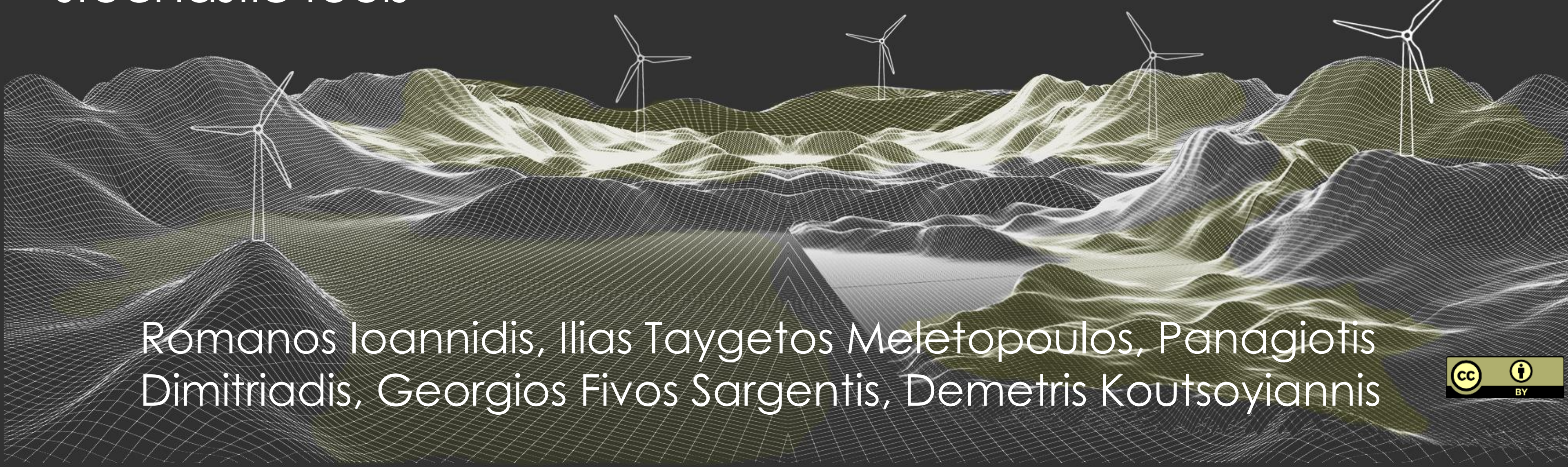
EGU General Assembly Vienna, 2020

National Technical University of Athens
School of Civil Engineering

Investigating the spatial characteristics of GIS visibility analyses

and their correlation to visual impact perception with stochastic tools



Romanos Ioannidis, Ilias Taygetos Meletopoulos, Panagiotis Dimitriadis, Georgios Fivos Sargentis, Demetris Koutsoyiannis

Abstract

In the effort to manage and mitigate landscape impact by works of infrastructure, various methods have been developed to quantify and evaluate visual impact, ranging from photo-montage and digital representation to Geographic Information Systems (GIS) viewshed analyses. These methods can be divided into two broad categories; quantitative methods that mainly focus on calculating the extents of the area affected, in each case, and qualitative methods that focus on the perception of the landscape transformation by individuals.

In this study we develop an evaluation methodology for quantitative methods of visibility analysis that generate Zone of Theoretical Visibility (ZTV) maps. In particular, we utilize stochastic tools to correlate spatial patterns of visibility analysis maps to increased qualitative concerns that are connected with opposition to projects of infrastructure. A stochastic computational tool (2D-C) is used of the analysis of images. 2D-C is a tool capable of characterizing the degree of variability in images using stochastic analysis, and thus, the change in variability vs. scale, among images. The methodology investigated incorporates 2D-C in a GIS environment for landscape impact management and proposes a procedure to assess impacts which can aid relevant policy.

Introduction (1)

Works of civil infrastructure generate important transformations to the natural and cultural attributes of landscapes. Thus, various methods have been developed for the management and mitigation of landscape impacts from works of infrastructure. These methods are used to quantify and evaluate visibility and generated visual impacts and overall, to assess the significance of aesthetic transformations to landscapes. Such methods range from photo-montage and digital representation to Geographic Information Systems (GIS) viewshed analyses. renewable energy (RE) is the focus of most of such analyses.

It is now widely accepted that landscape impacts are generated through the visibility of renewable energy projects. This so-called visual impact, is certainly, in part, subjective, put can extend several kilometers away from the project's locations. Visual impacts of RE developments have been analyzed in literature (Apostol et al., 2016; Frolova et al., 2015; Stevenson and Griffiths, 1994; Stremke and van den Dobbelsteen, 2012; Vissering et al., 2011) as well us in institutional environmental impact assessment guidelines (Hellenic Ministry of Environment, Energy & Climate Change, 2008; Horner & Maclennan and Envision, 2006; New South Wales Government [NSW Government], 2016).

Methods of assessing landscape impacts from RE can be divided into two broad categories; quantitative methods that mainly focus on calculating the extents of the area affected, in each case, and qualitative methods that focus on the perception of landscape transformations by individuals.

Research Questions

In this study, we develop an evaluation methodology for quantitative methods of visibility analysis that generate Zone of Theoretical Visibility (ZTV) maps incorporating qualitative (perceptual) evaluation in a method that has so far been primarily quantitative (spatial). Through this analysis we address the following research questions:

1. What insights can be gained on negative aesthetic perception on civil infrastructure and in this instance wind energy infrastructure using the 2D-C stochastic analysis (Sargentis et al., 2019)?

2. ZTV analyses have been recognized for their value in the spatial quantification of landscapes (Ioannidis et al. 2020). However, they luck in terms of qualitative analysis of landscape transformations. What are the elements they might miss?

3. How can these elements be quantified and incorporated into GIS visibility analyses to render them more valuable from a qualitative perspective as well?

Methodology outline (1)

The following methodology was used for the evaluation of quantitative methods of visibility analysis that are used to generate Zone of Theoretical Visibility (ZTV) maps.

1. Four theoretical scenarios were developed aiming to test four completely different topographical terrain conditions for the installation of a wind turbine:

- Wind turbine on flat terrain
- Wind turbine on the slopes of ridges
- Wind turbine on top of a hill
- Wind turbine in the center of a valley

2. Theoretical 3-d models were designed for each scenario including basic terrain forms and the installation of a wind turbine.

3. ZTVs were calculated for each scenario for a single wind turbine with a height of 120 m.

Methodology outline (2)

4. In each scenario, a theoretical observer was placed at a distance of 1 km from the turbine. The exact location of the observer was selected aiming for the most representative position of an observer in the landscape with the particular terrain characteristics.

