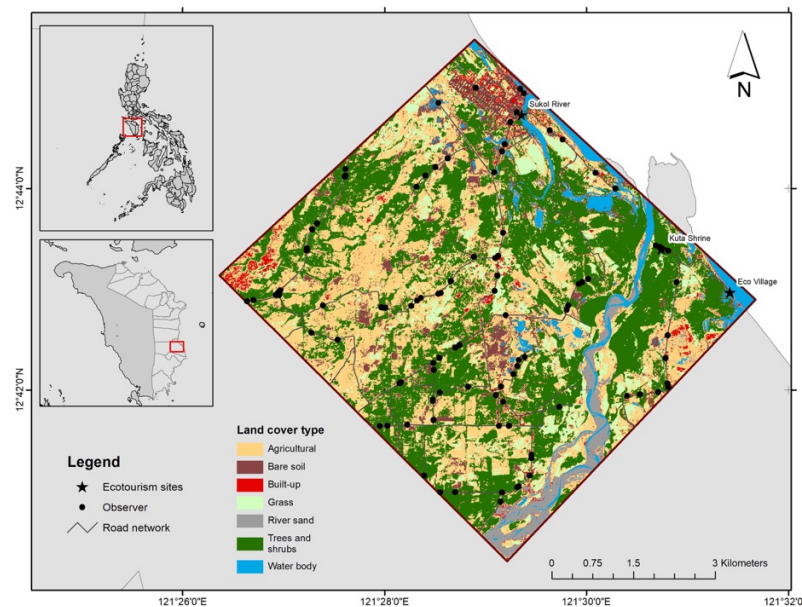


Figure 1. The study area and its existing land cover map, Bongabong, Oriental Mindoro, Philippines.

Data processing and analysis workflow are shown in Fig. 3. Visibility analyses used: 1) Light Detection and Ranging (LiDAR) derived Digital Terrain Model (DTM) and Digital Surface Model (DSM) at 1m spatial resolution; 2) Synthetic Aperture Radar (SAR) DEM at 10m spatial resolution; 3) Advanced Land Observing Satellite (ALOS) DSM at 30m spatial resolution; and 4) Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2). Visibility analyses were carried out in ArcGIS 10.5 through its visibility toolset using default settings. Input observer location was randomly established along major roads and compared with the observer location at three ecotourism sites. Land cover types were derived from PlanetScope imagery using supervised image classification techniques.

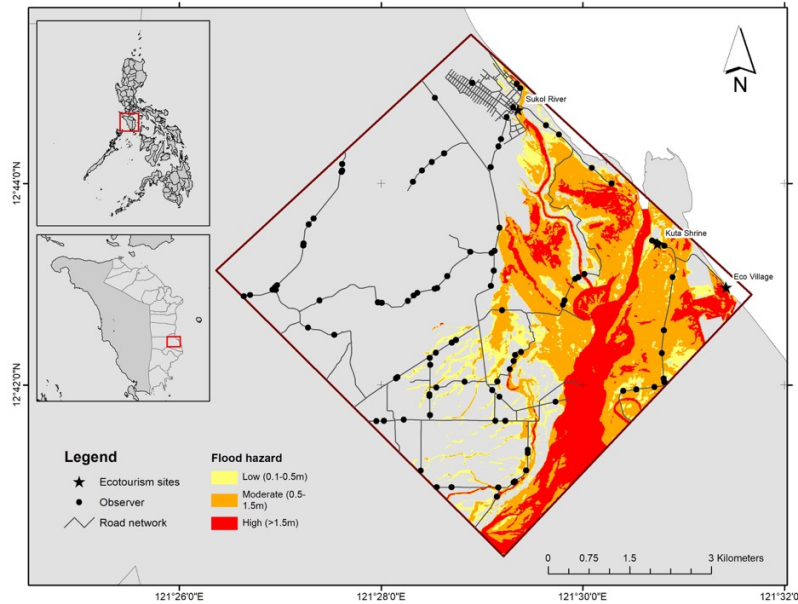


Figure 2. Flood hazard map of the study area based on a 25-year rain - return period, Bongabong, Oriental Mindoro, Philippines.

