**Spatiotemporal Dynamics of the Chicagoland Mesocarnivore Guild**

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***Introduction***

This document describes the model structure developed and used to analyze the data collected on the guild of meso-carnivores inhabiting Chicago greenspaces. These data were collected via the Lincoln Park Zoo’s Urban Wildlife Institute’s camera trap study, which was initiated in 2010 and expanded in 2011. For more details on the study design, see section “Chicago Wildlife Watch”.

***Model Development***

Here, we outline the mathematical modeling framework used to analyze the Chicagoland meso-carnivore data. The specific model is a partially observed Markov Process (POMP) model (a.k.a. state-space model or stochastic dynamical model), wherein a Markov Process describes a latent state that is only partially observed. We would like to make inferences about the dynamics of the latent state (the meso-carnivore guild), but we must account for the reality that we only partially observed it. To do this, we separate the latent process from the observation process as two components to our model.

First, we have the underlying, unobserved “latent” process that is Markovian (here we assume first-order):

(1a)

for a series of time points , where is a function and are parameters in the most general sense possible to start. The latent state is then observed via a separate process :

(1b)

for that same series of time points , where again is a function and are parameters the most general sense possible to start. and can, but do not need to, share similarities with and . Each of these component models will be elaborated on in an ensuing subsection. First, we focus on the latent model (1a), then move to the observation model (1b).

**Latent Model**

Fundamentally, we are interested in understanding the spatial and temporal dynamics of a guild of species. We consider that the guild is comprised of N species () that are distributed across K sites (k) during T distinct time periods (. The specific occurrence, z, of species *i* at site *k*  during time period *t* is given by . For a given time period t, the occurrences of all N species across all K sites can be combined into an N x K matrix :

In addition to being affected by its own occupancy at a given site during a given time period, a species’ future occupancy is likely also influenced by the presence of other species at that site (*e.g.*, via competition) as well as the presence of the species itself at other sites (*e.g.*, via dispersal). Thus, in a general sense, we can re-write Equation 1a as

(2a)

which is to say that the occurrence of a species within a site at a given time period is a function of the occurrence matrix at the previous time period and some parameters.

The occurrence of a given species at a given site during a given time period, , is a variable that can take only one of two states: present () or absent (), and as such can be represented as Bernoulli process.

(2b)

Basically now, rather than predict future occurrence directly, current occurrence predicts the probability of future occurrence, . We can consider that this probability varies among species, sites, and time periods, such that we would be interested in the values .

(2c.1)

(2c.2)

Here I have pulled out the component function that predicts because it is this aspect of the model that will vary as we complicate things (i.e., Equation 2c.1 doesn’t change as we make 2c.2 more specific).

Given that occurrence only has two states (present/absent), we can write out a simple path classification for states in times *t* and *t+1*:

|  |  |  |
| --- | --- | --- |
|  |  | |
|  | 0 (absent) | 1 (present) |
| 0 (absent) |  |  |
| 1 (present) |  |  |

where is the probability of colonization and is the probability of persistence (including both “internal persistence” and “rescue effects”).

Formally:

(2d.1)

(2d.2)

(2d.3)

therefore

(2e)

Each of the component probabilities (colonization and persistence) is therefore a function of the occupancy state and some parameters:

(2f.1)

(2f.2)

Finally, given that our model is Markovian, we have to define the initial state . We consider that specific occupancy at time *t = 0*, , and therefore its probability, , can be described as a function of the general occupancy probability for the species at that time, and some parameters:

(2f.3)

Thus, our general latent model is:

(2g.1)

(2g.2)

(2g.3)

(2g.4)

(2g.5)

**Observation Model**

The specific occurrences are never truly known, but rather are inferred from a series of independent observations () for species *i* at site *k* during time period *t*, during which it is assumed that does not change.

The specific observed presence/absence of species *i* during observation *j* of time period *t* at site *k* is and the total # of observed presences of species *i* at site *k* during the observations of time period *t* is ,

(3a)

Thus, across all species and all sites at time period *t*, we have an N x K matrix of total observed presences and a N x K matrix of # of observations made ():

(3b.1)

(3b.2)

The relationship between observed presence/absence and true state presence/absence can be described as a finite mixture of binomial variables (Royle and Link 2006):

|  |  |  |
| --- | --- | --- |
|  |  | |
|  | 0 (true absence) | 1 (true presence) |
| 0 (observed absence) |  |  |
| 1 (observed presence) |  |  |

where

and

The general assumption of occupancy models is that (no false detection) and thus that .

We don’t necessarily need to make that assumption, but if we relax it, we come to a situation where there is identical support for multiple distinct parameter sets (see Royle and Link 2006) because one does not definitively know whether any site is actually occupied. A sensible *a priori* constraint would be that true detection is more likely than false detection: .

These two probabilities ( and ) sum to give an overall probability of detecting species *i* at site *k* during an observation from time period *t* (regardless of whether it is “truly” there), denoted :

Thus,

(3c.1)

and

(3c.2)

where (3c.1)

We consider that these two probabilities are functions of the occurrence state at that time, such that

(3d.1)

(3d.2)

Thus, our general observation model is:

(3e.1)

(3e.2)

(3e.3)

(3e.4)

**Combined Model**

Combining Equations 2g (latent model) and 3e (observation model), we achieve our full model:

(4a.1)

(4a.2)

(4a.3)

(4a.4)

(4a.5)

(4a.6)

(4a.7)

(4a.8)

(4a.9)

Clearly, all of these functions and parameters are general, such that we still have to articulate exactly how occupancy state at time *t* translates to occupancy at *t + 1* and observation at *t*. However, Equation 4a gives us the general framework within which we can basically specific a whole suite of models to explain our data.

***Parameters/Relationships of Interest***

Here we list out all of the factors/parameters/relationships that we think might influence occupancy or detection, grouped by the relevant probability of interest

𝛷 γ

spp ixns spp ixns human/dog presence other spp presence

prey prey other spp presence species

area area temp family (taxonomic)

isolation/connectivity isolation/connectivity area forest cover

temp/Jday temp/Jday forest cover observer

site type site type species expert vs citizen

urbanization urbanization observer

species species expert vs citizen

***Chicago Wildlife Watch***

***References***