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Mapping resource selection functions in wildlife studies: Concerns and recommendations

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Predicting the spatial distribution of animals is an important and widely used tool with applications in wildlife management, conservation, and population health. Wildlife telemetry technology coupled with the availability of spatial data and GIS software have facilitated advancements in species distribution modeling. There are also challenges related to these advancements including the accurate and appropriate implementation of species distribution modeling methodology. Resource Selection Function (RSF) modeling is a commonly used approach for understanding species distributions and habitat usage, and mapping the RSF results can enhance study findings and make them more accessible to researchers and wildlife managers. Currently, there is no consensus in the literature on the most appropriate method for mapping RSF results, methods are frequently not described, and mapping approaches are not always related to accuracy metrics. We conducted a systematic review of the RSF literature to summarize the methods used to map RSF outputs, discuss the relationship between mapping approaches and accuracy metrics, performed a case study on the implications of employing different mapping methods, and provide recommendations as to appropriate mapping techniques for RSF studies. We found extensive variability in methodology for mapping RSF results. Our case study revealed that the most commonly used approaches for mapping RSF results led to notable differences in the visual interpretation of RSF results, and there is a concerning disconnect between accuracy metrics and mapping methods. We make 5 recommendations for researchers mapping the results of RSF studies, which are focused on carefully selecting and describing the method used to map RSF studies, and relating mapping approaches to accuracy metrics.

Contents

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1. Introduction

Understanding the spaced used by animals is an important component to wildlife management, conservation and population health. For example, predicting a species' distribution has been used to inform endangered species management and habitat conservation efforts (Dzialak et al., 2013; Dzialak, Olson, Harju, Webb, & Winstead, 2012; Fortin, Courtois, Etcheverry, Dussault, & Gingras, 2008; Richardson, Stirling, & Hik, 2005; Roever, VanAarde, & Leggett, 2013). As one example, such modeling has been employed to address concerns including the evaluation of conservation networks for African elephants (*Loxodonta africana oxyotis*; (Roever et al., 2013)). Predicting species distributions has also been used to evaluate anthropogenic effects on wildlife distribution (Bleich, Davis, Marshal, Torres, & Gonzales, 2009; Hebblewhite & Merrill, 2008; Jiang, Ma, Zhang, & Stott, 2009; Johnson et al., 2005; Merkle, Krausman, Decesare, & Jonkel, 2011; Seip, Johnson, & Watts, 2007). For example, Johnson et al. (2005) modeled the potential distribution for three arctic species and evaluated the effect of mineral exploration on habitat suitability in an effort to inform management. Species distribution modeling is also an important tool for evaluating the effect of environmental and climatic changes on habitat use (Alamgir, Mukul, & Turton, 2015; Ramirez-Villegas et al., 2014). Additionally, predicting the spatial distribution of a species has also played a role in understanding the distribution of important animal diseases (Brook & McLachlan, 2009; Dugal, Beest, Wal, & Brook, 2013; Morris, Proffitt, Asher, & Blackburn, 2015; Proffitt et al., 2011). For example, studies have modeled the interaction of disease reservoirs and susceptible hosts. Proffitt et al. (2011) identified regions where elk (*Cervus elaphus*) and livestock were at risk of commingling in a brucellosis endemic region, and Morris et al. (2015) predicted landscapes where elk distributions may overlap with an anthrax zone in the Greater Yellowstone Ecosystem.

Each of the examples above employed some form of species distribution modeling. Generally, these approaches aim to measure non-random relationships between locations that describe an animal's position in space and environmental conditions. Recent advancements in the availability of spatial environmental data, wildlife telemetry technologies, and developments in modeling methods have transformed the realm of species distribution modeling (Elith & Leathwick, 2009). Digital elevation models of the earth surface, climate parameters, and remotely sensed imagery of land surface conditions are accessible for landscapes across the globe (in many cases at no cost), and software to integrate and analyze these data sets in a geographic information system (GIS) framework is widely available. Wildlife tracking has been transformed by the advent of satellite telemetry, which allows animals to be tracked 24 h a day with global positioning system (GPS) locations recorded in rapid succession for extended periods of time. The implementation of GPS telemetry has led to extensive datasets and the accompanying development of quantitative methods for their analysis (Hebblewhite & Haydon, 2010). The integration of detailed environmental information and fine spatial-temporal scale wildlife location data provides an exciting opportunity to address critical questions related to wildlife conservation and management through species distribution modeling. The notable increase in studies employing species distribution modeling in recent years reflects the importance of these models and their applicability to a wide range of ecological, management and conservation objectives. At the same time, the expansive data sets and complexities associated with modeling approaches raises important concerns about the accurate and appropriate implementation of modeling approaches (Cagnacci, Boitani, Powell, & Boyce, 2010; Hebblewhite & Haydon, 2010).