5. The view of the observer towards the wind turbine was captured inside the 3d environment the model.

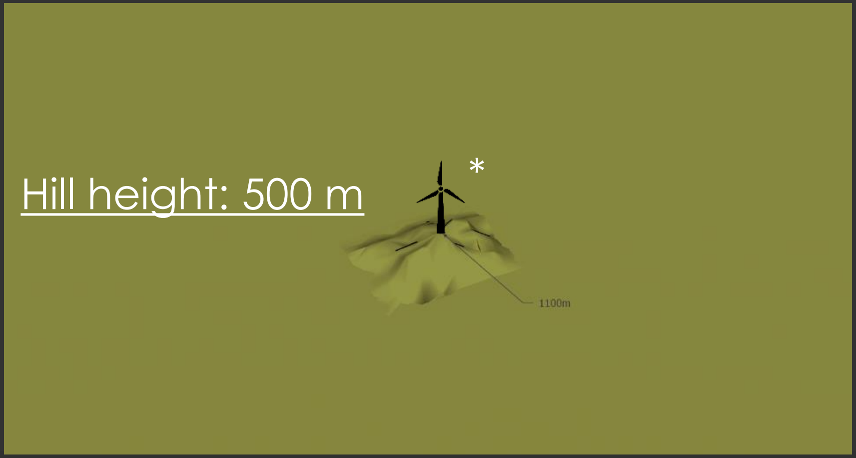
6. A stochastic computational tool (2D-C) was used for the analysis of the following, each one in four different scenarios:

- The images of the view of the observers towards the wind turbines
- The images of the view of the observers towards the wind turbines if the wind turbine was not present
- The calculated the zones of theoretical visibility

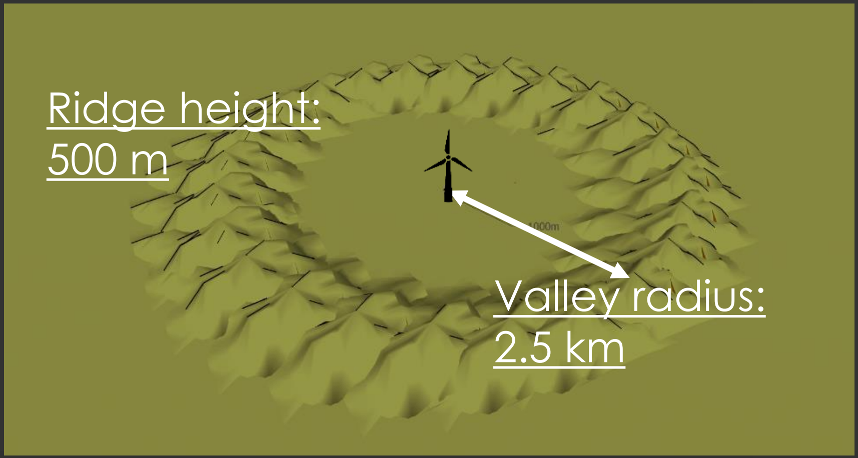
7. Using the 2D-C tool the degree of variability was calculated for the examined images as well as the change in variability vs. scale, among images.

Theoretical Scenarios (3d models)

1. Wind turbine on top of a hill



2. Wind turbine in the center of a valley



3. Wind turbine on the slopes of ridges

4. Wind turbine on flat terrain

* The wind turbine is depicted larger than original dimensions (120 m) used in the model.

Zones of theoretical visibility

Definition:

The method of "zone of theoretical visibility" (ZTV) (Hankinson, 1999) is a type of viewshed analysis. It is also called "zone of visual impact/influence"(Wood, 2000) and it involves the calculation of a binary map with the use of GIS technology that presents the areas from which an object, e.g. a wind turbine, is visible and the areas from which it is not. Viewshed and ZTV analyses abide by one basic principle; a digital elevation model of the area of interest is used, in which the locations of the objects that cause visual impact are pinpointed and their visibility is calculated radially with a line-of-sight test.

As is expected, the theoretical maximum distance of visibility of wind turbines is particularly important for the results of ZTV analyses. It is thus analyzed in detail in the following section. Other parameters that differentiate ZTV analyses are the incorporation of adjustments to elevation according to land-use height (Rodrigues et al., 2010), the inclusion of visibility of wind turbines from regions sharing borders with the area examined (Möller, 2010), observer height and observed object height (Scottish Natural Heritage [SNH], 2014).

Zones of theoretical visibility

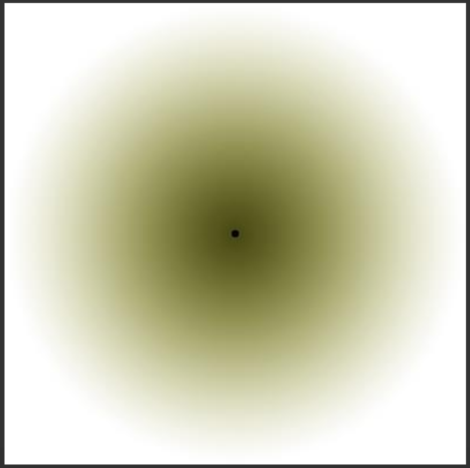
Distance of dominant visibility:

The distance of visual/landscape prominence or domination exceeds from 1 to 6.4 km away from the location of wind turbines. Indicatively, The Sinclair – Thomas matrices (Buchan, 2002) present 4 km as the radius of dominant impact for wind turbines with heights from 90 to 100 m while Sullivan et al. present 6.4 km as the radius in which a wind turbine is considered a "commanding visual" (Sullivan et al., 2012), Bishop, Stevenson and Griffiths, SNH and Buchan present 2 km for dominant visibility (Bishop, 2002; Buchan, 2002; Scottish Natural Heritage [SNH], 2009; Stevenson and Griffiths, 1994) and finally Vissering et al. (Vissering et al., 2011) present 4 km. In our analysis, we used **4 km** for the calculation of ZTV's which is slightly above the average of all of the above distances that are examined

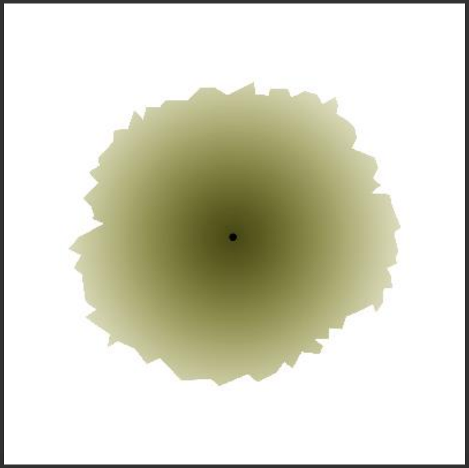
The maximum distance of visibility or visual threshold defines the geographic extends of the area that is investigated for visibility. The distance in which wind turbines are considered visible, ranges from 2 to 48 km in literature. The studies at lower end of the range, i.e. distances smaller than 16 km, include Bishop (Bishop, 2002) Betakova et al. (Betakova et al., 2015) and the Thomas Matrix and Sinclair Matrix, as cited by Sullivan et al. (Sullivan et al., 2012). In more recent studies, the trend is the promotion of larger distances for the calculation of ZTV for average-sized wind turbines is larger, like 48 km by Sullivan et al. (Sullivan et al., 2012), 20 km by Bishop (Bishop, 2002) and 16 to 40 km by Vissering et al. (Vissering et al., 2011). Since the average of the aforementioned estimates is around 20 to 25 km, the distance of maximum visibility was not incorporated in our analysis, as wind turbines where hardly noticeable in the 3d model.

