Estimating the cumulative effect and the zone of influence from multiple anthropogenic infrastructures on biodiversity

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Abstract

We compare distance and density and do the math to compute the zone of influence and cumulative influence for anthropogenic infrastructures.

Old titles:

Estimating the zone of influence and cumulative anthropogenic footprint of infrastructures on animal space use

Density are more suitable in assessing cumulative impacts than the distance to the nearest feature

Estimating the magnitude and zone/scale of influence from multiple anthropogenic infrastructures on biodiversity

1 Introduction

Human-induced land cover modifications and infrastructure from industrial development are spread and increasing at an accelerated pace across all regions of the world (Venter et al., 2016; Ibisch et al., 2016), including all global biodiversity hotspots (Sloan et al., 2014), and are among the main causes of biodiversity declines (Benítez-López et al., 2010; Newbold et al., 2015). Most new landscape changes take place not in intact habitats but in landscapes already permeated by multiple human disturbances to wildlife (Barber et al., 2014; Kowe et al., 2020). As a consequence, the influence of such new modifications might accumulate and interact in complex ways with the preexisting anthropogenic stressors, potentially leading to impacts higher than those of each separate source of disturbance. This process is called "nibbling" or "piecemeal development" (Nellemann et al., 2003) and have recently been addressed under the name of cumulative anthropogenic impacts on biodiversity (Gillingham et al., 2016). Indeed, cumulative effects are a central issue in ecological studies and environmental impact assessments and a priority for making effective, knowledge-based decisions on land use planning, designing mitigation actions, and avoiding higher effects of industrial development on ecosystems (Laurance and Arrea, 2017; **?**). Yet, the operationalization of modeling approaches and frameworks to account for cumulative effects in its several dimensions is yet to get mature.

Even though anthropogenic infrastructure have direct effects where they are built (e.g. road kills and habitat modification from road building), they might also indirectly influence species and ecological processes up to several kilometers from the infrastructure locations, e.g. by creating avoidance and reducing the probability of animal occurrence (Trombulak and Frissell, 2000; Torres et al., 2016). Therefore, two key factors to be assessed in cumulative impact studies are the magnitude of the effect from infrastructure and the scale or area where this effect is present. Understanding the *effect size* is generally the main aim of most research focused on impacts and is tackled by estimating which factors influence focal organisms and processes and how strongly they are affected, generally through a combination of biological and environmental data and statistical modeling [REF]. The *scale* or *zone* of influence (ZoI) corresponds to the area within which there are detectable effects from different landscape modifications on the process of interest, but is commonly expressed in terms of distances — the distance from or radius around the disturbance sources which defines the affected area (e.g. Polfus et al., 2011; Boulanger et al., 2012). The term "scale" has been used in multiple contexts in ecology (e.g. scale as landscape grain and extent; spatial and temporal scales and the scale of ecological organization; Wiens 1989; scale or level of animal habitat selection; Lima and Zollner 1996) and has led to important advances in ecological theory (Fahrig, 2003; McGarigal et al., 2016). However, to avoid misunderstandings with the nomenclature, here we use the term Zone of Influence (ZoI) to refer to the area or distance from infrastructure where there is any effect on biodiversity.

Infrastructure and disturbance impacts can accumulate at least over time and space, by the sum or interaction of the effects of different types of infrastructure or multiple features of same-type infrastructure (Wiens, 1989; Wolfe et al., 2000). The effects of multiple types of infrastructure and landscape modification are generally included in ecological models by careful evaluation of their correlations (Dormann et al., 2013) and subsequently through the inclusion of additive or interactive terms in statistical model specification, to control for their mutual potential influence on the studied system [REF]. This allows one to estimate the coefficients (or slopes) for each infrastructure or their combination and have measures of effect size for each of them. Alternatively, other studies combine multiple disturbances in a single measure of cumulative effect before starting the statistical modelling (Polfus et al., 2011; Venter et al., 2016; Tucker et al., 2018). As for the influence of multiple infrastructure of the same type, most commonly they are either considered by changing the variable's level of spatial organization (e.g. urban areas or wind parks instead of a combination of buildings and turbines, respectively) or ignored by considering only the effect of the nearest infrastructure feature [REF].

