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Agent-based simulation of Muscovy duck movements using observed habitat transition and distance frequencies

James H. Anderson [a,*], Joni A. Downs [b], Rebecca Loraamm [c], Steven Reader [b]

[a] Department of Industrial and Systems Engineering, University of Oklahoma, United States
[b] School of Geosciences, University of South Florida, United States
[c] Department of Geography and Environmental Sustainability, University of Oklahoma, United States

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ABSTRACT

This paper presents an agent based model simulating animal tracking datasets for individual animals based on observed habitat use characteristics, movement behaviours and environmental context. The model is presented as an alternative simulation methodology for movement trajectories for animal agents, useful in home range, habitat use and animal interaction studies. The model was implemented in NetLogo 5.1.0 using observed behavioural data for the Muscovy duck, obtained in a previous study. Four test scenarios were completed to evaluate the fidelity of model results to behavioural patterns observed in the field. Results suggest the model framework illustrated in this paper provides an effective alternative to traditional animal movement simulation methods such as correlated random walks.

1. Introduction

Researchers simulate tracking data for individual animals for a number of purposes relevant to both GIScience and ecology. A popular reason is to generate a complete baseline dataset of known tracking data to test methods that are useful for analysing samples of VHF, GPS, or satellite data collected in the field. For example, simulated tracking data are routinely used to test methods of home range analysis, where the performance of different techniques is evaluated for samples of different sizes, tracking intervals, or other qualities (Downs & Horner, 2009, 2012; Getz et al., 2007; Girard, Ouellet, Courtois, Dussault, & Breton, 2002; Laver & Kelly, 2008). Simulated animal tracking data are also widely used as reference datasets for the purposes of quantifying animal interactions. Here, observed data are compared to simulated data to determine if animals come into contact more or less frequently than expected at random (Long, Nelson, Webb, & Gee, 2014; Miller, 2012, 2015; Richard, Calenge, Said, Hamann, & Gaillard, 2013). Similarly, simulated animal movement data are used to study habitat preferences of animals through the use of step selection functions, which compare observed tracking data to simulated random movement data to infer resource selection (Duchesne, Fortin, & Rivest, 2015; Forester, Im, & Rathouz, 2009).

There are several ways that animal tracking data for individuals have been simulated in practice. The first approach is to generate point patterns of data that conform to particular statistical distributions, such as Poisson clusters or bivariate normal mixtures (Gitzen & Millspaugh, 2003; Gitzen, Millspaugh, & Kernohan, 2006). Sometimes the geometries of these patterns are modified to create locational data that conform to particular shapes (Downs & Horner, 2008). Alternatively, the density of points in a core location are artificially increased for the purpose of creating data with non-stationary spatial properties consistent with repeated use of a nest or den site (Downs et al., 2012). Often times, the generated point data represent an animal's known locations, and simulated tracking data are created by randomly sampling specified numbers of points from the distribution. The downside of point pattern approaches is that the locational data are not generated with explicit time stamps. This means that consecutive points in the dataset are not modelled as components of a continuous movement trajectory, which makes the data less representative of animal movements (Downs, 2010).

Tracking data have been more realistically modelled using random walk models, such as correlated random walks, Lévy walks and step selection functions which simulate an ordered set of spatial locations that constitute a movement trajectory (Bartumeus, Da Luz, Viswanathan, & Catalan, 2005; Bergman, Schaefer, & Luttich, 2000; Byers, 2001; Codling, Plank, & Benhamou, 2008; James, Plank, & Edwards, 2011; Thurfjell, Ciuti, & Boyce, 2014). Random walk models generally use two main parameters to model movement: turn angle and step length. In practice, these two parameters have specified frequency distributions that are used to control the properties of the modelled trajectory, such as whether sharp turns or long steps are more or less likely. Tracking data is simulated in this way by randomly generating values from those distributions and plotting the resulting spatial coordinates over

* Corresponding author.
E-mail address: jhowardanderson@ou.edu (J.H. Anderson).

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time. Extensions to random walk models use maximum likelihood approaches to model and incorporate the effects of resource availability and habitat configuration from observed animal paths into simulated trajectories (Moorcroft, Lewis, & Crabtree, 2006). Additionally, the simulated data can be constrained to specific spatial areas, such as known home ranges, so that they better correspond to observed data or conform to particular sizes or shapes (Jeanson et al., 2003; Miller, Christman, & Estevez, 2011; Miller, 2012). A limitation of this approach is that turn angles are not always good predictors of animal movements (Holloway & Miller, 2014; Nams, 2013; Wilson et al., 2013). It is possible that some species do not have preferences for turning at particular angles, or that other contextual factors such as habitat preferences play larger roles in determining how animals move about space.