Zones of theoretical visibility

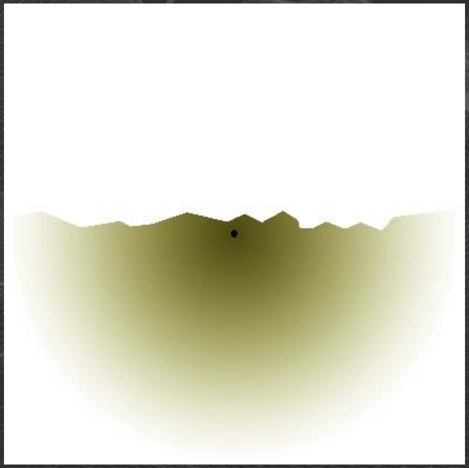
1. Wind turbine on top of hill



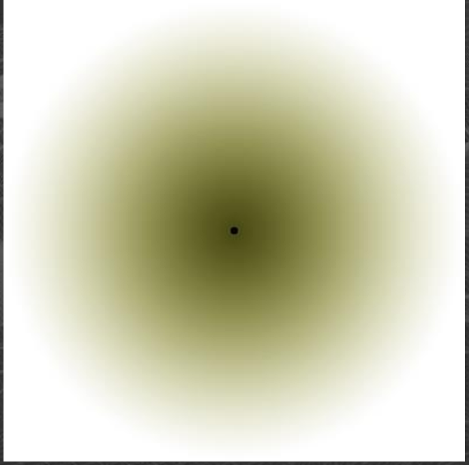
2. Wind turbine in the center of valley



3. Wind turbine on the slopes of ridges



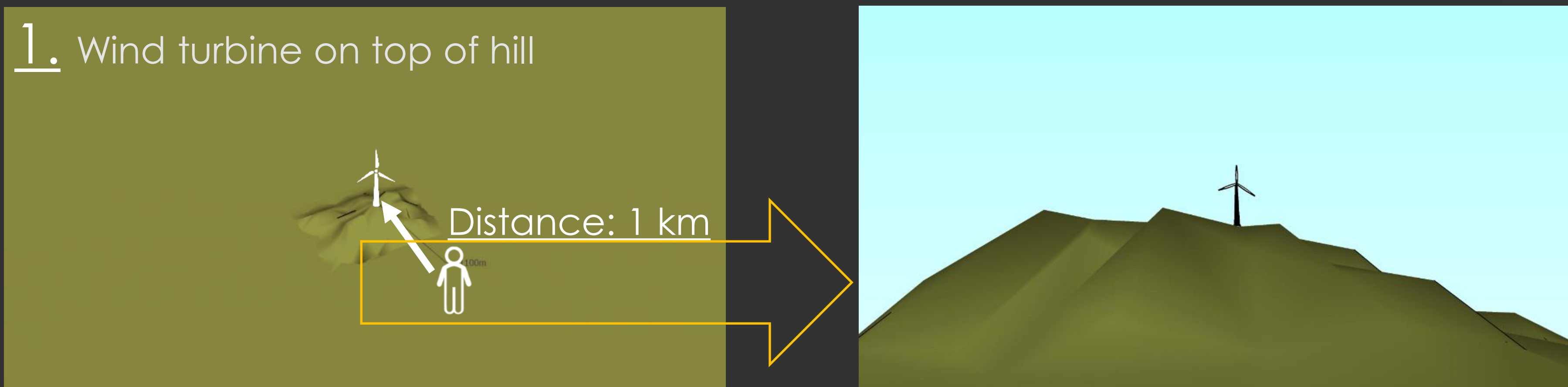
4. Wind turbine on flat terrain



Theoretical observers (1)

1. Placing

2. View of observer

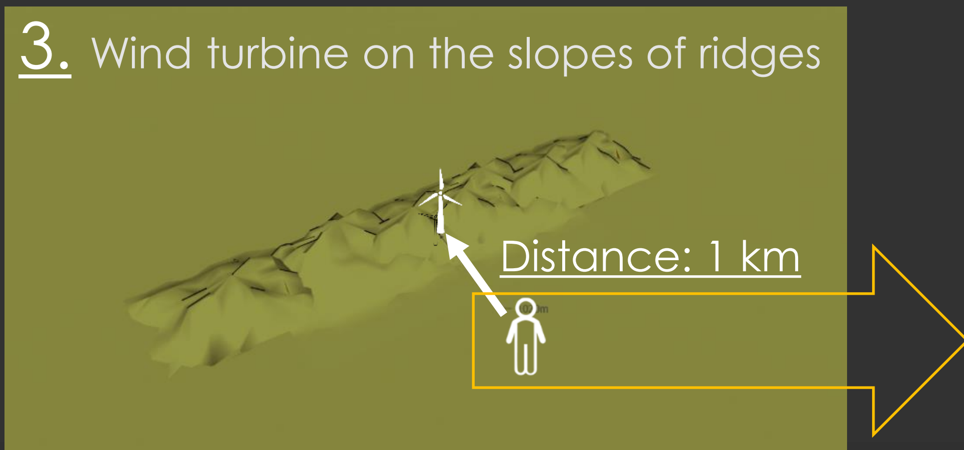


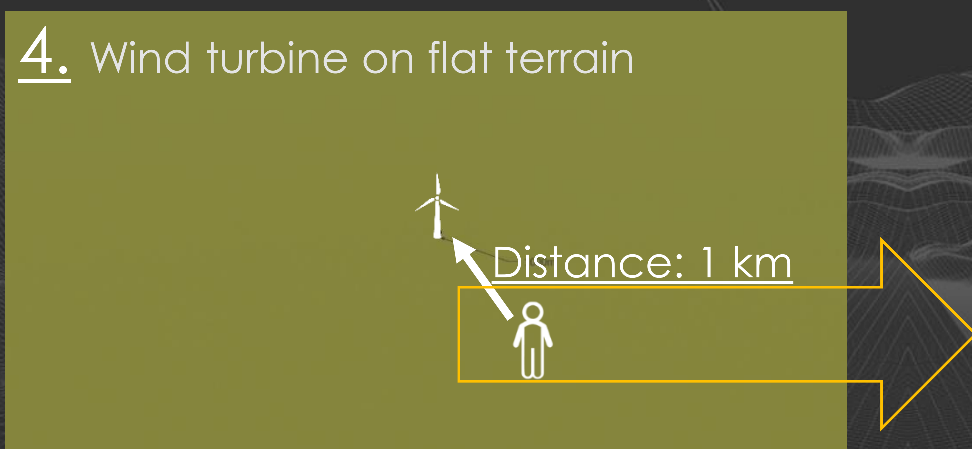
Wind turbine is depicted here larger than original dimensions (120 m) used in the model.