The determination of the ZoI for multiple infrastructure is trickier than assessing their effect size **(or maybe it is inherently linked?)**. When estimating the ZoI, the concept of ecological threshold (Huggett, 2005) and analytical procedures developed therein are commonly used (Ficetola and Denoël, 2009). Under this framework, the estimation of the zones of influence is often carried out by fitting piece-wise regression models or other non-linear functions (such as an exponential decay or generalized additive models; Skarin et al., 2018; Ficetola and Denoël, 2009) to the measured response of an ecosystem to an infrastructure as a function of distance. This distance is typically the distance to the nearest instance of this infrastructure type, ignoring potential additive or cumulative effects of multiple instances or features of an infrastructure (e.g Torres et al., 2016). Besides, this approach is common when the threshold is assessed for only one or a few types of infrastructure (e.g. Boulanger et al., 2012), since its computation requires repeated fitting and might become impracticable for a large number of factors (Lee et al., 2020).

Another approach to estimate the ZoI may be found under the umbrella of the discussion about *scales* of effect, prevalent mainly in the context of species-landscape relationships. In this context, the number of features is averaged for multiple spatial extents surrounding focal study sites (Jackson and Fahrig, 2015) or filtered using neighborhood analysis over several different extents or radii (also called scales), creating a series of infrastructure density maps (McGarigal et al., 2016). Each of these maps is tested against the ecological response variables to assess the extent where the effect is stronger, either a priori to select biologically meaningful scales, based on R^2, information criteria such as AIC or BIC, or other measures of model performance and explanatory power (Jackson and Fahrig, 2015), or a posteriori (after model fitting) to chose the best scales (Thompson and McGarigal, 2002). This approach characterizes what is called multi-scale analyses, in contrast to single-scale analyses in which the effect of all variables is evaluated with the same extent (e.g. Zeller et al., 2017). Multi-scale analyses brought important advances for landscape and impact studies (Fahrig, 2003; McGarigal et al., 2016), even though in many of them the scale of effect was not properly evaluated (Jackson and Fahrig, 2015). However, the key here is that these approaches have hardly been put into the framework of cumulative impact assessment (but see Polfus et al., 2011).

I need to review this paragraphs later to make sure the idea of "scale" is not confusing. Maybe replace by more precise terms, when possible.

Building upon this literature, we propose an approach to estimate the effect size and ZoI of multiple features of an infrastructure and test if their effects accumulate. First, we derive the estimation methods based on either the distance to the nearest feature or the cumulative influence of multiple features (Fig. **??**), using habitat selection analyses as an example. Second, we perform simulations to distinguish in which scenarios the spatial variation converge or diverge between these two methods. Finally, we illustrate them by assessing the cumulative effects on space use of the tundra's flagship species, the mountain reindeer. We also provide functions and tools to allow an easy implementation of the cumulative approach presented here in R (R Core Team, 2020) and GRASS GIS (GRASS Development Team, 2017) through the `oneimpact` R package. Even though our examples focus on animal space use, we believe this approach is relevant for ecological studies and impact assessments over several fields, from genetics to organisms to populations and communities.

2 Deriving the estimation of the cumulative influence of multiple features

We first derive **(or describe?)** the cumulative influence of multiple features of an infrastructure type, e.g. roads, houses or tourist resorts, on space use. To illustrate it, we use as an example a habitat selection analysis, which aim at discriminating what sets of environmental conditions are selected or avoided by animals, based on ecological data such as species occurrence or movement data and use-availability designs (Johnson et al., 2006; Thurfjell et al., 2014). The main element in habitat selection approaches is the habitat selection function (HSF) $w(\mathbf{X})$, a function proportional to the probability of selection of a given space resource unit, depending on the frequency of used and available resource units (Thurfjell et al., 2014). The HSF $w(\mathbf{X})$ is function of a vector of predictor variables $\mathbf{X} = X_1, X_2, ..., X_k$, which here correspond to k different types of infrastructure, but might also represent other landscape modifications or spatiotemporal variables. In its parametric form, the HSF might be represented by

$$w(\mathbf{X}) = \exp\left(\beta_0 + \overbrace{\beta_1 X_1}^{\text{A) Infrastructure type 1}} + \overbrace{\beta_2 X_2}^{\text{B) Infrastructure type 2}} + \underbrace{\beta_{12} X_1 X_2}_{\text{D) Interaction infrastructure types 1 and 2}} + ... + \overbrace{\beta_k X_k}^{\text{C) Infrastructure type k}}\right) \tag{1}$$

where β_k represents the effect size (or coefficient/slope) of the infrastructure of type k. In its simplest form, here *the cumulative effect of different types of infrastructure* is given by the additive effects of the k infrastructure types (e.g. terms A, B, and C in equation 1) and possibly by interaction terms between variables (such as term D in equation 1, with an interaction coefficient β_{12}), that allow for non-linear effects.

