Advancing beyond static representations of movement in spatial analysis

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Summary

Methods used to generate movement and couple it with the environment are strongly integrated within GIScience. This study explores how systematically altering the conceptualisation of movement, environmental space, and temporal resolution affects the results of habitat selection analyses using both real-world case studies and simulated data. Only segment conceptualisations modelled the expected movement-environment relationship with increasing linear feature resistance. This suggests that spatial statistics employed to investigate movement-environment relationships should advance beyond conceptualising movement as the (relatively) static conceptualisation of vectors and moves and replace these with (more) dynamic aggregations of longer-lasting movement processes such as segments and areal representations.

KEYWORDS: Geocomputation; Movement; Simulations; Spatial Statistics;

1. Introduction

Movement data are becoming ubiquitous in GIScience, and this spatiotemporal geographic information has improved our understanding of many of the geographic processes we study. Laube (2017) recently described six semantic levels of quantifying movement in a GIScience context (Figure 1) that range from an instantaneous level, to an interval aggregated level, and finally to a global aggregation. These varied conceptualisations of the moving object all represent slightly different movement processes and different conceptualisations have all been used within spatial analysis and modelling. This choice of movement conceptualisation and environmental space can potentially have long-lasting implications on any management strategy resulting from these spatial statistics; however, no formal analysis has investigated how the conceptualisation of movement in relation to the movement space influences movement-environment inferences.

Subsequently, the aim of this study is to explore how systematically altering the conceptualisation of movement and environmental space affects the results of spatial-temporal analyses using both real-world case studies and simulated data. This study explores three main questions: 1) does the conceptualisation of the moving object and environmental space influence a) the model performance and b) the environmental preference of habitat selection? 2) does the habitat selection methodology correctly identify environmental preferences of animal movement using a virtual ecologist approach? and 3) does systematically varying the temporal resolution of the virtual data used in the statistical model change the environmental preference identified?

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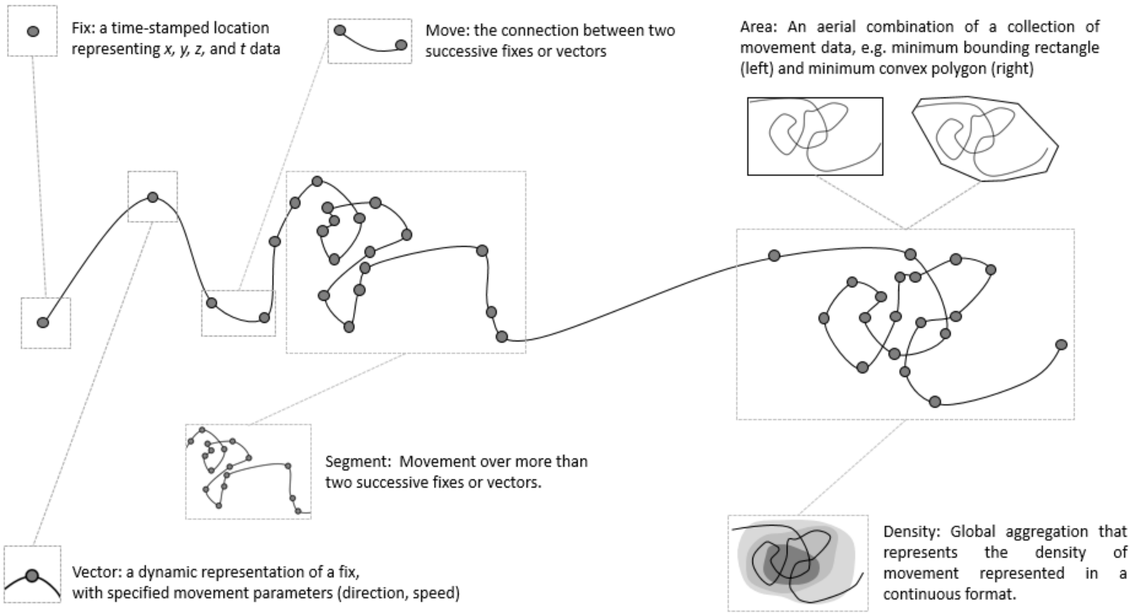

