Cat abundance sampling

I used two common, reproducible methods to estimate cat abundance at each site: distance transects and camera traps. Distance sampling involves counting individuals along a straight-line transect and recording the perpendicular distance of each individual from the transect line (Buckland et al. 2001). The probability of detecting an individual is assumed to decrease as a function of distance from the observer. This approach allows generation of an estimate of abundance in the transect area (Buckland et al. 2001). I conducted six distance transects at each site (n = 53) between June and August of 2016. To conduct a transect, I walked 200m along a road centered at an NN site and stretching 100m in opposite directions from the site center. I counted any cats I could see and estimated their perpendicular distance from the transect.

In addition to distance transects to measure cat abundance, I deployed Reconyx PC800 Hyperfire (Holmen, WI) motion-sensor cameras at a subset of the sites (n = 48). One camera was deployed per site. Cameras were set about 0.5m above the ground and programmed to take five photographs when triggered, with no delay period between triggers to minimize the chance of missing an individual cat.

Each camera was deployed for a total of three weeks at each site, divided into three one-week deployments. I deployed a camera at each site for one week per month (June, July, August), and site order was randomized within each month to avoid temporal clustering of site visits. I conducted distance samples upon camera setup and removal. Camera position was not changed between deployments, with one exception due to an RV obstructing the detection area.

Analysis

Statistical analysis of transect and camera data was carried out using the package *unmarked* (Fiske and Chandler 2011) in program R (Team 2014). I fit generalized distance-sampling models of Chandler et al. (2011) to transect data using function *gdistsamp*. These are hierarchical maximum-likelihood models that allow for the estimation of parameters:

λ Abundance in the transect area

ϕ Probability that an individual is available for detection

*p* Probability that an individual that is available is detected

I fit N-mixture models (Royle 2004) to camera data using function *pcount*. These are maximum-likelihood models that allow for the estimation of parameters:

λ Abundance in the sampled area

*p* Probability that an individual in the sampled area is detected

I used the Akaike’s Information Criterion, AIC (Akaike 1998), to select the best model from a set of candidate models. Maximum-likelihood models are susceptible to over-fitting with a small sample size. I accounted for small sample size following the method of Hurvich and Tsai (1989), which yields corrected AIC values (AICc). This measure penalizes models with more estimated parameters, accounting for the reduction in negative log-likelihood in over-parameterized models. Models with a ΔAICc value of less than 2 was considered to have substantial support (Burnham and Anderson 2003). AICc weights, the ratio of the likelihood of a model to the sum of the likelihood of the rest of the model set, were calculated to determine the relative weight of each model in the set.

Using this construct, I examined the human demographic and land-use variables influencing cat abundance (Table 1). Impervious surface and canopy cover percentage were obtained from the National Land Cover Database (Fry 2011) and measured at each study site using the *raster* package in R (Hijmans and van Etten 2014). Site demographic information was obtained from the U.S. Census Bureau (citation). Covariates potentially influencing detection, *p*, and availability for detection, ϕ, (Table 1) were obtained from Weather Underground (citation) or, in the case of transect time, recorded at the time the transect was conducted. To better compare model β estimates, all variables were scaled by subtracting each value by the variable mean and dividing by the standard deviation.

First, I developed null abundance models to compare detection covariates. For transects, these covariates included transect time, temperature, and dew point. For cameras, I considered daily high temperature, daily low temperature, and daily low dew point detection covariates. Mammal activity is known to vary with temperature (Konecny 1987), time of day (Jones and Coman 1982), and humidity (Vickery and Bider 1981). The best supported detection covariates that I used in subsequent model comparisons for transects were time (ϕ) and temperature (*p*). For cameras, the best supported detection covariate was daily low dew point. Next, I tested the alternate hypotheses of a linear or quadratic relationship between cat abundance and urbanization by building a set of candidate models including three related urbanization covariates in linear and quadratic form. Finally, I built a set of candidate models for each dataset including the best-supported urbanization measure and other demographic variables (Table 1). Because multiple models in a set may provide useful information about responses to predictor variables (Burnham and Anderson 2003), I averaged model β estimates and standard errors by their AICc weights.

Because distance-sampling models (Chandler et al. 2011) provide estimates of abundance within a discrete transect area, an estimate of cat population density at each site can be determined. The transect area is two hectares, so abundances estimates were divided by two to give density estimates in cats per hectare. Density estimates could not be determined from camera data because the sampled area is not defined for N-mixture models (Royle 2004).

Table 1. Land-use and demographic variables potentially influencing cat abundance; time and climate variables potentially influencing cat detection and availability for detection.

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Description | Parameter | Model set |
| imp | Percent impervious surface in 100m radius of site | λ | Both |
| imp2 | Pervious surface, quadratic term |  | Both |
| can | Percent canopy cover in 100m radius of site | λ | Both |
| can2 | Canopy cover, quadratic term |  | Both |
| density | Human population density within site’s census tract | λ | Both |
| density2 | Human population density, quadratic term |  | Both |
| age | Median age in census tract | λ | Both |
| income | Median income in census tract | λ | Both |
| eduHS | Percent individuals in census tract with high school degree | λ | Both |
| eduC | Percent individuals in census tract with bachelor’s degree | λ | Both |
| marred | Percent married individuals in census tract | λ | Both |
| time | Time of transect, in minutes after midnight | ϕ*, p* | Transect |
| temp | Temperature at the time of the transect | *p* | Transect |
| dew | Dew point at the time of the transect | *p* | Transect |
| tempH | Daily high temperature | *p* | Camera |
| tempL | Daily low temperature | *p* | Camera |
| dewL | Daily low dew point | *p* | Camera |

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