To derive the cumulative effect of multiple infrastructure of the same type, we start by defining verbally two representations of the spatial influence of infrastructure: the influence of the nearest feature alone and the cumulative influence of multiple features (Fig. 1). First, within the ZoI, the influence of an infrastructure feature (e.g. a house) might be either constant (threshold curve, Fig. 1A) or decrease as one moves away from the infrastructure (e.g. linear and Gaussian curves, Fig. 1A). Whether the influence of a given infrastructure follows one of these or other curves is to be determined empirically. Second, the effect of the infrastructure might depend either on the nearest infrastructure alone or on the cumulative influence of several infrastructure (Fig. 1B). In the former case, the influence is similar when one approaches a single, isolated house or a small village, for example. In the latter, the influence of nearby houses accumulate and might be greater than that of a single, isolated house.

[Figure 1 about here.]

To translate those representations into a mathematical form, now we decompose each of the terms A, B, C, ..., in equation 1. Suppose that in the landscape there are n_k features of the same type of infrastructure k, and let the influence of the feature i of an infrastructure k be $\phi_{i_k} = f(\Delta_{i_k}; \zeta_k)$, where Δ_{i_k} is the distance to a feature (i_k) of infrastructure type k and ζ_k is its zone of influence (see Fig. 1A). We can sum the effect of each of them on animal space use, so that the linear terms in equation 1 become:

$$\beta_k X_k = \sum_{i=1}^{n_k} \beta_{i_k} \phi_{i_k} \tag{2}$$

Typically, only the nearest feature is considered, resulting on the implicit assumption that $\beta_i = 0$ for all $i > 1$ (where the features are ordered by increasing distance) and

$$\beta_k X_k = \beta_{1_k} \phi_{1_k} \tag{3}$$

However, possibly a more reasonable assumption would be that $\beta_{i_k} = \beta_{i+1_k} = \beta_{i+...} = \beta_k$, i.e. that all features of a given type present the same influence and all β's are identical. Thus:

$$\beta_k X_k = \beta_k \sum_{i=1}^{n_k} \phi_{i_k} = \beta_k \phi_{cum_k} \tag{4}$$

where $\phi_{cum_k} = \sum_{i=1}^{n_k} \phi_{i_k}$ is the cumulative influence measure and is proportional to what has been called the 'density' of features in space (e.g. Panzacchi et al., 2015), and might be easily calculated using geographical information systems. Equation 4 presents the simplest possibility of considering the cumulative effect of features of the same type.

Analogous to Lee et al. (2020)'s recasting of the identification of the ZoI of a single (i.e. the nearest) infrastructure as a model selection rather than a parameterization problem, with this formulation we can also estimate the cumulative effect size and the ZoI of features using model selection.

3 When the influence of the nearest feature and the cumulative influence converge?

Whether the spatial variation represented by the cumulative influence of multiple features of an infrastructure is similar or not to the distance to the nearest feature depends on the spatial distribution of the infrastructure as well as its zone of influence. To test when they converged and diverged, we simulated landscapes with a constant number of point features (e.g. houses, tourism cabins; $n = 100$) distributed following different patterns, in a gradient of clustering, from regular and random to clustered (Fig. 2). For each scenario we calculated the two measures of influence (nearest feature and cumulative) for a gradient of values of ZoI (from 250 m to 10 km), using a linear decay function ((”Bartlett” or tent-shaped, for which the ZoI is easily defined when the function decreases to zero; Harris, 1978)), and compared the resulting influence spatial patterns through a Pearson correlation (see details in the Appendix 1).

[Figure 2 about here.]