Figure 1 Diagram to illustrate the different conceptualisations of movement along a single movement trajectory

2. Methods

Habitat selection is defined simply as the probability that a specific habitat will be used by an animal when it encounters it (Lele et al. 2013). Habitat selection analysis develops a function that is proportional to the probability of the use of a resource unit by an organism (Manly et al. 2002). The ‘used’ observations are compared to a set of ‘alternative’ observations that the object theoretically could have selected, with a set of environmental variables that characterise ‘selection’ identified from the statistical model (Figure 2). Habitat selection has been implemented across multiple conceptualisations of movement, including ‘fixes’ (Figure 2a; resource selection analysis – RSA), ‘vectors’ and ‘moves’ (Figure 2b; step selection analysis – SSA), and ‘segments’ and ‘areas’ (Figure 2c; path selection analysis – PathSA).

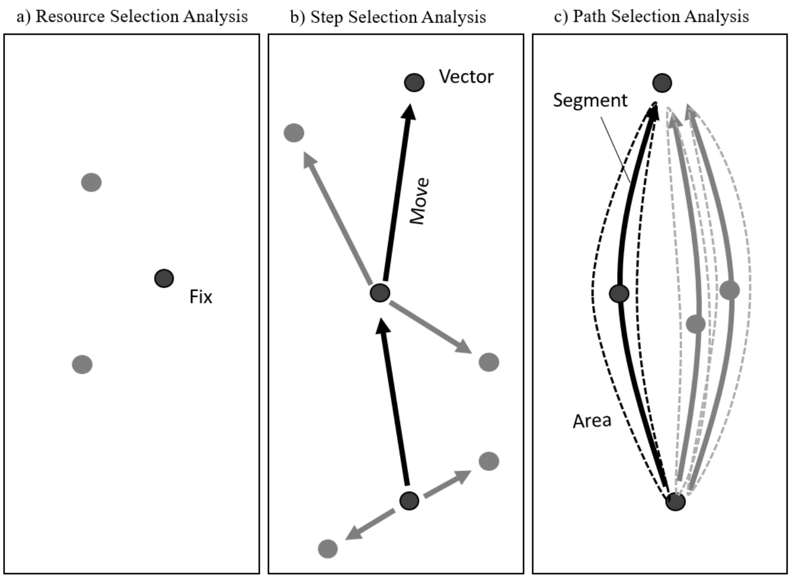

Figure 2 Habitat selection analyses that compare an observed (black) movement observation to a set of alternative (grey) movement observations that an individual could have theoretically taken.

Using conditional logistic regression, habitat selection $\hat{w}(x)$ is defined as:

$$\hat{w}(x) = \exp(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n) \qquad (1.0)$$

where β_n is the coefficient estimated by the conditional logistic regression for the variable x_n. Observations with higher $\hat{w}(x)$ values have a higher likelihood of being chosen by the individual, meaning such an approach can identify the influence the environment can have on habitat selection and movement. In habitat selection studies, land cover has predominantly been measured as a binary variable recorded at the exact coordinate of the vector. Linear features have been incorporated in statistical models more sporadically, despite the potential that these features could have important implications on movement in natural and urban settings. Table 1 outlines six methods of incorporating linear features (LFs) used in this study, the justification for use as an environmental covariate, and the movement conceptualisation that the method can be coupled with. Land cover was incorporated in a consistent manner across all six models in Table 1 following the predominant method used in habitat selection studies: value or proportion of land cover along or within the movement conceptualisation.

Table 1 Outline of the six models that investigate the relationship between movement and linear features (LFs).