Theoretical observers (2)

1. Placing

2. View of observer





Wind turbine is depicted here larger than original dimensions (120 m) used in the model.

Stochastic 2D-C - Theory (1)

Stochastic analysis in 2d:

For the aesthetic analysis of the examined landscapes a stochastic picture-analysis methodology is used. In particular examined pictures of observer view are digitized in 2d grayscale color and a climacogram is calculated, based on the geometric scales of adjacent pixels (Tyralis et al., 2018). The methodology war originally developed for the aesthetic analysis of paintings (Sargentis et al., 2018; Sargentis et al., 2020) but has also been applied in the analysis of landscapes (Ioannidis et al., 2019; Sargentis et al., 2019)

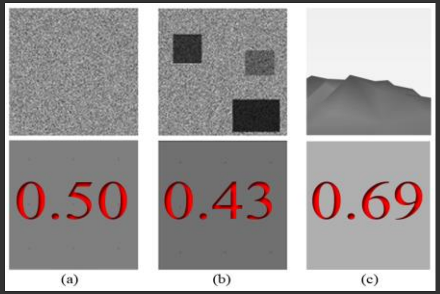
In order to obtain data for the evaluation of art paintings, each image of art painting is digitized in 2D based on a grayscale color intensity (thus this climacogram studies the brightness of an image) and the climacogram is calculated based on the geometric scales of adjacent pixels. Assuming that our sample is an area nΔ × nΔ, where n is the number of intervals (e.g., pixels) along each spatial direction and Δ is the discretization unit (determined by the image resolution, e.g., pixel length), the empirical classical estimator of the climacogram for a 2D process can be expressed as:

$$\underline{\hat{\gamma}}(\kappa) = \frac{1}{n^2/\kappa^2 - 1} \sum_{i=1}^{n/\kappa} \sum_{j=1}^{n/\kappa} \left(\underline{x}_{i,j}^{(\kappa)} - \underline{\bar{x}} \right)^2$$

where the "^" over γ denotes estimate, κ is the dimensionless spatial scale, $\underline{x}_{i,j}^{(\kappa)} = \frac{1}{\kappa^2} \sum_{\psi=\kappa(j-1)+1}^{\kappa j} \sum_{\xi=\kappa(i-1)+1}^{\kappa i} \underline{x}_{\xi,\psi}$ is the sample average of the space-averaged process at scale κ, and $\underline{\bar{x}} = \sum_{i,j=1}^{n} \underline{x}_{i,j} / n^2$ is the sample average. Note that the maximum available scale for this estimator is n/2

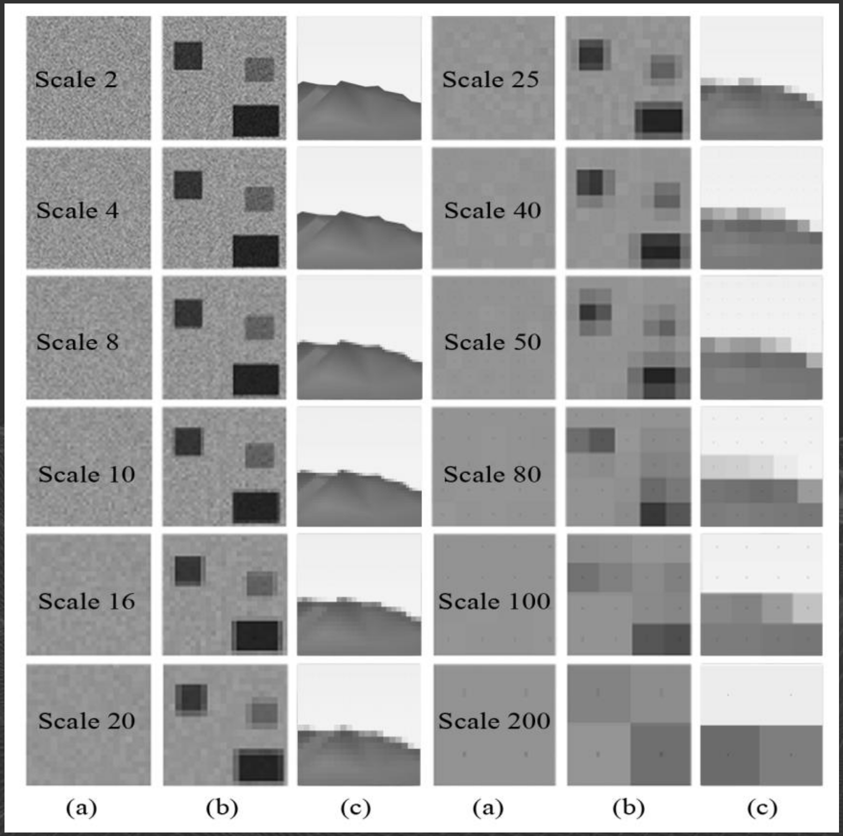
Stochastic 2D-C - Theory (2)

Benchmark of image analysis; (a) White noise; (b) Image with clustering; (c) landscape; the lower row depicts the average brightness in the upper one



white=1
black=0

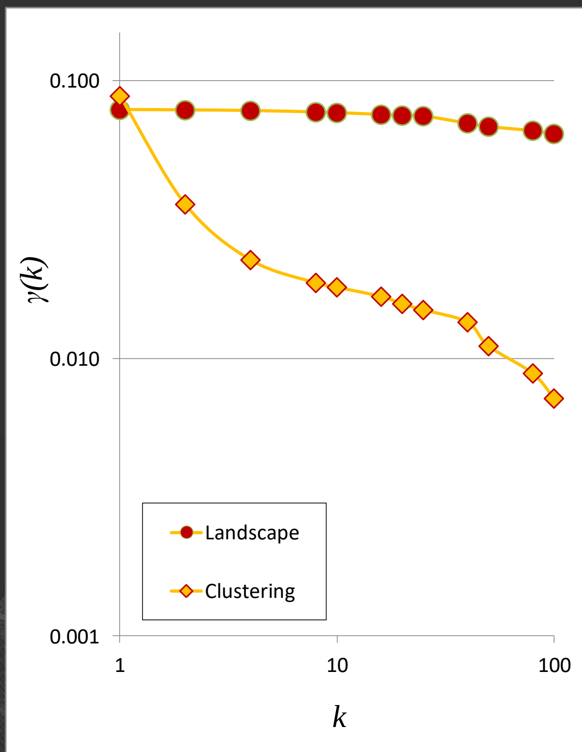
Steps of analysis (example)