We also calculated the logarithm of the Euclidean distance to the nearest

4 Empirical demonstration: cumulative influence of houses on reindeer space use

For our empirical demonstration we used GPS tracking data from the Hardangervidda reindeer population in Southern Norway, which is the largest population of wild mountain reindeer in Europe. We used data from XXX individuals during the summer season (see Panzacchi et al., 2015, for further details). To account for bio-climatic-geographical variation in environmental characteristics we used the four components from a large principal component (PC) analysis conducted for Norway (Bakkestuen et al., 2008), which correspond to: (1) PC1 - continentality, (2) PC2 - altitude, (3) PC3 - ruggedness, and (4) PC4 - solar radiation; we included a quadratic term for PC1 and PC2. We used the SatVeg map with 21 vegetation classes, which we further grouped (see Table 1). To keep model fitting relatively simple we included two anthropogenic variable: private and tourist cabins, for which we estimated the cumulative effects and footprint. There are a total of 13,015 private cabins compared to only 26 tourist cabins within the study area. Furthermore, we did not perform model selection, but compared models based on different representation of the influence of private cabins.

We estimated the effect of both private and tourist cabins for 8 ZoI: 100, 250, 500, 1000, 2500, 5000, 10000, and 20000 meter. For each ZoI, we used three shapes for the changing effect over the ZoI (see Figure **??**): threshold, linear decline, and half-normal ($\phi_{i_k} = \exp(-2.77(\Delta_{i_k}/\zeta_k)^2)$), and two assumptions for the effect of additional features (see Figure): $\beta_i \neq 0$ for $i = 1$ and $\beta_i = 0$ for all $i > 1$ (i.e. only the nearest feature has an effect) versus $\beta_i = \beta$ for all i (i.e. all features contribute to a cumulative effect). With all combinations, we fitted a total of 2304 (i.e. $(8 \times 3 \times 2)^2$) RSFs. The RSFs were fitted using the `survival` library in R (Therneau, 2020; Terry M. Therneau and Patricia M. Grambsch, 2000), we selected the best model based on AIC. We then used 99 bootstraps to estimate the standard errors for this model. Note that the ZoI is not well defined for functions with an infinite domain, such as the Gaussian. We therefore linked to ZoI to the function's half-life (i.e. where the influence has halved), thus the half-life of the Gaussian function corresponded to half the distance of the ZoI as it is for the linear shape (the influence at the ZoI has then dropped to $1/16 \approx 0.06$; we computed the influence until 2.55 $\times$ the half-life, when it has dropped further to $e^{-4.5} \approx 0.01$).

5 Results

5.1 Model selection and estimates

Table 1: Parameter estimates for the best model (lowest AIC)

Variable	Estimate	Std. Error	p-value
tourist cabins	-2.41×10^{-2}	5.82×10^{-4}	< 0.001
private cabins	-4.40×10^{-8}	1.39×10^{-9}	< 0.001
exposed ridges	0.38	0.14	0.0067
grass ridges	0.95	0.14	< 0.001
heather ridges	0.89	0.13	< 0.001
lichen	1.04	0.17	< 0.001
heather	0.93	0.13	< 0.001
heathland	0.85	0.13	< 0.001
meadows	0.90	0.15	< 0.001
early snowbed	0.66	0.13	< 0.001
late snowbed	0.47	0.14	< 0.001
bog	0.87	0.15	< 0.001
glacier	-0.35	0.32	0.2801
other	-6.16	175	0.972
water	-1.44	0.20	< 0.001
poly(pc1, 2)1	272.46	10.26	< 0.001
poly(pc1, 2)2	-261.78	10.82	< 0.001
poly(pc2, 2)1	-476.01	37.52	< 0.001
poly(pc2, 2)2	-148.44	22.46	< 0.001
pc3	-77.37	23.63	0.0011
pc4	111.12	23.61	< 0.001

6 Discussion

There is an urge to assess, debate, and inform scientists, decision-makers, and the public in general about the past, current, and future effects of global infrastructure on biodiversity (Laurance, 2018). Here we gave a step further in discussing and proposing a way to conduct studies, test for the cumulative effects of multiple infrastructure features of the same type, and pointed to evidence of cumulative effects and situations when they might be more prevalent.