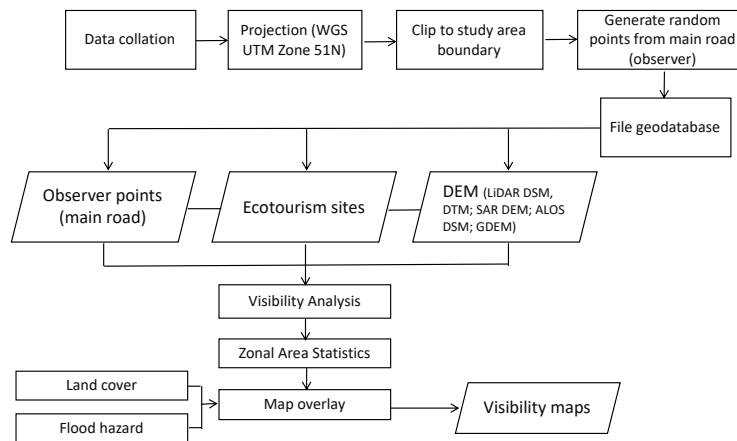


Figure 3. Data processing and analysis workflow.

The data were collected from various sources while globally available surface data were downloaded from their respective access websites (Table 1).

Table 1. Summary of data sources used in the study.

Data	Format	Source
Road network	Vector (polyline)	PHIL-LiDAR 1 UPLB
Political boundary	Vector (polygon)	Philippine Statistics Authority (PSA) and National Mapping and Resource Information Authority (NAMRIA) in the context of the 2015 census
Flood hazard (~10m spatial resolution)	Vector (polygon)	PHIL-LiDAR Program: https://lipad.dream.upd.edu.ph
Ecotourism sites	Vector (point)	Local Government Unit Bongabong, Oriental Mindoro
LiDAR DSM & DTM (~1m spatial resolution)	Raster	PHIL-LiDAR 1 UPLB
SAR DEM (10m spatial resolution)	Raster	PHIL-LiDAR Program: https://lipad.dream.upd.edu.ph
DSM (30m spatial resolution)	Raster	Advance Land Observing Satellite (ALOS): https://www.eorc.jaxa.jp/ALOS/en/aw3d30/index.htm
GDEM (30m spatial)	Raster	ASTER Global DEM: https://gdex.cr.usgs.gov/gdex/

resolution)		
Satellite imagery (~3m spatial resolution)	Raster	Planet Team (2017). Planet Application Program Interface: In Space for Life on Earth. San Francisco, CA. https://api.planet.com .

3. RESULTS AND DISCUSSION

Results showed that LiDAR-derived elevation models offer greater and finer details concerning the visibility of landscapes along the main roads compared to SAR DEM, ALOS DSM, and ASTER GDEM, respectively (Fig. 4 and 5). With three ecotourism sites as observer location, analysis showed that there were less visible areas of the landscape using LiDAR DSM (Fig. 4a) than LiDAR DTM (Fig. 4c). On the other hand, when an observer is traveling along the road, visible areas are more substantial in LiDAR DTM than LiDAR DSM (Fig. 4b and 4d). DTM represents the bare ground of the earth which has less surface obstruction from the standpoint of an observer location. DSM practically represent the entire surface of the landscape, including natural and human-built structures.

Regardless of spatial resolution, visible areas of the study area along the main roads using SAR DEM (30.07 km²), ALOS DSM (30.16 km²) and ASTER GDEM (30.18 km²) is comparable to LiDAR-derived DTM (25.77 km²) (Figs. 4d, 5b, 5d, and 5f; Table 2). On the other hand, areas visible to the identified ecotourism locations were limited or small compared to that of observer location along the main road (Fig. 4a, 4c, 5a, 5c, and 5e). While LiDAR DSM offers very high-resolution information. However, it may not be ideal for visibility analysis over more extensive landscape area and best suited for smaller ones.