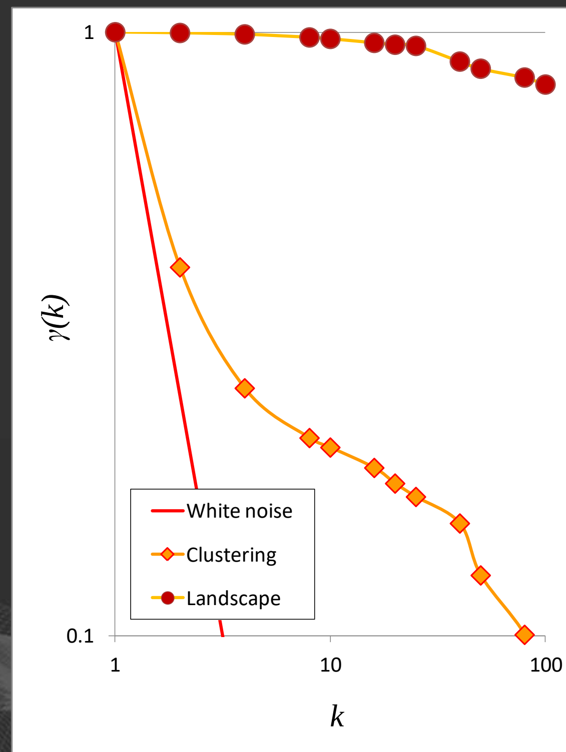
Example of stochastic analysis of 2D picture (Sargentis et al., 2020); Grouped pixels at different scales k = 2, 4, 8, 16, 20, 25, 40, 50, 80, 100, 200 used to calculate the climacogram; (a) White noise; (b) Image with clustering; (c) landscape .

Stochastic 2D-C - Theory (3)

Results of analysis (example)



(a) Climacograms of the benchmark images.



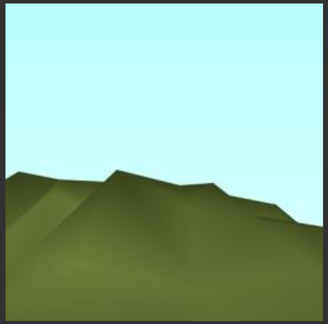
(b) Standardized climacograms of the benchmark images.

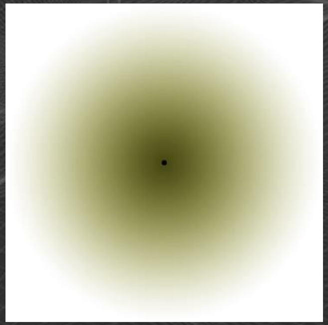
The presence of clustering is reflected in the climacogram, which shows a marked difference for the random white noise. Specifically, the variance of the clustered images is notably higher than that of the white noise at all scales, indicating a greater degree of variability of the process. Likewise, comparing the clustered image and the landscape, the latter has the most pronounced clustering behavior and a greater degree of variability.

Stochastic 2D-C - Analysis (1)

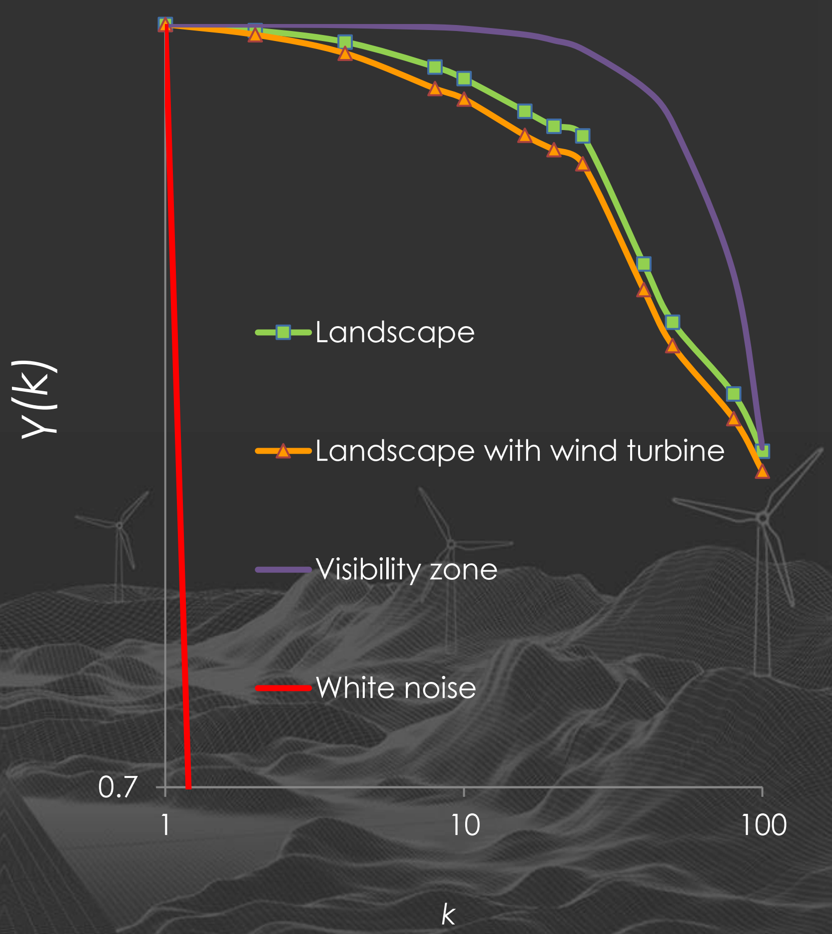
Pictures Analyzed

1. Wind turbine on top of hill





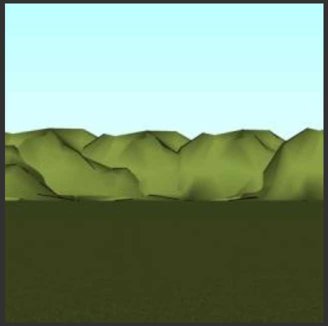
Climacogram

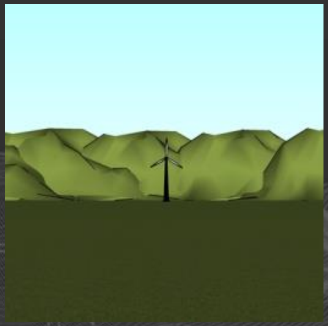


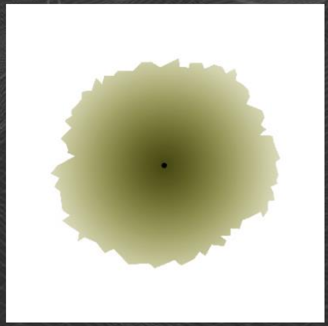
Stochastic 2D-C - Analysis (2)

