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A Field-Based Time Geography for Wildlife Movement Analysis

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Abstract

Field-based time geography is proposed as a new, specialized model for estimating wildlife utilization distributions (UDs) and home ranges. Field-based time geography represents the combining of classical time geography with least-cost path analysis. Here the derivation of field-based time geography is emphasized, paying particular attention to how it can be implemented in wildlife analysis. An example showing caribou movement in northern British Columbia is used to demonstrate field-based time geography and compare it with the Brownian bridge model, a popular method for delineating wildlife UDs. The results show how field-time geography is able to better represent the structure and barriers of the landscape, and provide alternative insights into wildlife space use. The entire process is implemented in R, making it attractive to movement ecologists.

1. Introduction

One of the fundamental pieces of spatial information used in the study of wildlife movement is the home range. A home range is broadly defined as the area an animal uses in its normal day-to-day activities (Burt, 1943). From a GIScience perspective, a home range is a polygon, and thus represents this area discretely. Recognizing that animals typically do not use their home ranges evenly, alternatively a utilization distribution (UD) can be estimated, which represents the home range as a two dimensional probability density surface, where the values indicate the probability of observing the animal at different locations within (and outwith) the home range (Worton, 1989). Typically, a UD is represented as a raster grid after selecting an appropriate spatial resolution. After creating a UD it is common to estimate the home range simply as a % volume contour of the UD (most commonly the 95% volume contour).

Many methods have been proposed for estimating UDs and home ranges and there is little consensus on which is best. Historically, kernel density estimation (Worton, 1989) has been the preferred approach, however in recent years Brownian bridges (Horne et al., 2007) have become increasingly popular. Time geographic methods have also been proposed as powerful alternatives for delineating home ranges (Long and Nelson, 2012) and UDs (Downs et al., 2011). However, one limitation that is present in all currently available home range and UD methods is the assumption that wildlife move within a homogeneous arena. That is, the underlying environment has no influence on the model used to calculate the home range and UD. By failing to consider how the underlying landscape characteristics (e.g., topography, structure, land cover) contribute to the formation of home ranges and UDs, current approaches fail to adequately capture how a heterogeneous environment contributes to observed movement patterns. In many cases, the natural environment constrains the area potentially visited by an animal, and thus home ranges and UDs are incorrectly estimated.

To address this limitation, this paper proposes field-based time geography as a new tool for estimating wildlife UDs. Field-based time geography was originally proposed by Miller and Bridwell (2009) in the study of transportation, and thus focused on applications on a spatial network. Here, the conceptual framework outlined by Miller and Bridwell (2009) is extended to the study of wildlife movement in a two-dimensional field. In this context, field based time geography represents the marriage of time geographic theory (Hägerstrand, 1970) with popular GIS methods for studying least-cost paths in spatial fields. This paper outlines the formulation of field-based time geography for generating wildlife UDs. Using an example where caribou (*Rangifer tarandus*) were tracked via GPS in northern British Columbia, Canada, field-based time geography is compared to the Brownian bridge estimator, demonstrating how the approach can be used in real applications.

2. Methods

2.1 Field-based time geography

Field-based time geography extends the classical definition of time geography (Hägerstrand, 1970) in an effort to estimate the unequal movement probabilities within the bounding structure of space-time prisms (Miller and Bridwell, 2009). Movement possibilities are limited not only by the upper bounds on animal movement (e.g., maximum travelling speed) but also the characteristics of the landscape through which the animal moves. Thus, field-based time geography requires a cost (resistance) surface which defines the speed at which an animal can navigate the landscape, which is practically implemented as a raster grid.

For a given pixel i with 8 cardinal neighbours (other definitions are possible) let c_{ij} be travel cost (in units of time) to go from pixel i to neighbour j. In practice c_{ij} will be related to the movement ability of the animal and, importantly, to the characteristics of the landscape, such as topography, land cover, and the presence of barriers. Then let $\boldsymbol{N}$ represent the network graph which consists of all transitions c_{ij} for all pixels in the study area. Using a network optimization algorithm (e.g., Dijkstras algorithm), based on $\boldsymbol{N}$, we can compute the minimum cost of movement between any two locations on the graph $\boldsymbol{N}$ in units of time.