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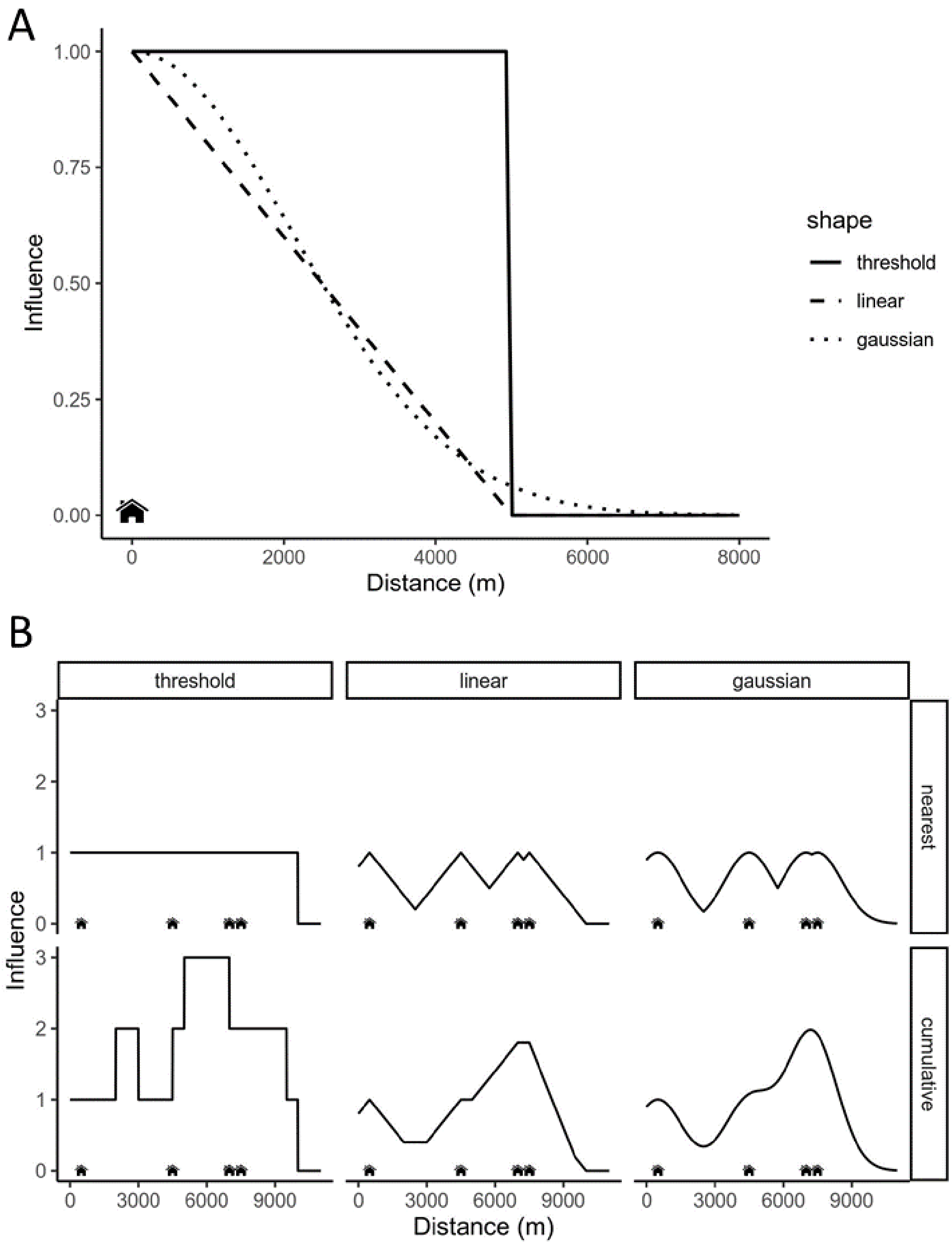

Figure 1: Illustration of the influence (ϕ_{i_k}) of houses against the distance from the houses (Δ_{i_k}), simplified for one dimension. (A) Examples of shapes according which the influence of the house might vary. A house has only an influence within its zone of influence (here $ZoI = \zeta_{i_k} = 5,000$). For the threshold/step shape, the influence remains constant within the ZoI and drops to zero outside, whereas for both the linear and Gaussian shapes it declines monotonically within the ZoI. For functions that asymptotically approach zero, a cutoff must be selected to characterize the ZoI (e.g. when the influence is $\phi_{i_k} < 0.05$). (B) Representation of the influence of multiple houses by considering only the nearest feature or the cumulative influence of multiple features, for different influence shapes. If only the nearest house affects space use, the influence will not go above one; when all houses act cumulatively, their cumulative effect can be much higher than one.