Model	*Description*	*Reasoning*	*Conceptualisation*
LF_mean	Measures the mean value to the LF from, along, or within the movement conceptualisation	Used to identify movement towards (negative coefficient), away (positive coefficient), or in parallel to roads (equal to reference).	Vector; Move; Segment; Area; Density
LF_prop	Measures the proportion of the movement conceptualisation that is within a buffer of the LF (distance to correspond with suggested movement step lengths and impact distances)	Proportion of time within a LF buffer indicates usage of LF, proposed to overcome limitation of unlikely nature of movement step falling exactly on the one-dimensional line.	Vector; Move; Segment; Area; Density
LF_min	Measures the minimum distance to the LF from the movement conceptualisation	Used to identify movement towards (negative coefficient), away (positive coefficient), or in parallel to LFs (equal to reference).	Move; Segment
LF_cross	Binary value representing whether the LF has been crossed by the movement conceptualisation	Used to indicate whether animals will use or cross LF (1), or whether they avoid them (0).	Move; Segment
Non-LF_agg	Landscape reclassified into a binary space (linear or non-linear). The degree of aggregation of non-linear patches in the area., calculated from the adjacency matrix, which shows the frequency with which different pairs of patch types appear side-by-side in the landscape. prop.like.adjacencies in *spatialEco* (Evans 2017)	Used as a measure of connectivity for non-linear landscapes in the study area. A higher aggregation indicates less LFs, with linear landscapes used more (negative coefficient) or less (positive coefficient) by animals.	Area; Density
Non-LF-conn	Landscape reclassified into a binary space (linear or non-linear). Metric describing the physical connectedness of the non-linear patches. patch.cohesion.index in *SpatilEco* (Evans 2017)	Used as a measure of connectivity for non-linear landscapes in the study area. A higher cohesion indicates less LFs, with linear landscapes used more (negative coefficient) or less (positive coefficient) by animals.	Area; Density

Telemetry data of oilbirds (*Steatornis caripensis*) in Venezuela and Burchill's zebra (*Equus quagga burchelli*) in Botswana were obtained from Holland et al. (2009) and Bartlem-Brooks et al. (2013a) respectively via Movebank (Holland et al. 2012; Bartlem-Brooks et al. 2013b). Vectors, moves, segments, areas, and densities were all included in the spatial analysis, with model performance evaluated using Akaike Information Criterion (AIC). Fine-scale movement was simulated using a discrete-step process of one-minute time-steps over 24-hours on a 665 x 591 rectangular grid of 100m cells in the *SiMRiv* package (Quaglietta and Porto 2018). Land cover was generated by creating a random raster of three categories, with each land cover attributed a value representing resistance to movement of 0.75, 0.25, and 1.00. The decision to simulate one low resistance (0.25), one high resistance (0.75) and one completely avoidable (1.00) land cover mimics the inferences from the two case studies that animals have a primary, secondary, and an avoidable land cover preference. In total, 500 simulations were run for the five landscape configurations of land cover and LF resistance, which resulted in 2500 simulations. These simulations were treated as the 'observed' movement features, with 'alternative' movement features generated including vectors, moves, and segments using the same methodology as outlined for the real-world case studies.

3. Results

The MCP and KDE conceptualisations of movement reported lower AIC values when the landscape was parameterised as the aggregation (N-LF_agg) and connectedness (N-LF_conn) of the non-LF landscape (Figures 3a-b) compared with the LF_mean and LF_prop parameterisations within the same area. When coupled with the standardised coefficient results (Figures 4c-d), both species were more likely to select movement paths with a lower aggregation or connectivity than the alternative movement option. This suggests that both species are using landscapes that are fragmented by LFs more so than those that are not, inferring a preference for landscapes dominated by LFs. While similar preferences for movement towards LFs was identified across movement and environmental conceptualisations for oilbirds (with the exception of LF_min), both avoidance of LFs using LF_mean, LF_prop, and LF_min parameterisations, and attraction to LFs using LF_cross, N-LF_agg, and N-LF_conn was identified for zebras.