A somewhat less explored but promising approach to simulating animal tracking data for individuals involves using an agent-based model (ABM). Spatially-explicit ABMs are routinely used to model movement in complex geographical systems for a wide range of applications, such as modelling disaster response (Widener, Horner, & Ma, 2015), pedestrian behaviour (Torrens et al., 2012), traffic (Manley, Cheng, Penn, & Emmonds, 2014), crime (Malleson & Birkin, 2012), urban processes (Ettema, 2011), and humanitarian relief (Crooks & Wise, 2013). ABMs have been used to model animal movements, though generally the purpose is to model how animals interact with one another and the environment across space and time in order to understand dynamic population and landscape processes, rather than to explicitly simulate tracking data per se (McLane, Semeniuk, McDermid, & Marceau, 2011). Tang and Bennett (2010) provide an excellent review of ABMs for animals, some examples include those developed to model migration (Bennett & Tang, 2006), population dynamics (Carter, Levin, Barlow, & Grimm, 2015), predator-prey interactions (Ringelman, 2014), and group behaviour (Bonnell et al., 2013; Strombom et al., 2014).

Though random walk models may appear similar in function to simple ABMs, more complex ABMs could potentially be used to simulate more realistic tracking data for individual animals for testing home range estimation methods, studying interactions, and related purposes. The ABM approach differs from random walk models and their derivatives as ABMs generate movement trajectories based on context-aware decision-making logic defined for each fundamental actor in the ABM model environment. The resulting ABM-generated movement trajectories represent the aggregate of actor decisions. Consequently, the ABM approach offers an alternative to empirical reduction or model fitting on a priori animal trajectory datasets, as used in random walk implementations or step selection functions (Epstein, 1999). This paper presents an ABM that simulates animal tracking data for individual animals based on observed movement behaviour and environmental context. The model uses three main behavioural variables—habitat transition, step length, and return time—that operate within the context of an environment of habitat types. The goal is to develop an alternative platform for simulating animal locational data for future studies, though the model is created specifically for Muscovy ducks (*Cairina moschata*) in a study area where one year of field data on their habitats and movements were collected. The paper is organised as follows. Section 2 describes the modelling framework. Section 3 provides an overview of the field observations, model simulations, and methods of analysis. The corresponding modelling and analysis results are detailed in Section 4. Finally, discussions and conclusions are presented in Section 5.

2. Model framework

2.1. Overview

Tang and Bennett (2010) provide a detailed review of spatially-explicit ABMs and their features. Minimally, an ABM requires three basic components: agents, environment, and behaviour. Agents are the fundamental actors in an ABM; they move about and interact with the model environment according to sets of behavioural rules. The model environment provides the context for agent movement and interaction. For animals, the environment is generally modelled as a set of discrete patches of habitat that may or may not have other attributes. Behavioural rules control how the agents move within the environment, for instance by specifying possible step lengths or types of habitats that can be occupied. Movements and actions carried out by agents occur at discrete time steps, or ticks. At each tick, random behaviours are selected by the model and enacted by agents. In more complex models, agents have internal states that influence their behaviour, enabling agents to interact; influencing one another and the environment (Ahern, Smith, Joshi, & Ding, 2001).

In our model for simulating the movements of a single animal, though, we specify a single agent—an individual Muscovy duck. The model environment is composed of a grid of cells, or patches, classified by habitat types relevant to the species of interest. The duck agent starts the day at a designated known shoreline roosting location. After that, the duck's movement is controlled by three sets of behavioural rules that are explicitly linked to one another: habitat transition, step length, and return time. The model simulates the duck's movement every 15 s within and between habitats in the environment over 28 15-hour diurnal periods from 06:00:00 to 21:00:00. The 9-hour night time period, when the duck is expected to roost in the same location on the shoreline, is not modelled. The model output includes the duck's position and habitat at each time step. The model is implemented in NetLogo version 5.1.0, as described below (Fig. 1).

2.2. Agents

The animal species selected for this model is the Muscovy duck. The Muscovy duck is a species of waterfowl native to South and Central America, though populations have been introduced nearly worldwide and are considered invasive in some locales. Though there is little published literature on introduced Muscovy ducks, a population of about 120 individuals at the University of South Florida campus in Tampa, FL, is relatively well studied (Anderson, 2012). A previous study by Downs et al. (under review) documented habitat use and behavioural patterns of this population. There, Muscovy ducks occupied urban environments where open water was present. They utilized five main habitat types during the daytime: water (pond, lake, or wetland), shoreline (edge of pond, lake, or wetland), grass (open lawn), tree and shrub cover, and urban (roads, buildings, parking lots, sidewalks, etc.). They roosted on shoreline overnight, typically returning several times per day. Additionally, Muscovy ducks are capable of flight, however they fly relatively infrequently, locomoting mostly by walking and swimming. Movement data collected at the same time but not published with those observations are reported here and used to inform the agent's behavioural rules (see Section 2.4).

2.3. Model environment

The model environments consisted of rectangular grids of cells classified by habitat type. For this study, two model environments, or habitat maps, were used for comparison: an observed study area and a random habitat map (Fig. 2). The study area consisted of a 0.28 km^2 area that included a pond where a portion of the behavioural data were collected. The study area was divided into square grid cells at a 5 m resolution. The choice of a 5 m cell resolution was motivated by the distribution of distances in observed duck movements, the size and habitat gradient in the study area, and the need for abstraction in terms of the model implementation. The 5 m resolution represents a compromise level of abstraction where both habitat type gradient could be effectively captured and animal movements effectively simulated. Duck agent location is understood by the model in terms of continuous X/Y coordinates, an agent can be located at any location within any habitable environment cell. The study area comprised 86 rows and 132 columns of cells. Each cell