The construction of field-based time geography follows classic time geography by considering the intersection of space-time cones. For an intermediate time point t between two fixes a and b, where $t_a < t < t_b$, first calculate C_{ai}, which is the cost (in units of time) from the location of fix a to pixel i based on the network $\boldsymbol{N}$ (similarly compute C_{ib}). If location (pixel) i is accessible at time t (i.e., $C_{ai} \leq t\text{-}t_a$; and $C_{ib} \leq t_b\text{-}t$) then location i is within the potential path space at time t (PPS_t). Next we compute the minimum time budget required to reach each location within PPS_t:

$$TB_i = C_{ai} + C_{ib} \quad \forall\, i\, \in PPS_t \tag{1}$$

Here we estimate the probability an animal visited a given pixel at time t as:

$$\hat{P}_{it} \propto \frac{1}{TB_i} \tag{2}$$

$$P_{it} = \frac{\hat{P}_{it}}{\sum_{\forall i} \hat{P}_{it}} \tag{3}$$

Equation (2) states that the probability of an animal visiting a pixel i at time t is proportional to the inverse of the time budget required to get to location i. The formulation of $\hat{P}_{it}$ in equation (2) has the desired effect of associating visit probabilities with travel cost, and simultaneously considers this cost relative to the minimum of all possible routes in the potential path space, but other definitions of $\hat{P}_{it}$ are possible, for example inverse aquared. With equation (3) the $\hat{P}_{it}$ are standardized so that $\sum P_{it} = 1$ for any time t. Standardizing so that $\sum P_{it} = 1$ is necessary to account for variations in the size of the PPS_t.

In order to compute animal UDs, we are interested in the cumulative visit probability P_i for any location i over the entire time interval between t_a and t_b, which can be defined straightforwardly as:

$$P_i = \int_{t_a}^{t_b} P_{it}\, dt \tag{4}$$

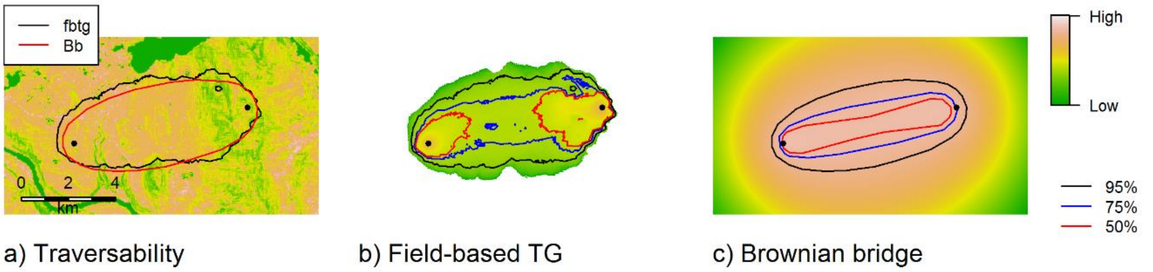
In practice, this integral is not easily defined, but we can approximate it using a set of equally spaced time spaces between t_a and t_b and performing numerical integration using the trapezoid rule. The surface given by $P_{\{i\}}$ will represent the UD for the animal between t_a and t_b. We can compute the surface $P_{\{i\}}$ recursively for each of the n-1 pairs of consecutive fixes in the telemetry dataset to estimate an overall UD.

2.2 Example: Caribou in northern British Columbia

For this example, we look at an individual caribou tracked with GPS during the year 2000 with a location fix recorded every 4 h. A cost surface to represent the time-cost of caribou navigation was derived using two datasets: a DEM derived slope dataset, and a land cover dataset, both with a spatial resolution of 25 m. Slope was translated into movement speed using a modified version of Tobler's (1993) hiking function with a maximum travelling speed of 3.6 km/h (Fancy and White, 1987). Realistically, caribou do not maintain such a speed over long periods, and three movement behaviour states (slow, medium, fast) were identified with maximum travel speed reduced appropriately in the slow (0.3 km/h) and medium (0.9 km/h) classes. Land cover was used to further restrict maximum travel speeds (based on Johnson et al., 2002). Specifically the maximum speed caribou could cross the following land cover classes was adjusted by: forest – 0.8, wetland – 0.5, snow/ice/rock – 0.5, and water – 0.1. To demonstrate the field-based time geography approach and compare with the Brownian bridge model a segment of particularly active movement (between 11h – 15h on 24-01-2000) was chosen, as well as the entire trajectory during the months Jan-Mar 2000 (n = 482 fixes). For this study, all analysis was conducted in R and specifically operations for computing travel costs were implemented using the package '*gdistance*' (Van Etten, 2015).