Figure 4 illustrates the coefficient values of the environmental covariates for the different movement conceptualisations and LF resistance values at each time-step derived from the virtual ecologist approach for the LF_mean model. The expected relationship for this model is for LF selection preference to increase positively as resistance increases (e.g., selection preference increases as the distance increases away from LFs). It was also expected that the land cover (LC1, LC2) coefficients would not change as the LF resistance was increased, as the resistance values for both LC1 and LC2 were held constant. Given the resistance values of 0.75 and 0.25 for LC1 and LC2, it was expected that selection into both of these habitats would be positive to reflect selection over LC3 (the reference habitat).

Segments were the only conceptualisation that accurately captured this expected pattern across all time-steps for all models (Figures 4), while vectors and moves resulted in habitat selection that identified both attraction and avoidance for all LF resistance values between 0.00 (attraction) and 1.00 (avoidance). For the vector and move conceptualisations, it was the shorter time-steps (1-minute, 2-minutes) that incorrectly modelled the movement-environment relationship as attraction when LF resistance was specified as 1.00, and it was the longer time-steps (5-minutes to 120-minutes) that correctly modelled the expected relationship. As the virtual data was simulated at 1-minute time-steps, the assumption was that the shorter temporal resolution would reliably capture the underlying relationship. Coarser time-steps of vectors and moves are characteristic of simplified (albeit linear) segments, suggesting that movement-LF relationships are only observable at the more aggregated movement conceptualisations. Due to longer time-steps of vectors and moves covering more of the spatial variation in the overall movement trajectory, the conceptualisations are capturing the extreme relationship, but as a construct of the temporal resolution.

