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.

When constructing models, I started with models in which abundance was not influenced by any covariates and compared a priori models of differing detection covariates. The best supported among these were used as the null abundance models. The best-supported null models are shown in Table 3, giving the covariates for detection, *p*, and availability for detection, ϕ, I used in subsequent models. 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/human population covariates in linear and quadratic form. Those models are shown in Table 4. 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, and time and climate variables potentially influencing detection and availability for detection.

|  |  |  |  |
| --- | --- | --- | --- |
| Model set | Variable | Description | Parameter |
| Both | imp | Percent impervious surface in 100m radius of site | λ |
| Both | can | Percent canopy cover in 100m radius of site | λ |
| Both | density | Human population density within site’s census tract | λ |
| 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 |
| Transect | 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* |
| Camera | tempH | Daily high temperature | *p* |
| Camera | tempL | Daily low temperature | *p* |
| Camera | dewL | Daily low dew point | *p* |

Table 2. Best-supported null abundance models. These detection covariates were then used to build subsequent models. A dot (.) represents constant abundance across sites.

|  |  |
| --- | --- |
| Model | Data set |
| λ(.) ϕ(time) *p*(time + dew × temp) | Transect |
| λ(.) *p*(dewL) | Camera |

Table 3. Alternate cat abundance models comparing urbanization/human population covariates and linear versus quadratic responses.

|  |  |
| --- | --- |
| Model | Data set |
| λ ~imp ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~can ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~density ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~imp + imp2 ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~can + can2 ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~density + density2 ϕ ~time *p* ~time + dew × temp | Transect |
| λ ~imp *p* ~dewL | Camera |
| λ ~can *p* ~dewL | Camera |
| λ ~density *p* ~dewL | Camera |
| λ ~imp + imp2 *p* ~dewL | Camera |
| λ ~can + can2 *p* ~dewL | Camera |
| λ ~density + hDensity2 *p* ~dewL | Camera |

Akaike, H., 1998. Information theory and an extension of the maximum likelihood principle, In Selected Papers of Hirotugu Akaike. pp. 199-213. Springer.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., Thomas, L., 2001. Introduction to distance sampling estimating abundance of biological populations.

Burnham, K.P., Anderson, D.R., 2003. Model selection and multimodel inference: a practical information-theoretic approach. Springer Science & Business Media.

Chandler, R.B., Royle, J.A., King, D.I., 2011. Inference about density and temporary emigration in unmarked populations. Ecology 92, 1429-1435.

Fiske, I., Chandler, R., 2011. unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. Journal of Statistical Software 43, 1-23.

Fry, J., Xian, G., Jin, S., Dewitz, J., Homer, C., Yang, L., Barnes, C., Herold, N., Wickham, J., 2011. Percent Developed Impervious. National Land Cover Database 2006., Multi-Resolution Land Characteristics Consortium (MRLC).

Hijmans, R.J., van Etten, J., 2014. raster: Geographic data analysis and modeling. R package version 2, 15.

Hurvich, C.M., Tsai, C.-L., 1989. Regression and time series model selection in small samples. Biometrika, 297-307.

Royle, J.A., 2004. N‐mixture models for estimating population size from spatially replicated counts. Biometrics 60, 108-115.

Team, R.C., 2014. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2013.