Estimating the cumulative effect and the zone of influence from multiple anthropogenic infrastructure 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 synergistic, interactive, or unpredictable outcomes, different from those of each separate source of disturbance (Johnson and St-Laurent, 2011). This process is called "nibbling" or "piecemeal development" (Nellemann et al., 2003) and have also been addressed under the name of cumulative anthropogenic impacts on biodiversity (Johnson et al., 2005; 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 impacts of industrial development on ecosystems (Laurance and Arrea, 2017). There have been increasing efforts to better define, review the literature, and create the basis to delineate frameworks for cumulative impact assessment (Johnson and St-Laurent, 2011; Gillingham et al., 2016), yet the operationalization of modeling approaches 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 (Johnson and St-Laurent, 2011). Understanding the *effect size* or *magnitude* 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 spatiotemporal *scale* or *zone* of influence (ZoI) corresponds to the area (and sometimes the time of the year) within which there are detectable impacts 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 (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 (Johnson and St-Laurent, 2011).

Infrastructure and disturbance impacts can accumulate at least over time and space, as a result of 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 for each infrastructure or their combination and have measures of the magnitude of the impacts 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 or other non-linear regression models (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 spatial and temporal *scales* of effect, common 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). These spatial scales are generally linked to the spatial and temporal dimensions of the infrastructure considered, as well as to the expected temporal scale of the biological response to such infrastructure. 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 (e.g. Zeller et al., 2017), in contrast to single-scale analyses in which the effect of all variables is evaluated with the same extent. Multi-scale analyses brought important advances for landscape and impact studies (e.g. 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, for instance, 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 magnitude of the impacts and the ZoI of multiple features of an infrastructure and test if their effects accumulate. First, we derive the estimation methods based on either the influence to the nearest feature only or the cumulative influence of multiple features (Fig. 1), 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 measures of influence. 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

Should we add some definitions here, before presenting the derivation? Such as the term "effect" (versus impact, influence). Johnson and St-Laurent (2011), for instance, use "the term effect to mean a change in the environment resulting from a human activity and the term impact to represent the consequences of such changes for wildlife populations" (p. 27).
There are other terms that can be confusing such as distance-weighting, filtering, neighborhood analysis etc, that point to the same or similar concepts but can create confusion or misunderstanding.

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; Fieberg et al., 2021). 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 of the effect) 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). Note that we refer to the term "influence" instead of "distance", since we are generally referring to decay functions that decrease towards zero as the Euclidean distance from the infrastructure increases, and possibly vanish at a given point (the zone of influence).

First, within the ZoI, the influence of an infrastructure feature (e.g. a house or road) 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 (Miguet et al., 2017). 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 linear terms (i.e. 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. Figure 1A shows a few possible shapes for the function ϕ_{i_k}. We can sum the effect of each feature on animal space use, so that the linear terms in equation 1 become:

Isn't it easier to read if I replace Δ_{i_k} by d_{i_k} and ζ_{i_k} by ZoI_{i_k}? These symbols are not often used along the text, and maybe it is easier to understand. Also, we are currently using the acronym ZoI along the whole text.

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

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 eq. 2 turns into:

$$\begin{aligned} \beta_k X_k &= \beta_{1_k} \phi_{1_k} \\ &= \beta_{1_k} \phi_{nearest_k} \end{aligned} \tag{3}$$

where $\phi_{nearest_k}$ is the influence of the nearest feature ($i = 1$) of the infrastructure type k (see Fig. 1). However, possibly a more reasonable assumption would be that $\beta_{i_k} = \beta_{(i+1)_k} = \beta_{(i+2)_k} = ... = \beta_k$, i.e. that all features of a given type present the same influence and all β's are identical. Thus, eq. 2 is reduced to:

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

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, e.g. through neighborhood analysis. 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 definition we can also estimate the cumulative effect size and the ZoI of features using model selection, which allows this to be done for different types of infrastructure. Beyond that, this formulation makes it possible to test for the presence of cumulative effects of anthropogenic landscape changes by comparing models with either of the two influence measures (equations 3 and 4), both based on the same decay function.