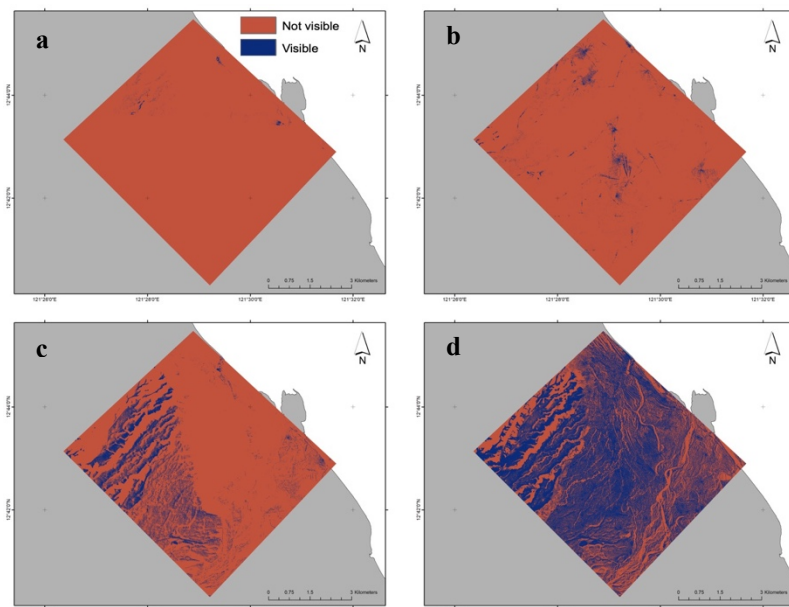


Figure 4. Visibility analyses maps for LiDAR derived DSM (a. ecotourism sites, b. major road) and LiDAR derived DTM (c. ecotourism sites, d. major road).

The analysis of landscape visibility without direct observation can be referred to as geometric visibility (Muñoz-Pedrerros, 2017; Nagy, 1994). It provides an indicative measure of visible areas of the landscape based on a set of observation points. For the promotion of ecotourism activities in an area, identification of what scenic areas can be seen along an established route is essential for planning, development, and implementation tourism plans (Muñoz-Pedrerros, 2017; Tveit, Ode Sang, & Hagerhall, 2018). LiDAR-derived surface data are inherently fine resolution compared to openly available surface data such as that of ASTER GDEM. Determining the acceptable data resolution for landscape visibility analyses can impact the data size and computational aspect (Qiang, Shen, & Chen, 2019). The extent of an area, accuracy of surface data, shape and number of landscape elements are essential considerations in identification of observer location (Weitkamp, Bregt, van Lammeren, & van den Berg, 2007). This study simulated what an individual can see within the landscape based on randomly established observer point along the road and three identified ecotourism locations using different resolution surface data. The initial findings suggest that moderate resolution surface data can be used for visibility analysis. The accuracy of such an analysis would, however, depend on the level of accuracy of the data.