Pictures Analyzed

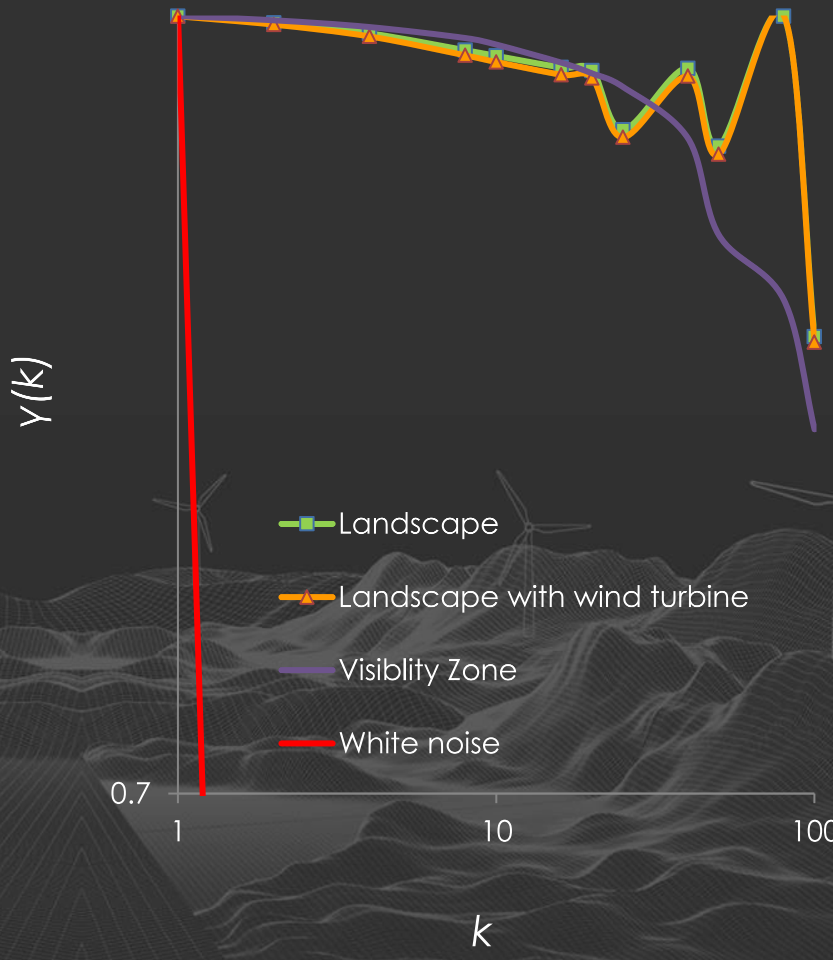
2. Wind turbine in the center of valley







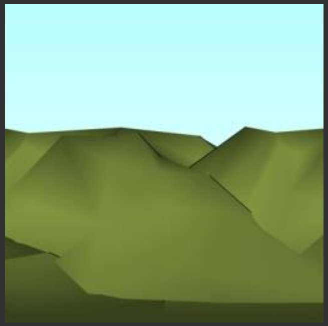
Climacogram

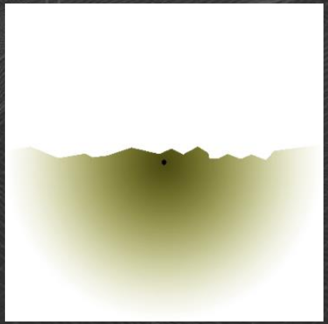


Stochastic 2D-C - Analysis (3)

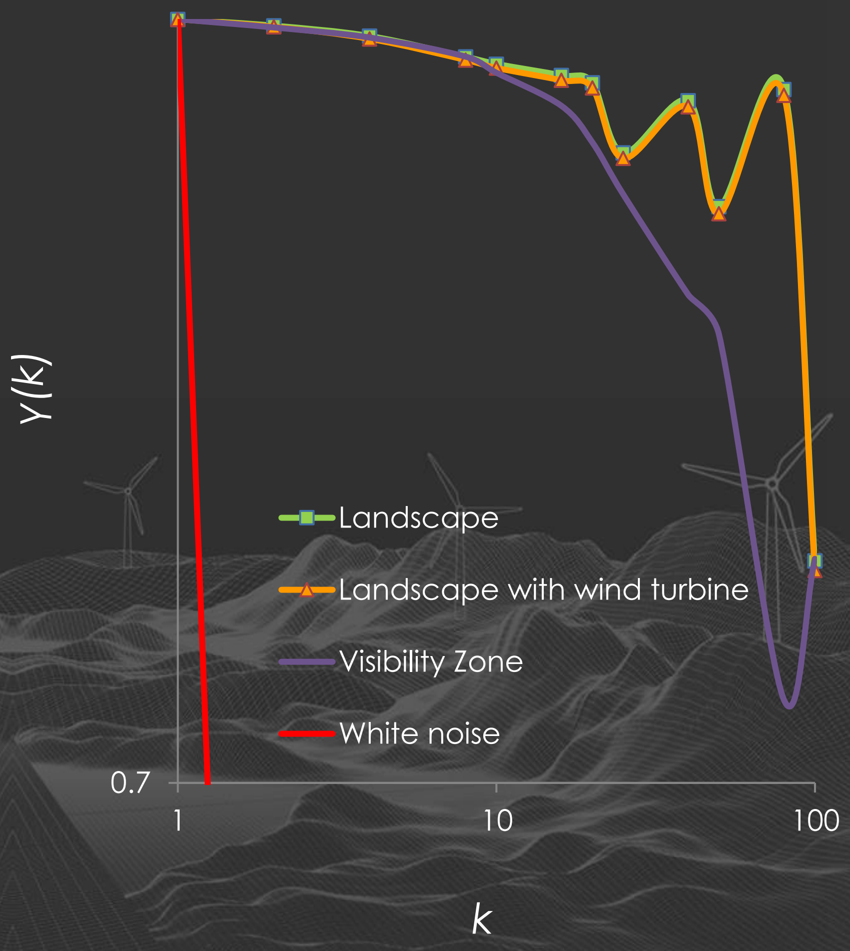
Pictures Analyzed

3. Wind turbine on the slopes or ridges





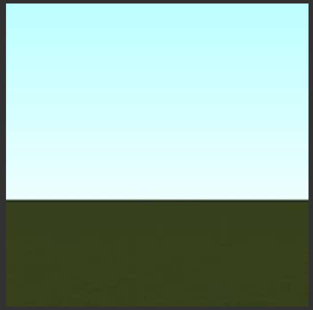
Climacogram

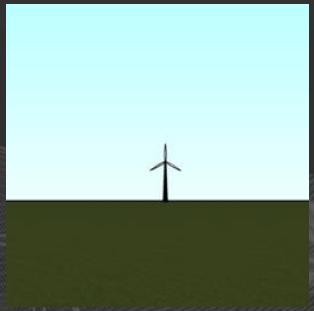


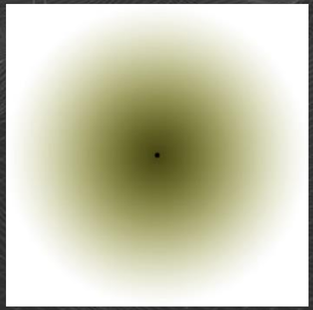
Stochastic 2D-C - Analysis (4)