3 When do the influence of the nearest feature and the cumulative influence diverge?

Whether the spatial variation represented by the cumulative influence of multiple features of an infrastructure is similar or not to the influence of the nearest feature depends on the spatial distribution of the infrastructure as well as its zone of influence. To illustrate when they converged and diverged, we simulated 30×30 km landscapes with a constant number of point features (e.g. houses, cabins, turbines; $n = 100$) distributed following different spatial patterns, in a gradient of clustering, from regular and random to clustered (Fig. 2; Appendix A). For each scenario we calculated the two measures of influence (nearest feature, $\phi_{nearest}$, and cumulative, ϕ_{cum}) for a range of values of ZoI (from 20 m to 12 km), using a linear decay function (Fig. 1; "Bartlett" or tent-shaped decay; Harris, 1978), for which the ZoI is easily defined as the distance at which the function decreases to zero. We then compared the resulting influence spatial patterns through Pearson correlation of the values of the two measures at the same coordinates (see details in the Appendix A).

[Figure 2 about here.]

When the ZoI is smaller than **half the minimum** distance between features, both measures of influence are similar and their correlation is maximum (Fig. 2; correlation $= 1$ for all ZoI values below the black dashed vertical line). This happens because the ZoI of each feature is not large enough to interact with each other. As the ZoI increases, the effect of nearby features starts to sum and the two measures of influence begin to represent different patterns of spatial variation. This is valid for scenarios with random, regular, and slightly clustered distributions of infrastructure features (Fig. 2A,B, Fig AXX in Appendix A). In contrast, as the distribution of features gets more clumped and in smaller clusters, (up to a limit with a single small cluster, Fig. 2C), the correlation between the influence measures goes through a point of inflection as the ZoI increases, beyond which it increased with ZoI (Fig. AXX in Appendix A). The point where the correlation between the influence measures stop decreasing is defined by the size of the clusters (grey dashed vertical line in Figs. 2B,C). For ZoI values larger than the cluster size, the two influence measures start to converge again. That is the point when it is not possible to distinguish between the effect of each feature alone, regardless of the influence measure, and the effect of a collection of features transforms into that of a "super-feature" (e.g. a group of houses or wind turbines behave as an urban area or a wind park, respectively).

Here we simulated landscapes with point infrastructure because of the simplicity to represent them and place them following different patterns. We believe these simple cases might provide insights on when $\phi_{nearest}$ and ϕ_{cum} are similar for other types of infrastructure, for instance linear infrastructure (e.g. roads, railways, and power lines) and higher dimensional landscape changes defined by polygons and areas (e.g. mining, forestry, and deforestation). However, we recognize that those patterns can get more complex as these structures and spatial patterns extend over large distances and areas, and a further assessment of when these influence measures converge might be needed.

better to place this paragraph in the discussion?

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

4.1 Study area, ecological data, and analysis

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 1A): 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 $e^{-4.5} \approx 0.01$).

4.2 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

5 Tools to assess cumulative influence of infrastructure

Talk about the `oneimpact` R package. Built based on the `terra` package and complements the `smoothie` package. It allows for flexible calculation of influence of nearest feature and cumulative influence or density measures. One can use pre-defined distance or decay functions (e.g. which ones are implemented) or define user-created filters to calculate those things. Also, it allows for calculation on R and GRASS GIS. R is easy to use and the most used tool by ecologists (REF?). On the other hand, R also allows a direct link with the powerfull algorithms of GRASS GIS, so that there operations might be performed for very large and fine-scale spatio-temporal datasets. An introduction to the essential functions to calulcate these two influence measures is found in Appendix D. Available on the Github repository at NINANor.