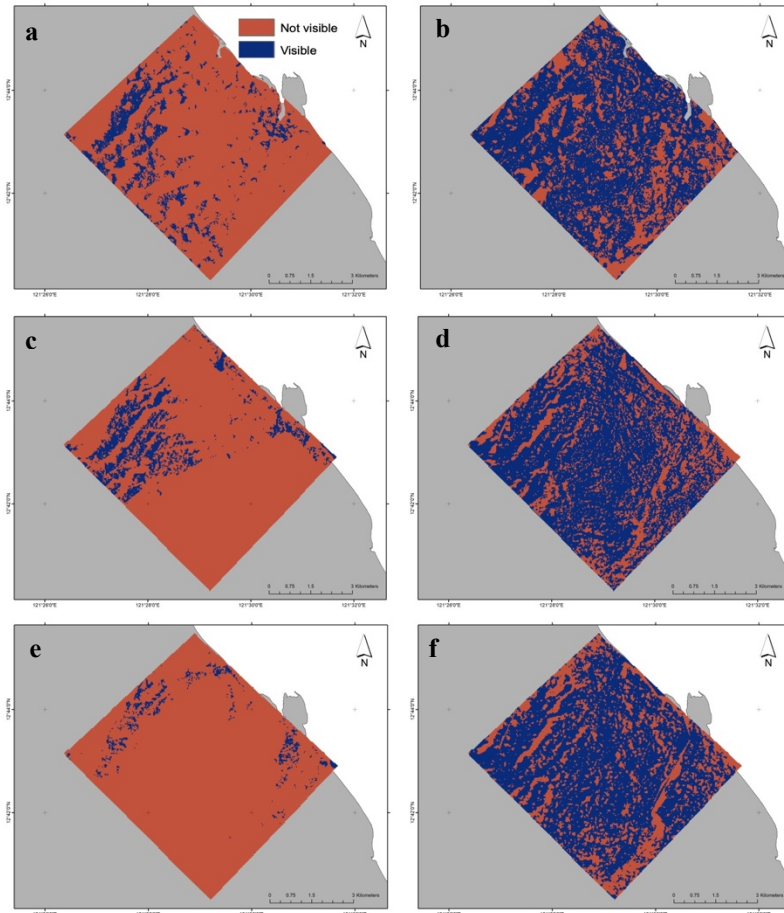


Figure 5. Visibility analyses map for SAR DEM (a. ecotourism sites, b. major road), ALOS DSM (c. ecotourism sites, d. major road) and ASTER GDEM (e. ecotourism sites, f. major road).

Table 2. Summary of visibility analyses area statistics.

Terrain model	Spatial Resolution	Visible (km ²)		Not visible (km ²)	
		Ecotourism	Main road	Ecotourism	Main road
LiDAR DSM	1m	0.1215	0.9298	45.6064	44.7981
LiDAR DTM	1m	5.5985	25.7722	40.1295	19.9558
SAR DEM	10m	5.7840	30.0681	39.2346	14.9505
ALOS DSM	30m	5.1300	30.1563	38.6766	13.6503
ASTER GDEM	30m	1.5579	30.1779	42.2487	13.6287

Computationally, LiDAR DTM took about 28 minutes to complete the visibility analysis compared to about 19 seconds for SAR DEM, and about 3 seconds for ALOS DSM and ASTER GDEM, respectively (Table 3). Given that this study only focused on a 46 km² landscape area, processing time would be longer for larger areas such as a province or a region. Moreover, computational time would also depend on the computer configuration and number of observation locations.

Table 3. Visibility analyses computational time (units in seconds).

Terrain model	Spatial Resolution	Ecotourism sites	Main road
LiDAR DSM	1m	60.00	1,715.40
LiDAR DTM	1m	59.50	1,689.00
SAR DEM	10m	1.10	19.03
ALOS DSM	30m	0.70	2.98
ASTER GDEM	30m	0.69	3.03

Optimization techniques such as the selection of key topographic locations and maximum location-allocation coverage in landscape visibility analysis can be done to reduce the processing time (Kim et al., 2004). Other research has implemented the simultaneous computation of viewshed algorithm to improve computation times for large high-resolution spatial data (Tabik, Zapata, & Romero, 2013). However, this study only explored how each set of surface data with various spatial resolution can be processed using the visibility toolset in ArcGIS 10.5 with the objective of identifying the ideal data for rapid landscape assessment. Landscape assessment is an important aspect of spatial planning to describe the general characteristics of an area, the environment character (e.g., visible space), establishing aesthetic and ecological qualities particularly (Poerwoningsih et al., 2016).