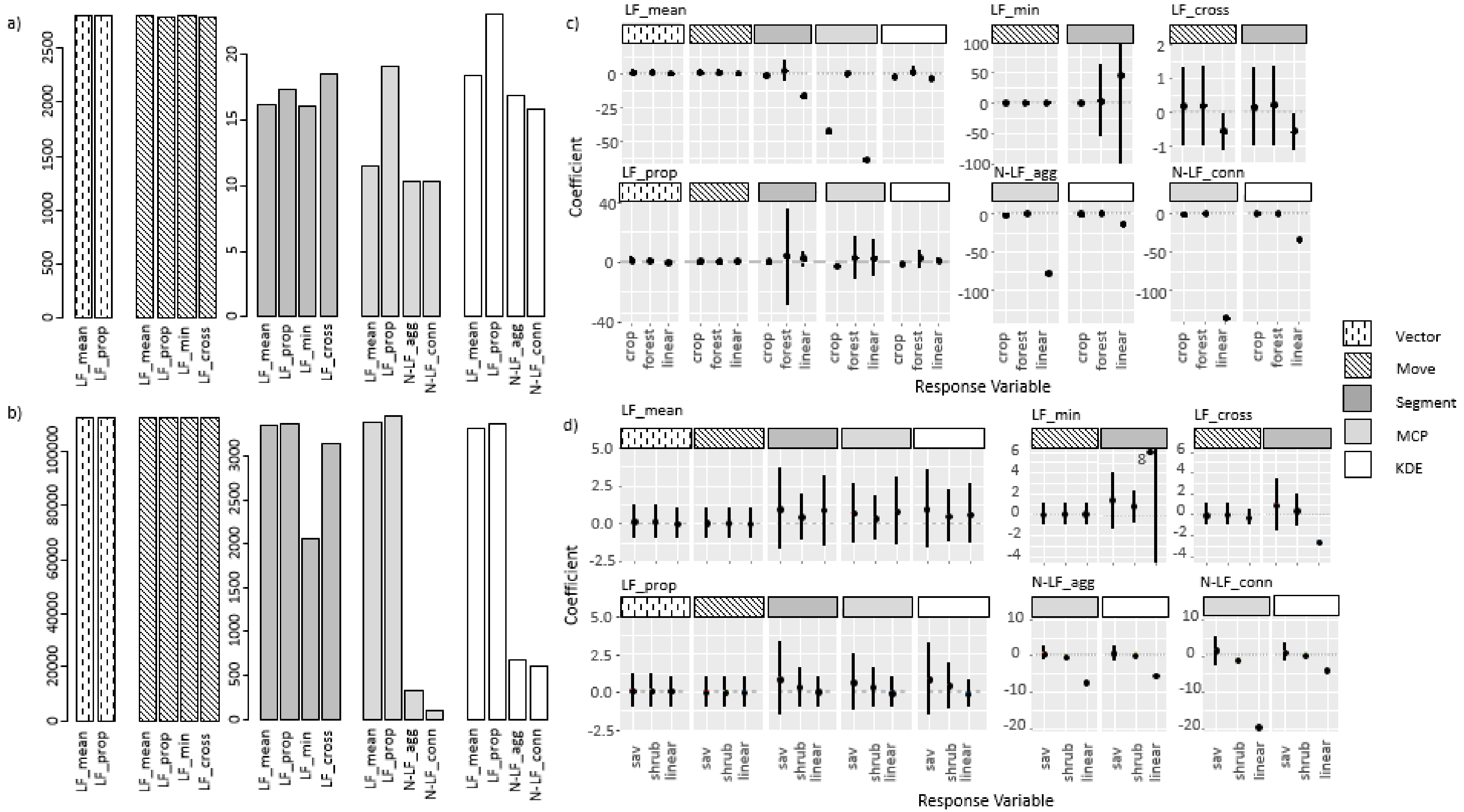

Figure 3 Akaike Information Criterion (AIC) scores for the different movement conceptualisations and linear feature (LF) representations for a) oilbirds and b) zebras. Standardised coefficient values with standard errors for the different models parameterised on movement conceptualisations and LF representation for c) oilbirds and d) zebras.