6 Discussion

There is an urge to evaluate, 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). Most of the decisions and regulations made for infrastructure projects are performed with little or no knowledge about the potential impacts on the ecosystems where they are built and the species living therein. Even when environmental impact assessments are well conducted, they hardly estimate the cumulative effects of those infrastructure with pre-existing ones or with other development projects planned for the same region (Laurance and Arrea, 2017). In great part, this happens because current approaches and tools still lack in their ability to incorporate cumulative effects (but see this and this reference for great recent advances). Building upon previous frameworks to understand cumulative impacts (Johnson and St-Laurent, 2011) and by adapting concepts and tools from the landscape ecology literature into the nearest and cumulative influence measures, here we gave a step further in developing a clear way to assess cumulative effects and impacts of infrastructure on biodiversity. The approach proposed here allows one to: (i) quantify the cumulative effect of multiple infrastructure of the same type; (ii) test whether there are cumulative effects for each type of infrastructure, by comparing the influence of the nearest feature and the cumulative influence as predictors of biological responses, within ecological models; and (ii) estimate the zone of influence for multiple types of infrastructure. Here we depict scenarios where each of the influence measures might converge or diverge, present a case study to illustrate it, and offer tools to allow their application in ecological studies and environmental impact assessments.

The formulation of the influence of the nearest feature (eq. 3) and the cumulative influence (eq. 4) as presented here makes it possible to compare whether there are cumulative effects of an infrastructure by comparing models with either of the influence measures, through model fit estimates (e.g. AIC or R^2; Jackson and Fahrig 2015). It also raises the possibility of finding the ZoI (or scale of effect, *sensu* Jackson and Fahrig 2015) and the decayment of the influence with distance (e.g. threshold or exponential decay, as in Miguet et al., 2017) only through model selection, without the necessity of performing complex parametrization of non-linear functions for (Lee et al., 2020). In great part, this is feasible because the computation of these predictor variables might be performed before model fitting. We also provide tools for this calculations, using both R and GRASS GIS environments, though the `oneimpact` R package. R is one of the most widely used programming languages in ecology (Lai et al., 2019). GRASS is less popular because of its specificity (it is not designed for data analysis) but is a powerful, free, and open-source GIS. To make it widely accessible to the ecologists used with R, the tools presented here provide an interface between R and GRASS, so that all the computation might be done from within R. Even though our current formulation (eq. 4) is maybe the simplest form of accounting for cumulative effects, more complex formats might be chosen, based on eq. 2, by changing the assumptions on the values of the effect sizes ($\beta's$) of each feature or the function shape of the decayment influence curves (Miguet et al., 2017). Yet, we believe out proposal might be very useful in ecological studies.

To understand in which cases it might be more interesting to test for presence of cumulative effects, we used simulated scenarios with point infrastructure spread following different spatial point patterns and we compared when the influence of the nearest feature and the cumulative influence of multiple features differ. For features that are regularly or randomly distributed, we found the two influence measures differ more strongly when the zone of influence increases. However, probably in most real situations infrastructure present some degree of clustering, for instance because they follow some pattern in the landscape (e.g. wind turbines built in mountain tops, REF?) or because they tend to be aggregated where there is already access through roads or waterways Barber et al., 2014. In this case, the cumulative influence differs most from the influence of the nearest feature when the zone of influence is close to the size of the clusters (e.g. urban centers or wind parks), so using measure of clustering might help indicate when it is expected to observe larger cumulative effects. Our simulated examples are limited to assess the influence of the spatial configuration of point-type infrastructure, but we believe they offer insights about when the influence measures are correlated even for other types of infrastructure. Yet, we recognize that for linear infrastructure (e.g. roads) or polygon-like landscape change vectors (e.g. mining areas, forestry or deforestation), the patterns of correlation between nearest and cumulative influence might be different and must still be assessed. In any case, as the ZoI is hardly known in advance for any system, we recommend a general approach of computing and using the two influence measures, to test if there is evidence of cumulative effects in the different ecological systems.

Check these results after re-running the case study analysis. In our case study with mountain reindeer in Norway, we found the support for cumulative effects of tourism cabins and resorts on the use of space by reindeer, with large zones of influence (up to 20 km). We also found an exponential decay of the influence of these infrastructure as one gets far from them, which means not all 20 km around resorts are affected equally, for instance. Add here some reference to Miguet and the definition of the area affected, and the consequences for management and conservation.