Pictures Analyzed

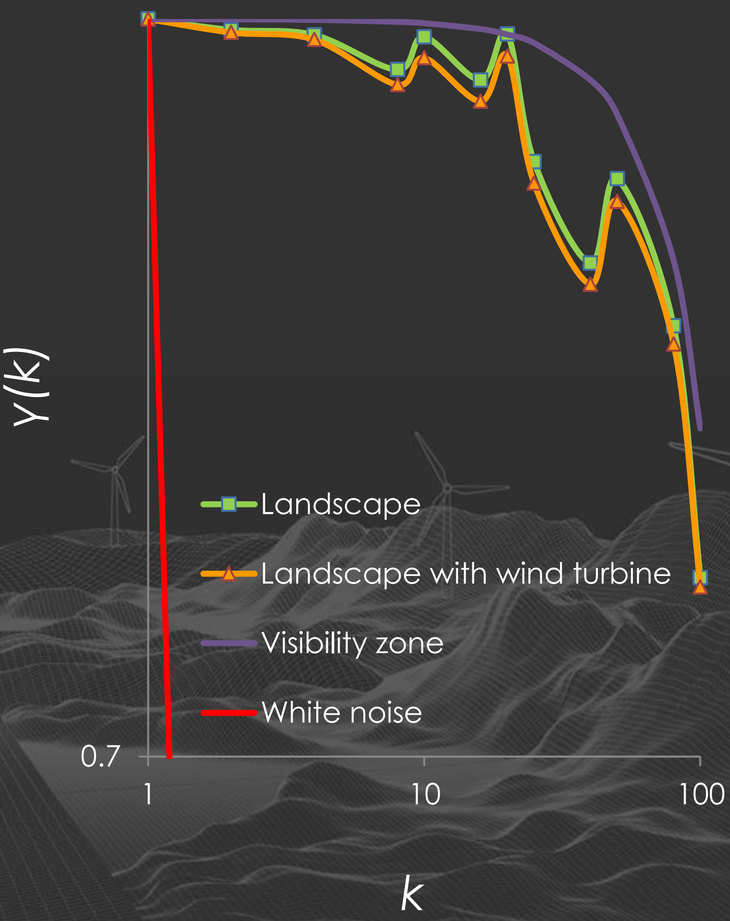
4. Wind turbine on flat terrain





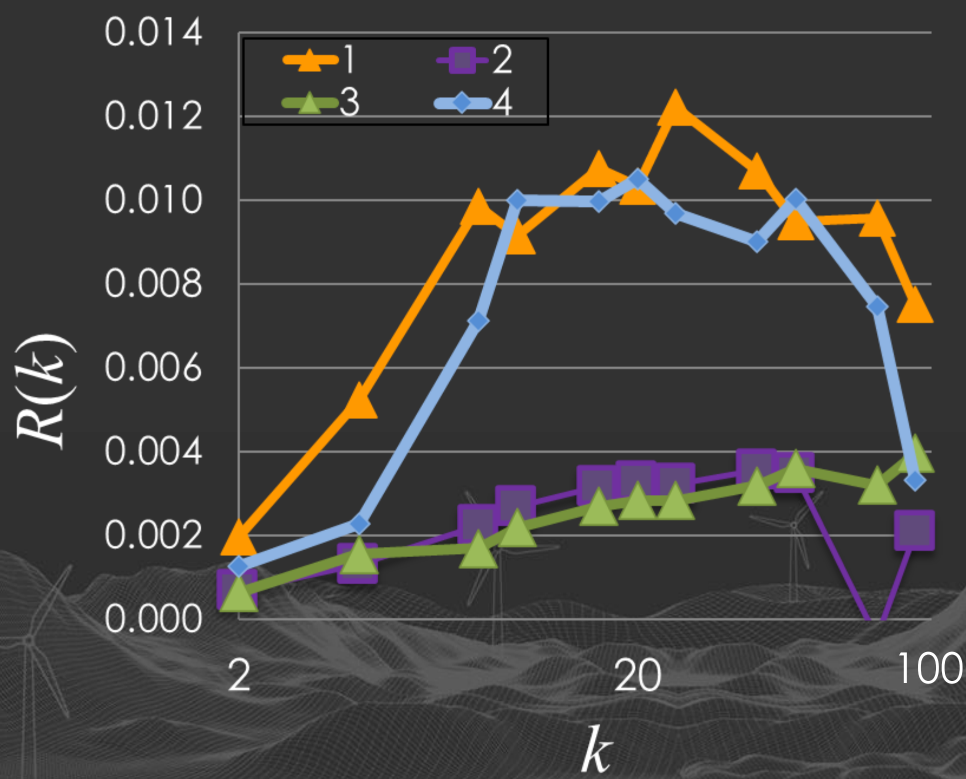


Climacogram



Stochastic 2D-C - Analysis (5)

Climacogram of deviations



Where $R(k) = \gamma(\kappa)_{\text{landscape}} - \gamma(\kappa)_{\text{landscape with turbine}}$

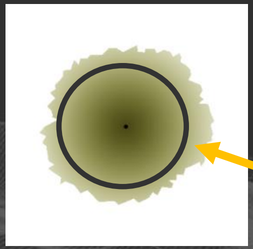
For each scenario, a new series were created by deducting the values of the climacogram of the picture of the landscape without the wind turbines from the climacogram of the picture including the wind turbine. These four new series are presented here.

Conclusions

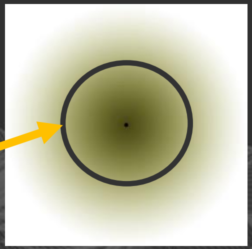
1. The examined observer views are grouped into two types, based on their stochastic behavior. In scenarios 1 and 4 the differences of the climacograms of the landscape before and after the installation of wind turbines are noticeably larger that in scenarios 2 and 3 (slide 21). This indicates that wind turbines that contrast with the sky generate greater visual heterogeneity and are thus more impactful to landscapes. Notably, these are the positions with the highest wind energy potential.

