Spatial Simulation to Project Dynamic Movement of Species

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Summary

Understanding the distributions of species is critical for biodiversity conservation, and species distribution models (SDMs) are a powerful GIScience framework for achieving this. Despite the vast potential of SDMs to address an array of challenges, they can be greatly improved by incorporating metrics that are developed based on spatial simulation. In this research, an individual-based model was used to simulate the dynamic relationship between movement and biotic resources for oilbirds in Venezuela. This simulation represented the sustainability of a neighbourhood, and improved the accuracy and ecological realism of the projection compared to other commonly applied SDM scenarios.

KEYWORDS: movement analysis; spatial simulation; species distribution modelling

1. Introduction

By understanding the factors that define a species geographic range, more precise estimations of resilience, range dynamics, and extinction can be made. Species distribution models (SDMs) are a widely accepted framework for achieving this, applying a correlative approach and extrapolating species-environmental relationships in space as well as time (Franklin 2009). However, the consideration of the different environmental factors that could influence a species distribution, and subsequent selection of these variables with which to train the model is an enduring issue (Guisan and Zimmermann 2000).

Soberón and Peterson (2005) developed the heuristic 'BAM' framework to illustrate the three most important factors in determining a species distribution (Figure 1). Biotic factors (**B**) represent interactions with other species (i.e. competition, food sources), abiotic factors (**A**) represent the physiological tolerances of a species (i.e. temperature, precipitation) and movement (**M**) refers to the area that has been or will be accessible to a species within a certain timeframe (i.e. dispersal, connectivity). While the importance of all three factors is well recognised in SDM research, the incorporation of movement has lagged (Holloway and Miller 2017). When movement has been incorporated in SDM, its almost exclusive conceptualization has been to couple the statistical model with a measure of dispersal in response to climate change or invasive spread (Miller and Holloway 2015), or as a measure of accessibility with which to select the appropriate spatial extent for model calibration (Qiao et al. 2015). Movement patterns range from dispersal into unknown landscapes to daily movements such as foraging and homing; however, these finer scale movement behaviours have yet to be incorporated alongside SDM, despite the important role they play in the maintenance of a mobile species distribution.

Moreover, movement and biotic interactions do not act independently of each other. Biotic resources deplete when organisms traverse through a landscape, and replenish while the individual is absent. Consequently, the three BAM factors do not operate in isolation, yet a static representation of biotic factors and movement may not reliably account for the complex relationship that exists between them. However, to-date, the BAM framework lacks the detail required to incorporate such dynamic relationships, and little (if any) research in the SDM discipline is actively being directed to address this

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essential issue.

Spatial simulation is an important analytical tool used to represent a geographic system to explore, understand and better predict the behavior of the system based on the emergent properties of individuals. Due to their potential to incorporate the inherent relationship between movement and the environment, spatial simulation models are increasingly being used to understand animal movement and plant dispersal (Tang and Bennet 2010), and are a burgeoning GIScience research area (Dodge 2016).

In this paper, I will explore how step-selection function (SSF) can be used as a basis for spatial simulation. Implementation of SSF to generate bias estimates in random walk models has not occurred, despite the potential to inform animal-environment movement decisions. This model will simulate the dynamic relationship between biotic resources and movement, which can then be used within the species distribution modelling framework. This will provide researchers with an improved understanding of the relationship between biotic and movement factors, something that has been absent in previous studies, as well as an improved understanding of which factors contribute to a species distribution.

2. Methodology

The oilbird (*Steatornis caripensis*) is found in northern South America with a large home range of approximately 44km (Holland et al. 2009). Subsequently, an individual oilbird most likely utilizes several areas of biotic resources, meaning this species would allow a successful exploration of spatial simulation of a dynamic movement-resource model. Maximum entropy (MaxEnt) was chosen as the statistical method to model the species-environment relationships. Five different BAM scenarios were analysed: A, B, BA, Classic BAM (cBAM), and Dynamic BAM (dBAM) (Table 1).

3. Results & Discussion

The individual-based model that simulated the dynamic relationship between movement and biotic resources improved the accuracy of projections compared to other commonly implemented BAM scenarios (Table 2). The Boyce Index (considered the most robust presence-only model) was highest for the dBAM model, suggesting that the incorporation of a spatial simulation that modelled the relationship between M and B significantly improved the SDM process.

The individual-based model removed the assumption of homogeneity within the conceptualisation of biotic resources across the oilbird's distribution. Subsequently, this model delineated between accessible and sustainable areas of biotic resources from isolated and unsustainable areas. This removed some of the uncertainty introduced by source and sink populations for mobile species and is supported by the spatial simulation contributing the most of all the 'BAM' variables used the final model (37.6%), which highlighted the strong influence of this variable on the projected distribution of oilbirds.