There are several methods that are frequently used to model wildlife and livestock distributions across multiple scales from local to global. Ecological niche modeling (ENM) approaches include a suite of methods (Peterson, 2011) that identify the potential distribution of species or communities (Alvarado-Serrano & Knowles, 2014; Ferrier & Guisan, 2006). ENM approaches can evaluate presence only, presence absence, or presence pseudo-absence occurrence data. Commonly, presence only modeling approaches capitalize on idiosyncratic data from field surveys, natural history collections, published ranges, and public databases for occurrence data for ENM models (Alvarado-Serrano & Knowles, 2014). These approaches often result in range-wide estimates of a species' distribution (Blackburn, 2010), though several studies have developed local scale niche-based geographic predictions.

Smaller scale, local studies often aim to model resources preferred or avoided by a population using resource selection function (RSF) modeling of wildlife telemetry data. One approach to RSF modeling is to compare the environmental or landscape attributes of used locations to the attributes of a set of available locations (Manly, McDonald, Thomas, McDonald, & Erickson, 2002). Used locations are frequently represented by telemetry fixes (e.g. GPS fixes or VHF relocations) or survey observations and available locations are defined by the researcher based on the spatial-temporal scale and scope of the research question. RSF model outputs are used to predict wildlife distributions; however, methods of mapping distributions from RSF model outputs are variable and often poorly described. The focus of this review is on the appropriate methods for mapping predicted species distributions from RSF outputs.

There has recently been an increased demand for mapped products in the fields of conservation and land management (Elith & Leathwick, 2009), which includes RSF studies. Mapping RSF outputs may make model results more accessible and relevant to managers (Johnson, Nielsen, Merrill, McDonald, & Boyce, 2006). For example, a map identifying the predicted resource selection of male elk during the anthrax season is likely more informative than reporting the sign and significance of model covariates for a manager implementing disease surveillance efforts (Morris et al., 2015). Maps illustrating predicted resource selection can provide an important tool to managers, highlighting the need for easily interpretable and accurate maps.

Presently, there is not a consensus in the literature on the most appropriate method for mapping RSF outputs. There are multiple challenges associated with RSF mapping and interpretation and the methods for mapping RSF results onto the landscape are variable and inconsistent across studies. For example, splitting RSF values into bins (e.g. (Morris et al., 2015)), converting RSF values into a binary variable (Oehlers, Bowyer, Huettmann, Person, & Kessler, 2011), and employing a linear stretch on RSF values rescaled from 0 to 1 (Hebblewhite & Merrill, 2008) have all been employed to map RSF outputs derived from the same modeling approach. There are also a large number of studies where methods for mapping RSF outputs are not reported (Proffitt et al., 2011), or map legends are nonexistent or uninformative. Even with appropriate map legends, interpreting RSF values is challenging, as these values are not equivalent to the true probability of selection (Keating & Cherry, 2004). Hirzel, Le Lay, Helfer, Randin, and Guisan (2006) suggested that displaying RSF results as a continuous surface can be misleading and RSF values should be reclassified, or binned, for map creation to provide honest and relevant predications. However, there has been minimal discussion on the most appropriate binning methods, and displaying RSF values as a continuous surface remains common (Brook & McLachlan, 2009; Dellinger, Proctor, Steury, Kelly, & Vaughan, 2013; Dugal et al., 2013; Fortin et al., 2008; Horne et al., 2014; Teichman, Cristescu, & Nielsen, 2013).