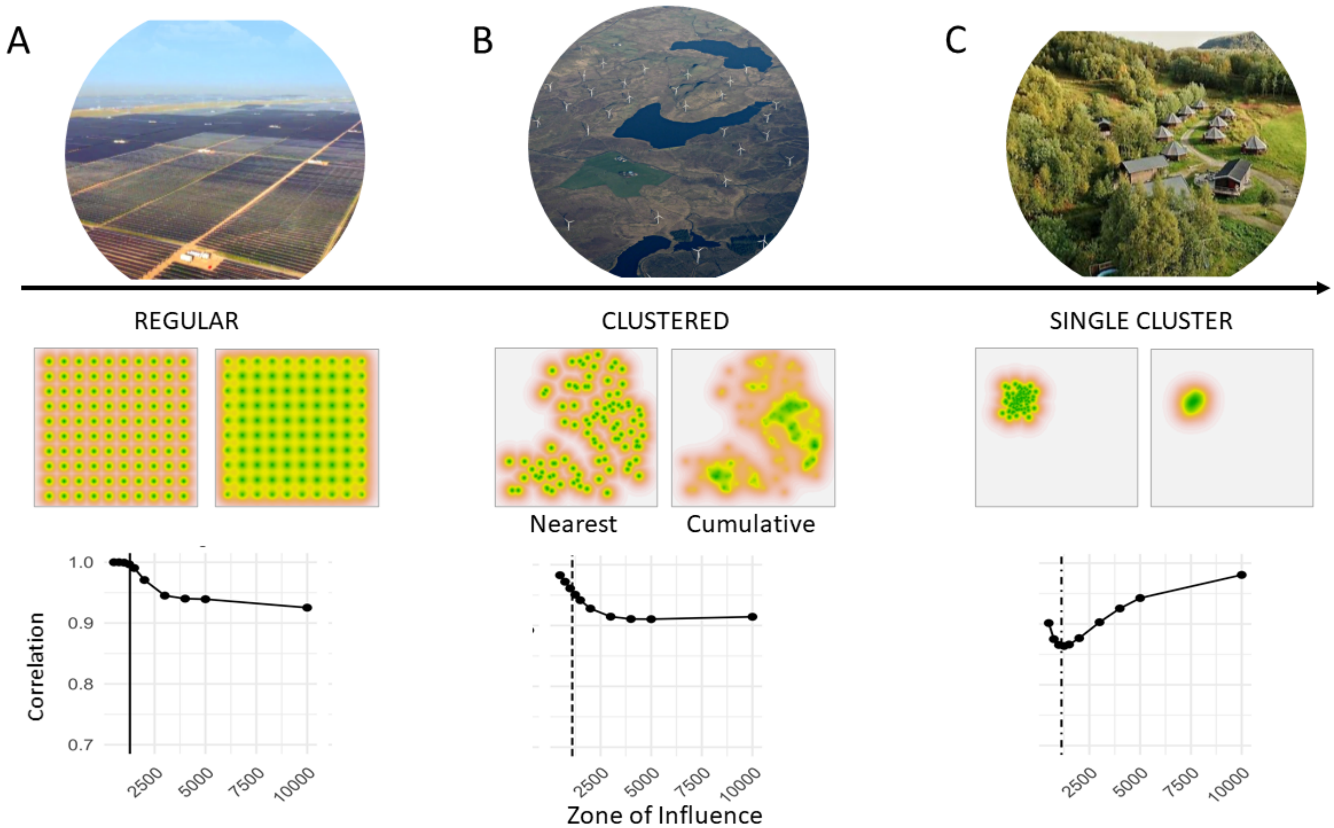

Figure 2: Representation of the nearest feature and cumulative influence in landscapes with point infrastructure spatially distributed in a gradient of clustering, from (A) a regular distribution (e.g. a large solar power plant in a flat area) to (B) a set of clusters (e.g. a wind industrial area formed by wind turbines built in the highest places) to (C) only one cluster (e.g. isolated village or urban center). The central panel shows a visual comparison between the nearest feature influence (left) and the cumulative influence (right) between simulated landscapes following each of those patterns when $ZoI = 3000m$ (higher than the average distance between infrastructure features, see Appendix B). The lower panel shows the correlation between the nearest and