It is important to remark is that the selection of the extent of the study area and the scales or zones of influence to be tested must be carefully selected, especially in the context of cumulative effects, when the interplay between multiple factors may produce complex setups. First, the effects of infrastructure on ecological processed might differ depending of the extent of the study area (Vistnes and Nellemann, 2008). For instance, Skarin and Åhman (2014) showed that, depending of the temporal and spatial range of the study, the same type of infrastructure might vary in their effect to ecological variables, from no effect to positive or negative effects. As we show here, the spatial configuration of features and the ZoI might affect if the effects of an infrastructure accumulate. However, the spatial pattern of features is also affected by the selection of extent of the landscape. As an example, if the biological response is measured and assessed in a study area that comprises 10 km around a wind farm, the distribution of wind turbines might look random or somehow aggregated. However, if the study area comprises a much bigger area and the biological response is expected to respond at larger extents, and the wind farm is only located in part of that, their distribution might appear very clumped. Second, the zones or scales of influence must be carefully selected. Depending on the biological response variable, the range of ZoI tested must encompass values much higher than the range size or even the average dispersal distance of an species (Jackson and Fahrig, 2012; Miguet et al., 2016). If the ZoI values are not properly defined, the "true" scale at which the ecological process being measured is affected might not be selected, and the resulting estimated ZoI might be wrong and mislead decisions based on that ´(e.g. Jackson and Fahrig, 2015).

Even though the examples given here focused on animal space use and habitat selection, the cumulative influence measure we presented is applicable over a wide range of fields within ecology. First, the formulation in equation 1 might be easily adapted to model other types of biological responses, such as population abundance **??**e.g.][], species richness **??**e.g.][] or other measures of biological diversity and ecological processes **??**e.g.][]. This might be achieved by setting the statistical models with the appropriate distributions, according to the the type of biological response variable (e.g., see Royle for models and model formulation), but the assumptions and use of the covariates and cumulative influence, as presented in eq. 2, 3, and 4 remain valid. Second, our approach might be used to calculate the nearest and cumulative influence measures either around sampling points (within discs or buffer areas; e.g. **?**) or calculated for the whole study area using multiple neighborhood sizes. The former might be particularly suited for ecological studies with a limited amount of sampling points, such as local landscape studies (e.g. **?**) or species distribution models based on occurrence data (e.g. **?**), or approaches that require a very fine scale (small grain) of the landscape, but might get computationally slow if the number of sampling points is too high. In the latter, the variables might be calculated for the whole study area and used to annotate data afterwards e.g. Zeller et al., 2017, allowing one to easily do that for thousands to millions of points, such as in movement ecology studies involving GPS data (e.g. Tucker et al., 2018; **?**). In this case, the same spatial variables might also be useful for multiple projects ans analyses in the same study area. The tools we provide here with the `oneimpact` R package might help with these tasks.

The cumulative influence proposed here is greatly influenced by the framework on cumulative effect assessment proposed by Johnson and St-Laurent 2011. Important to remember the definition of effect and impact, and that the influence measure proposed here is a component of the impact, when combined with the estimation of effect size. It also build on the studies of Martin, Miguet, and Jackson on the discussion about the scale of effect of covariates in space. Here we use the term ZoI to avoid confusion, but we should keep in mind that the idea behind the term effect (sensu Jackson) is similar to the

Maybe a paragraph about from where we build this approach (ref Johnson cum eff, refs for landscape ecology Miguet, Jackson, Macgarigal, Zeller), and emphasizing the nomenclature - this must be something to be cleared and not to cause further confusion to ecologists and conservation practioneers, and land use managers.

Recapture what we proposed in the intro and the results we found.

What scales should be tested for the determination of ZoI? Citar Jackson and Fahrig.

Acknowledgements

Supplementary Material

Appendix A. Simulating scenarios: Comparing the influence of the nearest feature with the cumulative influence
Appendix B. Simulating scenarios: Comparing Euclidean distances with the cumulative influence
Appendix C. Using neighborhood analysis to estimate influence measures
Appendix D. Cumulative effects of infrastructure on mountain reindeer
Appendix E. An introduction to cumulative effect assessment with the `oneimpact` package