Further investigation reveals that the visible areas along major roads of the landscapes using SAR DEM are predominantly agricultural lands and trees/shrubs accounting to about 11.0753 km² and 12.3320 km² of the total landscape area, respectively. Additionally, about 5.6125 km² and 2.5177 km² of the visible areas along major roads in this study are prone to moderate and high flooding, respectively.

Establishing visibility of the landscape at the human perspective as a realistic approach can be done but maybe be challenging (Nutsford, Reitsma, Pearson, & Kingham, 2015). Quantification of the landscape physical attributes can also be mapped as an important input for the decision-making process using landscape geographic models with the aid of digital surface data (Ramos & Pastor, 2012). The visibility analysis can be combined with other landscape attributes such as type of land use, and perceived value of the landscape in simulating the landscape experience when traveling on a set of observer location (Brabyn, 2015). An individual can assign multiple values to a landscape based on his/her experience but maybe complex in nature (Brown & Brabyn, 2012). The results of this study have identified and quantified initial landscape attributes such as land cover and its susceptibility to hazards like the flooding of the visible areas. However, assigning values to the identified landscape attribute was not done in this study.

4. CONCLUSION AND FURTHER RESEARCH

High spatial resolution elevation/surface data offer greater detail when it comes to visibility analysis of the landscape. However, processing high-resolution data over large landscapes may require considerable computational time. Moreover, its availability and accessibility may be limited. Thus, in areas where these data are not available, medium resolution elevation data such as ASTER GDEM can be used for rapid landscape assessments. This study has identified and quantified physical landscape attributes such as land cover and hazard susceptibility of visible areas in a landscape as initial input for further research on landscape quality assessment. Moreover, this preliminary research hopes to establish a rapid landscape assessment methodology that can be replicated in other areas.

Further research could be done to explore other landscape visibility models and algorithms in determining the ideal spatial resolution for various landscape sizes, and in improving the computational times especially when using high spatial resolution data sets over large areas. Comparison of the results with the latest ASTER GDEM v.3. could also be made. In other areas in the Philippines where LiDAR data is not available, it is suggested to conduct studies on the fusion of various surface model to provide better and more accurate terrain data. However, when only openly accessible data is available, moderate spatial resolution surface data could be used for rapid landscape assessment. A thorough research and ground validation studies should also be conducted to validate the findings of geometric visibility assessments.

5. ACKNOWLEDGEMENTS

The LiDAR derived datasets used in this study was from a Department of Science and Technology – Grants in Aid (DOST-GIA) funded project entitled “Project 4. LIDAR Data Processing and Validation in Luzon: MIMAROPA and Laguna (Region IV)” under the Program ‘PHIL-LIDAR 1. Hazard Mapping of the Philippines Using LIDAR- Program B. LIDAR Data Processing and Validation by SUCs and HEIs’ which the corresponding author served as the project leader.

6. REFERENCES

Ayad, Y. M., 2005. Remote sensing and GIS in modeling visual landscape change: A case study of the northwestern arid coast of Egypt. *Landscape and Urban Planning*, 73(4), 307–325.
<https://doi.org/10.1016/j.landurbplan.2004.08.002>

Bishop, I. D., 2019. The implications for visual simulation and analysis of temporal variation in the visibility of