2. Based on conclusion 1, we note that ZTV analyses cannot fully describe the visual impacts from civil infrastructure on their own and in particular in this instance, of wind energy developments. For example, in the area of visibility in scenarios 2 and 4 the visual phenomenon seems to be identical, even though scenario 4 is actually more impactful (or generally different), based on the stochastic 2D-C analysis.

Scenario 2



Scenario 4



Similar area

3. Based on the aforementioned insights, we conclude that indexes supported by stochastic 2D-C analysis could be incorporated in visual ZTV analysis to improve their accuracy and completeness of the analysis of visual-impacts from civil infrastructure.

See also **parallel presentations EGU2020-19832** (Sargentis et al., 2020b), for more theoretical background on stochastic 2D-C analysis, and **EGU2020-5484** (Manta et al. 2020) for its application in a case study.

References (1)

- Apostol, D., Palmer, J., Pasqualetti, M., Smardon, R., Sullivan, R., 2016. The Renewable Energy Landscape: Preserving Scenic Values in our Sustainable Future. Routledge.
- Betakova, V., Vojar, J., Sklenicka, P., 2015. Wind turbines location: How many and how far? Applied Energy 151, 23–31.
- Bishop, I.D., 2002. Determination of thresholds of visual impact: the case of wind turbines. Environment and Planning B: Planning and design 29, 707–718.
- Buchan, N., 2002. Visual Assessment of Windfarms Best Practice (Scottish Natural Heritage Commissioned Report No. F01AA303A). University of Newcastle, Newcastle.
- Dimitriadis, P., 2017. Hurst-Kolmogorov dynamics in Hydrometeorological processes and in the microscale of turbulence.
- Frolova, M., Prados, M.-J., Nadaï, A., 2015. Emerging renewable energy landscapes in Southern European Countries, in: Renewable Energies and European Landscapes. Springer, pp. 3–24.
- Hankinson, M., 1999. Landscape and Visual Impact Assessment. Handbook of Environmental Impact Assessment. Volume 1., 347–373.
- Hellenic Ministry of Environment, Energy & Climate Change, 2008. National Framework for Spatial Planning and Sustainable Development of renewable energy sources t [Εθνικό Πλαίσιο Χωροταξικού Σχεδιασμού & Αειφόρου Ανάπτυξης για τις ανανεώσιμες πηγές ενέργειας]. Athens.
- Horner & Maclennan, Envision, 2006. Visual representation of windfarms - Good practice guidance (Prepared for Scottish Natural Heritage, The Scottish Renewables Forum and the Scottish Society of Directors of Planning No. FO3 AA 308/2). Scottish Natural Heritage.
- Ioannidis, R., Dimitriadis, P., Sargentis, G.-F., Frangedaki, E., Iliopoulou, T., Koutsoyiannis, D., 2019. Stochastic similarities between natural processes and art: Application inthe analysis and optimization of landscape aesthetics of renewable energyand civil works, in: European Geosciences Union General Assembly 2019. EGU.
- Ioannidis, R., Koutsoyiannis, D., 2020. A review of land use, visiblity and public perception of renewable energy in the context of landscape impact (under review). Applied Energy.
- Manta, E., Ioannidis, R., Sargentis, G.-F., Efstratiadis, A., 2020. Aesthetic evaluation of wind turbines in stochastic setting: Case study of Tinos island, Greece, in: European Geosciences Union General Assembly 2020. https://doi.org/10.5194/egusphere-egu2020-18212
- Möller, B., 2010. Spatial analyses of emerging and fading wind energy landscapes in Denmark. Land Use Policy 27, 233–241. https://doi.org/10.1016/j.landusepol.2009.06.001
- New South Wales Government [NSW Government], 2016. Wind Energy: Visual Assessment Bulletin - For State significant wind energy development.

References (2)

- Rodrigues, M., Montañés, C., Fueyo, N., 2010. A method for the assessment of the visual impact caused by the large-scale deployment of renewable-energy facilities. Environmental Impact Assessment Review 30, 240–246.
- Sargentis, G.-F., Dimitriadis, P., Iliopoulou, T., Ioannidis, R., Koutsoyiannis, D., 2018. Stochastic investigation of the Hurst-Kolmogorov behaviour in arts, in: European Geosciences Union General Assembly 2018. EGU.
- Sargentis, G.-F., Dimitriadis, P., Ioannidis, R., Iliopoulou, T., Koutsoyiannis, D., 2019. Stochastic evaluation of landscapes transformed by renewable energy installations and civil works. Energies 12. https://doi.org/10.3390/en12142817
- Sargentis, G.-F., Dimitriadis, P., Koutsoyiannis, D., 2020a. Aesthetical Issues of Leonardo Da Vinci's and Pablo Picasso's Paintings with Stochastic Evaluation. Heritage 3, 283–305. https://doi.org/10.3390/heritage3020017
- Sargentis, G.-F., Ioannidis, R., Meletopoulos, I.T., Dimitriadis, P., Koutsoyiannis, D., 2020b. Aesthetical issues with stochastic evaluation., in: Geophysical Research Abstracts, Vol. 22. Presented at the European Geosciences Union General Assemply 2020, European Geosciences Union, VIenna. https://doi.org/10.5194/egusphere-egu2020-19832
- Scottish Natural Heritage [SNH], 2014. Natural Heritage Indicator - N3 Visual influence of built development. Natural Scotland - Scottish Government.
- Scottish Natural Heritage [SNH], 2009. Siting and Designing Windfarms in the Landscape. Version 1. Scottish Natural Heritage.
- Stevenson, R., Griffiths, S., 1994. The visual impact of windfarms: lessons from the UK experience. Harwell Laboratory, Energy Technology Support Unit.
- Stremke, S., van den Dobbelsteen, A., 2012. Sustainable Energy Landscapes: Designing, Planning, and Development. CRC Press (Taylor & Francis), Boca Raton, FL, USA.
- Sullivan, R.G., Kirchler, L.B., Lahti, T., Roché, S., Beckman, K., Cantwell, B., Richmond, P., 2012. Wind turbine visibility and visual impact threshold distances in western landscapes (operated under Contract No. DE-AC02-06CH11357). UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy Office of Science laboratory.
- Tyralis, H., Dimitriadis, P., Koutsoyiannis, D., O'Connell, P.E., Tzouka, K., Iliopoulou, T., 2018. On the long-range dependence properties of annual precipitation using a global network of instrumental measurements. Advances in Water Resources 111, 301–318. https://doi.org/10.1016/j.advwatres.2017.11.010
- Vissering, J., Sinclair, M., Margolis, A., 2011. A visual impact assessment process for wind energy projects. Clean Energy States Alliance.
- 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.