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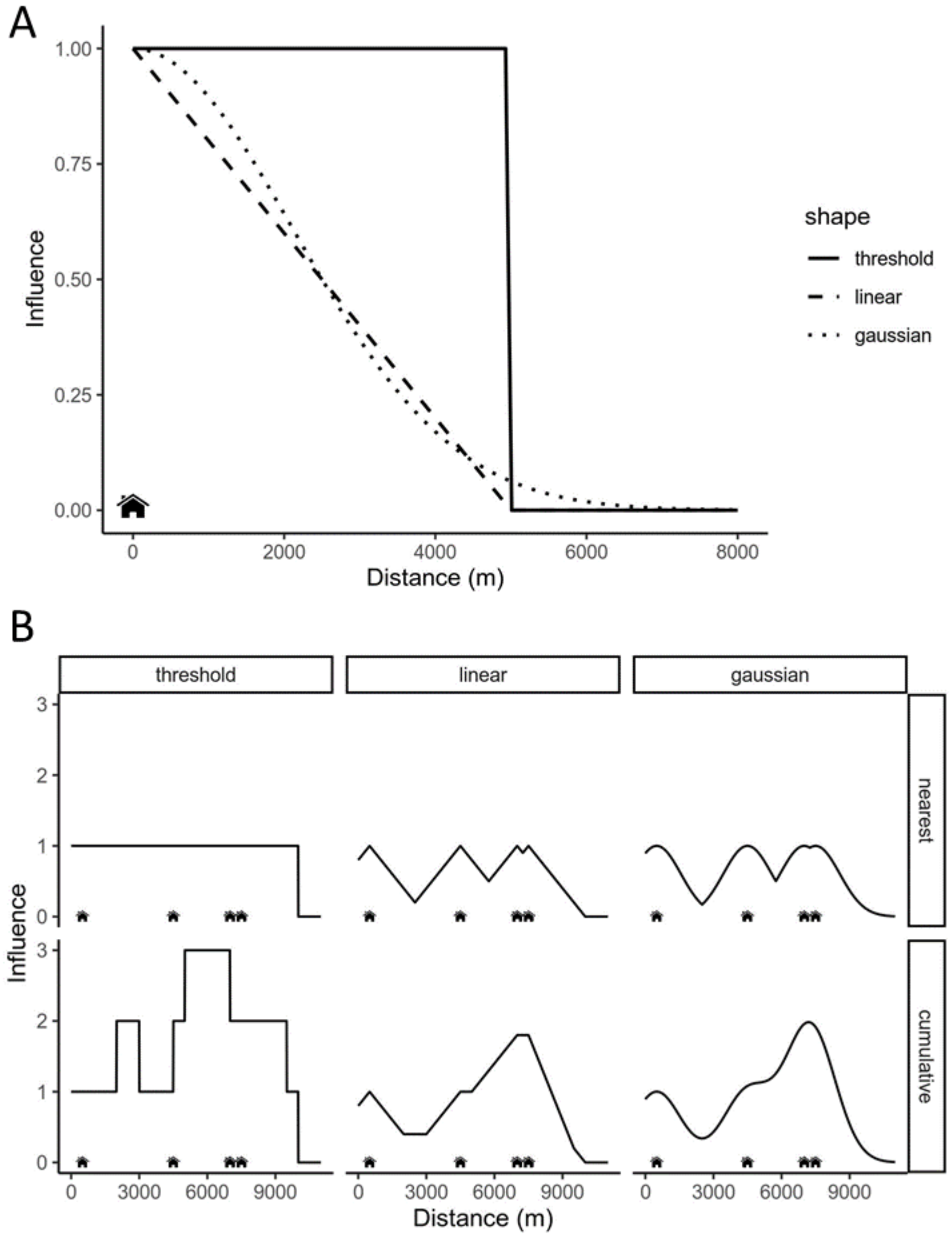

Figure 1: Illustration of the influence (ϕ_{i_k}) of infrastructure features against the distance from those features (Δ_{i_k}), simplified for one dimension and using houses as an example. (A) Examples of shapes according which the influence of the house might vary. A house has only an influence within 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 beyond it, 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.