- wind turbines. *Landscape and Urban Planning*, 184, 59–68. <https://doi.org/10.1016/j.landurbplan.2018.12.004>
- Brabyn, L., 2015. Modelling landscape experience using “experions.” *Applied Geography*, 62, 210–216. <https://doi.org/10.1016/j.apgeog.2015.04.021>
- Brown, G., & Brabyn, L., 2012. An analysis of the relationships between multiple values and physical landscapes at a regional scale using public participation GIS and landscape character classification. *Landscape and Urban Planning*, 107(3), 317–331. <https://doi.org/10.1016/j.landurbplan.2012.06.007>
- Crawford, D., 1994. Using remotely sensed data in landscape visual quality assessment. *Landscape and Urban Planning*, 30(1–2), 71–81. [https://doi.org/10.1016/0169-2046\(94\)90068-X](https://doi.org/10.1016/0169-2046(94)90068-X)
- Czyńska, K., & Rubinowicz, P., 2019. Classification of cityscape areas according to landmarks visibility analysis. *Environmental Impact Assessment Review*, 76, 47–60. <https://doi.org/10.1016/j.eiar.2019.01.004>
- Ervin, S., & Steinitz, C., 2003. Landscape Visibility Computation: Necessary, but Not Sufficient. *Environment and Planning B: Planning and Design*, 30(5), 757–766. <https://doi.org/10.1068/b2968>
- Fábrega-Álvarez, P., & Parcero-Oubiña, C., 2019. Now you see me. An assessment of the visual recognition and control of individuals in archaeological landscapes. *Journal of Archaeological Science*, 104, 56–74. <https://doi.org/10.1016/j.jas.2019.02.002>
- Franch-Pardo, I., Cancer-Pomar, L., & Napoletano, B. M., 2017. Visibility analysis and landscape evaluation in Martin river cultural park (Aragon, Spain) integrating biophysical and visual units. *Journal of Maps*, 13(2), 415–424. <https://doi.org/10.1080/17445647.2017.1319881>
- Hilal, M., Joly, D., Roy, D., & Vuidel, G., 2018. Visual structure of landscapes seen from built environment. *Urban Forestry & Urban Greening*, 32, 71–80. <https://doi.org/10.1016/j.ufug.2018.03.020>
- Kaku, K., 2019. Satellite remote sensing for disaster management support: A holistic and staged approach based on case studies in Sentinel Asia. *International Journal of Disaster Risk Reduction*, 33, 417–432. <https://doi.org/10.1016/j.ijdr.2018.09.015>
- Kim, Y.-H., Rana, S., & Wise, S., 2004. Exploring multiple viewshed analysis using terrain features and optimisation techniques. *Computers & Geosciences*, 30(9–10), 1019–1032. <https://doi.org/10.1016/j.cageo.2004.07.008>
- Lagmay, A. M. F., Racoma, B. A., Aracan, K. A., Alconis-Ayco, J., & Saddi, I. L., 2017. Disseminating near-real-time hazards information and flood maps in the Philippines through Web-GIS. *Journal of Environmental Sciences*, 59, 13–23. <https://doi.org/10.1016/j.jes.2017.03.014>
- Lopes, A. S., Macedo, D. V., Brito, A. Y. S., & Furtado, V., 2019. Assessment of urban cultural-heritage protection zones using a co-visibility-analysis tool. *Computers, Environment and Urban Systems*, 76, 139–149. <https://doi.org/10.1016/j.compenvurbsys.2019.04.009>
- Manchado, C., Otero, C., Gómez-Jáuregui, V., Arias, R., Bruschi, V., & Cendrero, A., 2013. Visibility analysis and visibility software for the optimisation of wind farm design. *Renewable Energy*, 60, 388–401. <https://doi.org/10.1016/j.renene.2013.05.026>
- Mohammed, M. P., 2018. Disaster Risk Reduction and Management of Tarlac City. *Procedia Engineering*, 212, 77–84. <https://doi.org/10.1016/j.proeng.2018.01.011>
- Muñoz-Pedrerros, A., 2017. THE VISUAL LANDSCAPE: AN IMPORTANT AND POORLY CONSERVED RESOURCE. *Ambiente & Sociedade*, 20(1), 165–182. <https://doi.org/10.1590/1809-4422asoc20150088r1v2012017>
- Nagy, G., 1994. Terrain visibility. *Computers & Graphics*, 18(6), 763–773. [https://doi.org/10.1016/0097-8493\(94\)90002-7](https://doi.org/10.1016/0097-8493(94)90002-7)
- Nutsford, D., Reitsma, F., Pearson, A. L., & Kingham, S., 2015. Personalising the viewshed: Visibility analysis

from the human perspective. *Applied Geography*, 62, 1–7. <https://doi.org/10.1016/j.apgeog.2015.04.004>