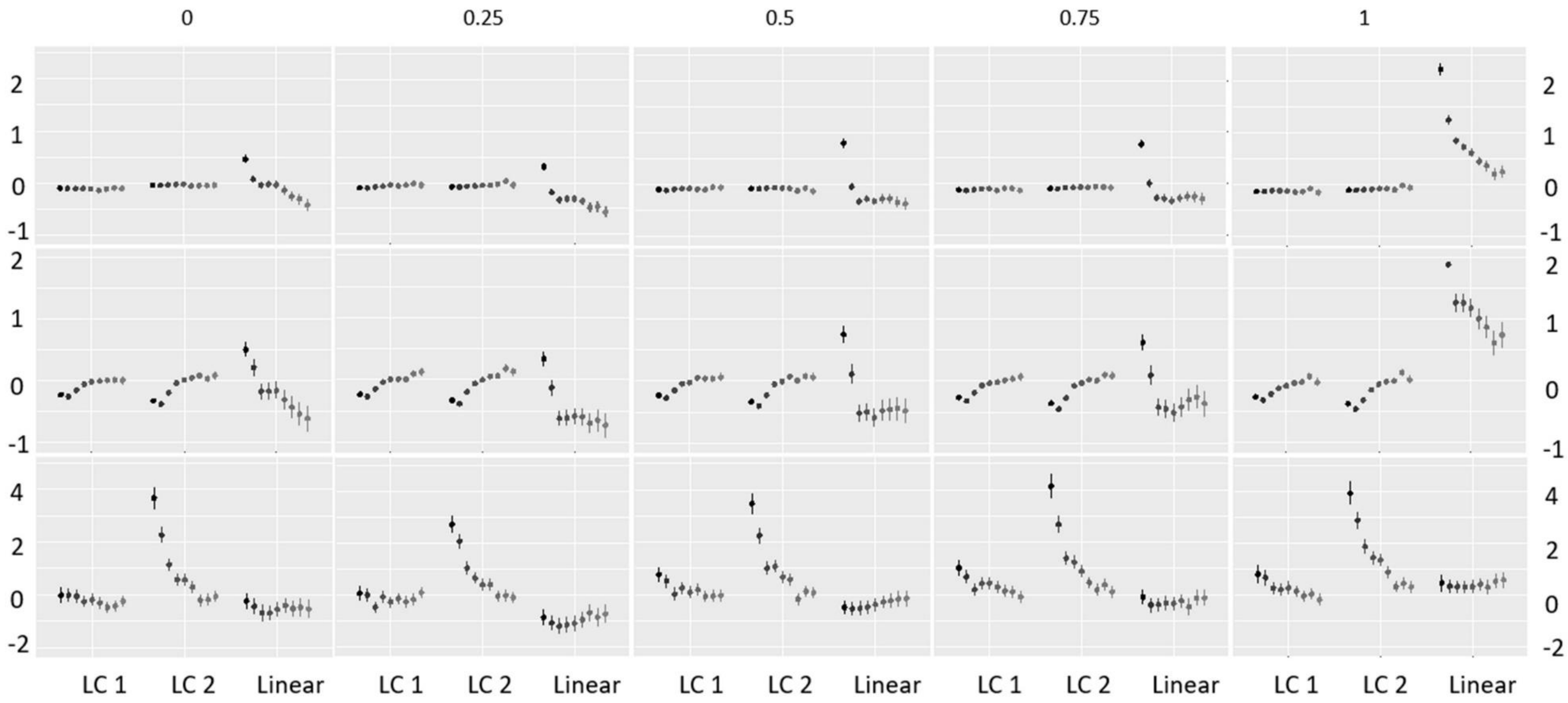

Figure 4 Standardised coefficient values for land cover (LC) and linear features (LFs) with 95% confidence intervals for the LF_mean (mean distance to LFs) for the virtual species. Results include the movement conceptualisations of vectors, moves, and segments. Resistance values (0, 0.25, 0.5, 0.75, 1) correspond to the resistance of linear features to movement in the simulations, with the expected movement-LF relationship to increase in selection preference as resistance increases (e.g., selection preference increases as the distance increases away from LFs), while movement-LC relationships should remain consistent as LF resistance is increased. For each variable, coefficient scores for 1-, 2-, 5-, 10-, 15-, 30-, 60-, 90-, and 120-minute time steps are reported left to right.

4. Conclusion

The relatively static treatment of movement in vectors and moves could explain the ability of segments to outperform these conceptualisations. When movement is represented as discrete entities, the underlying processes are masked as movement is not considered a process but an isolated event that is not directly informed by the movement decisions preceding or succeeding it. The ability of segments to correctly inform movement-environment (both land cover and LF) preferences (Figures 4) at all time-steps coupled with the inability of vectors and moves to inform on these preferences suggests that PathSA is required to effectively model the expected movement-environment relationships when investigating habitat selection.

Systematically altering the resistance of movement to LFs in the simulations allowed for the movement-environment relationship calculated from the conditional logistic regression to be examined. Expected movement-environment relationships were observed for segments when behaviour was complete avoidance (1.00) or attraction (0.00), yet inverted relationships were recorded across all resistance values for both vectors and moves as the time-steps were altered (Figures 4). These results suggest that vectors and moves are not suitable for modelling movement-LF relationships when individuals also made decisions on other land cover variables. This is particularly pertinent in landscapes where preference for LFs exists, but movement is not fixed to a LF network with discrete step choices based on other environmental factors masking movement-environment relationships at the individual aggregations in the statistical model. Subsequently, movement should be viewed at aggregated conceptualisations for the movement-LF relationships to be reliably modelled. Full results and discussion are available in Holloway (2019).

5. Biography

Paul Holloway is a lecturer in geographic information science and systems in the Department of Geography at University College Cork and a principal investigator in the Environmental Research Institute at University College Cork. Paul's research interests include using GIScience and spatial analysis to address a suite of ecological, environmental, and geographical issues, including, incorporating movement within species distribution models; investigating habitat selection of mobile animals; and using spatial statistics and simulation to investigate the effects of climate change in natural and agriculture systems..

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