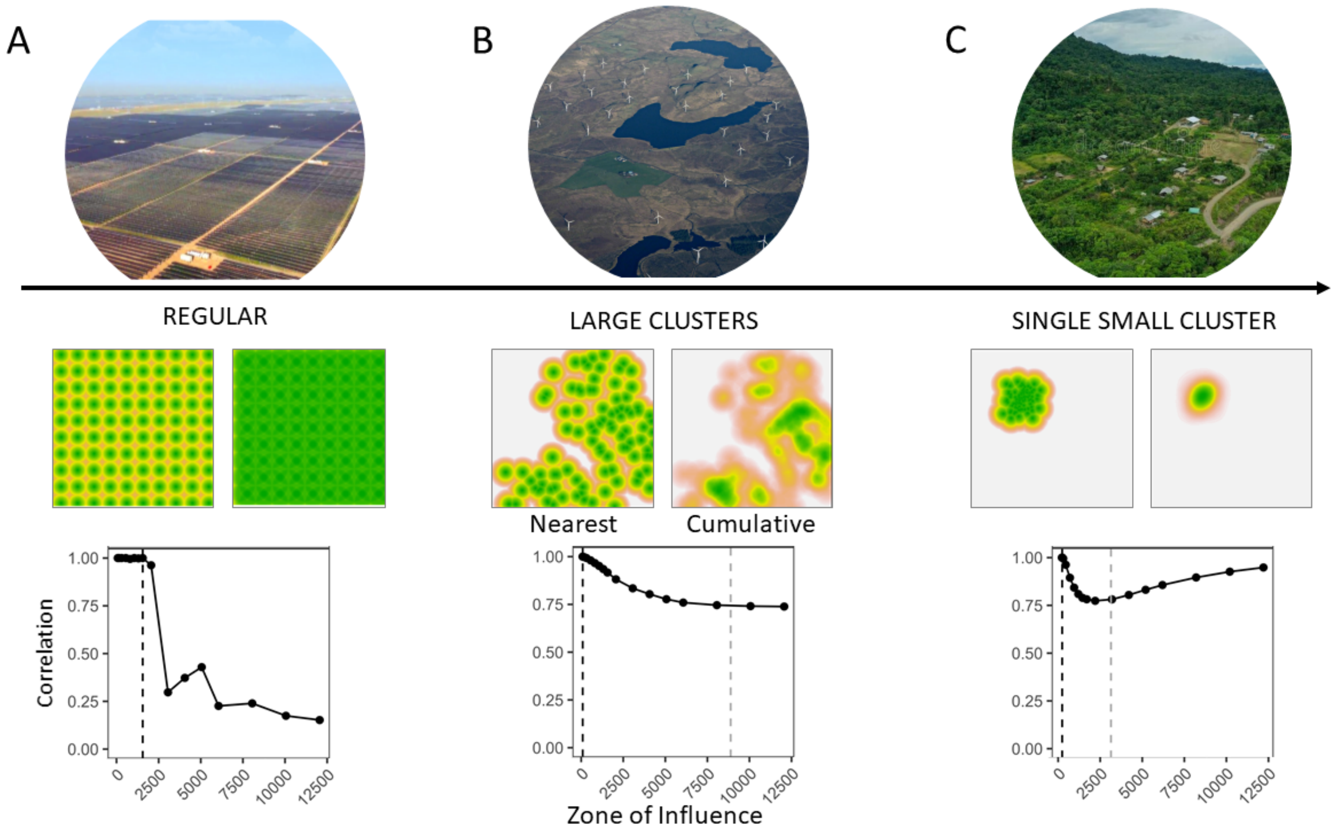

Figure 2: Representation of the influence of nearest feature ($\phi_{nearest}$) and the cumulative influence (ϕ_{cum}) in landscapes with point infrastructure spatially distributed in a gradient of clustering, from (A) a regular distribution (e.g. a large solar power plant in a flat area) to (B) a set of clusters (e.g. a wind industrial area formed by wind turbines built in the mountain tops) 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 A). The lower panel shows the correlation between the nearest feature and cumulative influence in each scenario, as their ZoI increases. The dashed vertical lines show half the the minimum distance between features (black), beyond which there are cumulative effects of the different infrastructure, and the size of the feature clusters (grey), beyond which the correlation stops decreasing.