O’Sullivan, D., & Turner, A., 2001. Visibility graphs and landscape visibility analysis. *International Journal of Geographical Information Science*, 15(3), 221–237. <https://doi.org/10.1080/13658810151072859>

Pinto-Correia, T., & Kristensen, L., 2013. Linking research to practice: The landscape as the basis for integrating social and ecological perspectives of the rural. *Landscape and Urban Planning*, 120, 248–256. <https://doi.org/10.1016/j.landurbplan.2013.07.005>

Planet Team, 2017. Planet Application Program Interface: In Space for Life on Earth. San Francisco, CA. <https://api.planet.com>.

Poerwoningsih, D., Antariksa, Leksono, A. S., & Hasyim, A. W., 2016. Integrating Visibility Analysis in Rural Spatial Planning. *Procedia - Social and Behavioral Sciences*, 227, 838–844. <https://doi.org/10.1016/j.sbspro.2016.06.153>

Qiang, Y., Shen, S., & Chen, Q., 2019. Visibility analysis of oceanic blue space using digital elevation models. *Landscape and Urban Planning*, 181, 92–102. <https://doi.org/10.1016/j.landurbplan.2018.09.019>

Ramos, B. M., & Pastor, I. O., 2012. Mapping the visual landscape quality in Europe using physical attributes. *Journal of Maps*, 8(1), 56–61. <https://doi.org/10.1080/17445647.2012.668763>

Raza, T., 2018. Localizing Disaster Risk Reduction and Climate Change Adaptation in Planners’ and Decision Makers’ Agenda: Technical Comprehensive Model, Quezon City, Philippines. *Procedia Engineering*, 212, 1311–1318. <https://doi.org/10.1016/j.proeng.2018.01.169>

Sahraoui, Y., Vuidel, G., Joly, D., & Foltête, J.-C., 2018. Integrated GIS software for computing landscape visibility metrics: XXXX. *Transactions in GIS*, 22(5), 1310–1323. <https://doi.org/10.1111/tgis.12457>

Sunak, Y., & Madlener, R., 2016. The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. *Energy Economics*, 55, 79–91. <https://doi.org/10.1016/j.eneco.2015.12.025>

Tabik, S., Zapata, E. L., & Romero, L. F., 2013. Simultaneous computation of total viewshed on large high resolution grids. *International Journal of Geographical Information Science*, 27(4), 804–814. <https://doi.org/10.1080/13658816.2012.677538>

Tveit, M. S., Ode Sang, Å., & Hagerhall, C. M., 2018. Scenic Beauty: Visual Landscape Assessment and Human Landscape Perception. In L. Steg & J. I. M. de Groot (Eds.), *Environmental Psychology* (pp. 45–54). <https://doi.org/10.1002/9781119241072.ch5>

Van Western, C. J., 2013. Remote sensing and GIS for natural hazards assessment and disaster risk management. In J. Shroder & M. P. Bishop (Eds.), *Treatise on Geomorphology*. (Vol. 3, pp. 259–298). Academic Press, San Diego, C.A.: Remote Sensing and GIScience in Geomorphology.

Weitkamp, G., Bregt, A., van Lammeren, R., & van den Berg, A., 2007. Three Sampling Methods for Visibility Measures of Landscape Perception. In S. Winter, M. Duckham, L. Kulik, & B. Kuipers (Eds.), *Spatial Information Theory* (Vol. 4736, pp. 268–284). https://doi.org/10.1007/978-3-540-74788-8_17

Wu, Y., Bishop, I., Hossain, H., & Sposito, V., 2006. Using GIS in Landscape Visual Quality Assessment. *Applied GIS*, 2(3), 18.1–18.20. <https://doi.org/10.2104/ag060018>