The results suggest that the novel incorporation of SSF within a spatial simulation model performs well. The biased correlated random walk model well represented the actual movement trajectories of individual oilbirds, and the advantage of using SSF within this framework was that the results of conditional logistic regression informed movement patterns. The simulation of movement based on observed patterns supports recent GIScience articles calling for such an approach (Dodge 2016) and results suggest that these models better illustrate the influences of the environment on actual movements.

4. Conclusion

The 'BAM' framework is an effective concept to identify the effects of biotic, abiotic and movement factors on a species distribution. However, the three 'BAM' factors do not operate in isolation, meaning a traditional static representation of biotic factors and accessibility may not reliably account for the complex dynamic relationship that exists between them. This research used spatial simulation to represent the dynamic relationship between biotic resources (**B**) and movement (**M**), improving both the accuracy and ecological realism of SDM projections compared to other widely used BAM scenarios. The use of step-selection function as an input into the spatial simulation was novel and the biased correlated random walk demonstrated realistic movement patterns. Integrating simulations of movement into an SDM framework was successful, and future research should continue to explore how GIScience approaches can aid in understanding the complex relationships within geographic systems.

Table 1 BAM scenarios used to explore oilbird distributional patterns

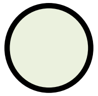
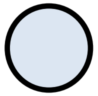
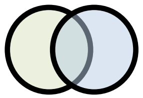
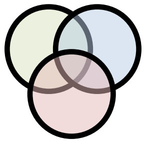
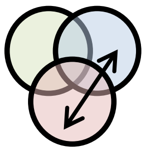
BAM Scenario	Explanation
A 	Abiotic factors (**A**) represent the physiological tolerances of a species (i.e. temperature, precipitation). Here, the 19 bioclimatic variables were considered as the abiotic factors.
B 	Biotic factors (**B**) represent interactions with other species (i.e. competition, food sources). A categorical variable representing presence or absence of the five species within the 10km observation were used as the biotic factors.
BA 	This scenario projects the invadable distribution (**G_i**) in the classic BAM framework. The 19 bioclimatic variables and the five presence absence maps of the food species were used as the input variables.
Classic BAM (cBAM) 	Movement factors (**M**) refer to the area that has been or will be accessible to a species within a certain timeframe. The presence or absence of the five fruit-bearing tree species will be identified within a focal area of 50km for each 10km observation. This will be represented by a categorical binary representation of presence / absence within a focal area of 50km, and the 19 bioclimatic variables.
Dynamic BAM (dBAM) 	Spatial simulation will be used to create a variable which summarizes the dynamic relationship between movement and biotic factors within the 50km focal area. The survival rate of 1000 oilbirds will be the input layer representing BM, and the 19 bioclimatic variables representing A. Full Overview, Design Concepts and Details are available here.

Table 2 The three accuracy metrics of the five BAM scenarios: Lowest possible threshold (LPT), minimum predicted area (MPA), and the Boyce Index (BI).

	LPT	MPA	BI
A	0.0002	0.0197	0.8210
B	**0.0172**	**0.0296**	0.0580
BA	0.0001	0.0256	0.7600
cBAM	0.0004	0.0220	0.6350
dBAM	0.0002	0.0271	**0.8920**

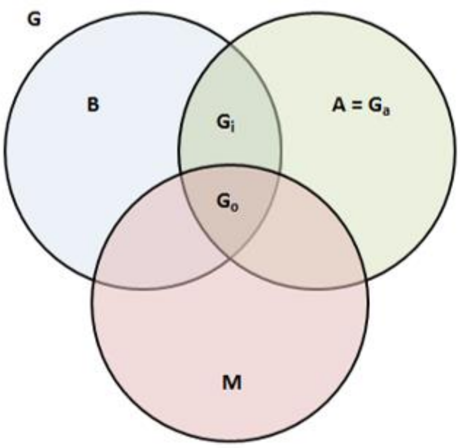


Figure 1 The 'BAM' Framework, which depicts the interaction between biotic (**B**), abiotic (**A**), and movement (**M**) factors. **G** is the geographic space in which the analysis occurs, $\mathbf{G_a}$ represents the abiotically suitable area, $\mathbf{G_i}$ s the invadable (abiotic and biotic) suitable area. Finally $\mathbf{G_o}$ represents the occupied (abiotic and biotic) suitable area and is therefore the actual distribution. Modified from Soberón (2007).

5. References and Citations

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7. Biography

Paul Holloway is a lecturer in geographic information systems in the Department of Geography at University College Cork. His research and teaching interests include using GIS and spatial analysis to address a suite of ecological, environmental, and geographic issues. His current research addresses the long-standing issue of how to incorporate movement at different spatial and temporal extents into species distribution models.