3. Results and Discussion

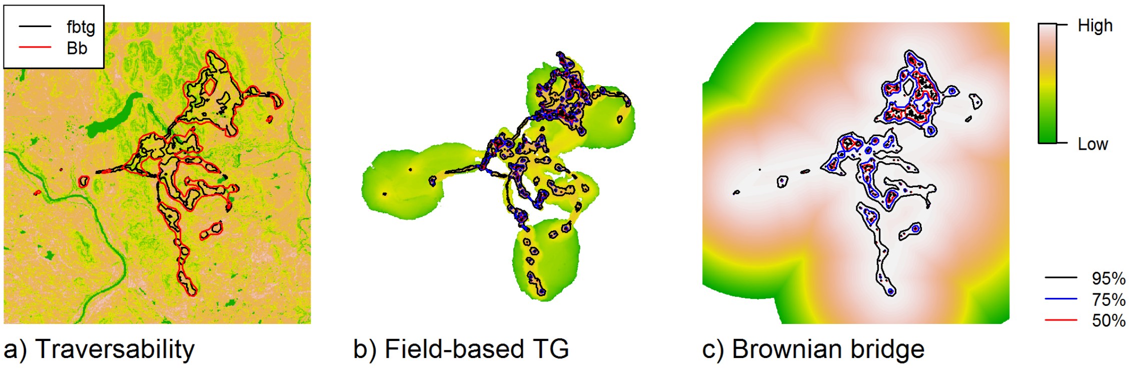
The field based time geography model offers unique insight into predicting animal movement probabilities when compared to Brownian bridges (Figure 1). In this segment, there is clearly a non-straight lowest cost path between the two fixes. In the area surrounding the fix on the right hand side we see the presence of topographical barriers that restrict movement, and thus shift probable movements away from the direct path between the two fixes.



a) Traversability b) Field-based TG c) Brownian bridge

Figure 1: Comparison of a) 95% volume contours for field-based time geography and Brownian bridges overlain on the traversability map (i.e., the inverse of travel cost), b) field-based time geography and c) Brownian bridge models for estimating movement probabilities (and subsequently utilization distributions) between two fixes of a single caribou between 11h and 15 h on 24-01-2000. The 95%, 75%, and 50% volume contours are shown for comparison.

When we compute the overall UD and home range for the months of Jan-Mar 2000 we see a similar result, whereby the field-based time geography UD places less emphasis in certain areas that represent barriers to movement. It is the ability to model such landscape heterogeneity that is lacking from current approaches. Field-based time geography % volume contours are similar in size to the Brownian bridge model which will make it attractive for users wishing to perform similar analysis. However, with field based time geography the output structure of the UD and size of the home range is dependent on the parameters used to generate the cost surface.



a) Traversability b) Field-based TG c) Brownian bridge

Figure 2: Comparison of a) 95% volume contours for field-based time geography and Brownian bridges overlain on the traversability map (i.e., the inverse of travel cost), b) field-based time geography and c) Brownian bridge models for estimating animal UDs for an individual caribou tracked via GPS during Jan-Mar 2000.

Field-based time geography represents a significant modification to current models used to estimate animal UDs and home ranges. To date no approach has taken advantage of modern GIS techniques for estimating travel costs between two locations, and subsequently, these approaches fail to adequately capture the heterogeneous nature of the landscape. Here field-based time geography was demonstrated using a complex natural landscape in northern British Columbia, but these same concepts could be applied in other environments, for example in marine and avian movement where currents and wind patterns will greatly influence movement potential. The approach has been implemented entirely in the statistical software R (see http://jedalong.github.io/wildlifeTG) which will make it attractive to movement ecologists.

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