



# UNDERSTANDING HUMAN-COYOTE ENCOUNTERS IN URBAN ECOSYSTEMS USING CITIZEN SCIENCE DATA: WHAT DO SOCIOECONOMICS TELL US?

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# TOPICS

- Background Information
- Hypotheses
- Methods
- Analysis/Results
- Discussion

# URBAN EFFECT ON BIODIVERSITY

- A once species-rich community is replaced with a community composed of a small number of generalists, native and non-native (Hobbs and Mooney 1998).
- Generalist species may persist in human-modified landscapes because of their high degree of behavioral flexibility which allows them to adapt quickly to a changing landscape.



# SYNANTHROPIC BEHAVIORS

- Several aspects of the coyote's ecology may be responsible for this.
- Absence of larger apex predators
- Dynamic diet
- Ability to Change activity patterns



# INCREASING CONCERN

- Coyote presence in human-dominated landscapes has been met with conflicting perceptions by human residents.



# QUANTIFYING URBAN HABITAT USE

- Increasing coyote occurrence and the potential for negative human-coyote interactions have prompted several efforts to quantify coyote habitat use in urban areas.

Radio Telemetry is the most popular method used to quantify urban coyotes' use of urban landscapes.



# CITIZEN SCIENCE APPROACH

- Citizen science is scientific research conducted, in whole or in part, by amateur or nonprofessional scientists



Citizen science has many advantages over traditional research. However, it has its own limitations.

# CITIZEN SCIENCE APPROACH

- Two studies have used citizen science data to map coyote habitat preference (Quinn 1995) or the likelihood of human-coyote encounters (Weckel et al. 2012).
- Quinn (1995) explored potential biases between using publicly reported sightings and telemetry data. Similar orders of habitat preference were derived from the two datasets.
- More recently, Weckel et al. (2012) used the locations of coyote sightings (determined by means of surveys sent home with K-12 students) and their proximity to roads, high-density development, forest, and open water to estimate the likelihood of human-coyote encounters in Westchester County, New York.
- The result was a predictive landscape model that accurately predicted the location of a hold-out set of sightings.

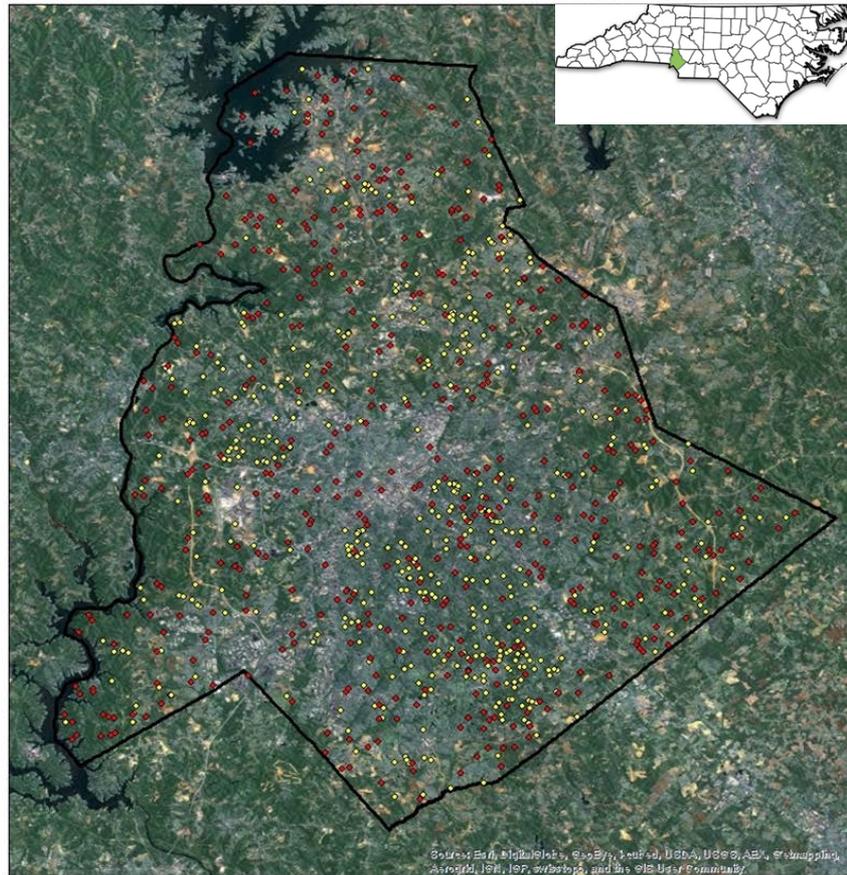
# SOCIOECONOMIC VARIABLES

- I hypothesize that:
  - residential areas with higher median household income typically provide more resources such as pets, pet food, and vegetative cover than residential areas of lower median household income.
  - a higher income may also suggest that residents place a higher value on their property and may therefore be more inclined to report coyotes as a possible nuisance.
  - residents with occupations that involve more outdoor activity (i.e. agriculture) will be more likely to witness a coyote than residents primarily working indoors.
  - higher densities of urban development may provide more food sources to the urban exploiter

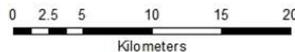
# HOW?

- I used a citizen science framework that consists of resident reported sightings in Mecklenburg County, North Carolina.
- The importance of socioeconomic variables as predictors was assessed using a multi-model inference approach.
- A predictive map was generated using model-averaged parameter estimates.
- Model Validation

# STUDY AREA



- ◆ Pseudo absences
- ◆ Coyote sightings



Mecklenburg County has seen a rapid increase in urbanization. Between 1976 and 2006, the percentage of urbanized land has increased from 12.5% to 57.6%. In the same time frame, Mecklenburg County's population has risen from 383,800 to 857,379. In 2013, the population is nearing 1 million.

# SIGHTINGS DATA

- In February 2012 the Mecklenburg County Department of Natural Resources launched a website to gather countywide coyote sightings.
- Used sightings submitted between February 1<sup>st</sup> 2012 and January 31<sup>st</sup> 2013 that contained spatial reference.
- 707 total sightings used for analysis
- Two-thirds (472) used for model development and calibration
- One-third (235) used for model validation
- 472 Pseudo-absences were randomly generated under the condition they were not in water

# PREDICTOR VARIABLES

Variable	Description
<b>agri</b>	Proportion of residents that are over the age of 16 that work in agriculture, natural resources, or hunting and fishing
<b>bachel</b>	Proportion of residents who have obtained a Bachelor's degree
<b>devin</b>	Building and road density
<b>farm</b>	Proportion of the area that is farmland
<b>forest</b>	Proportion of the land that is forest
<b>imperv</b>	Proportion of the land that is impervious
<b>manage</b>	Proportion of the land that is managed clearing (i.e. golf courses and parks)
<b>medhh</b>	Median household income
<b>water</b>	Proportion of the land that is water

**Table 1.** Predictor variables of coyote sightings in Mecklenburg County, North Carolina, USA.

# ANALYSIS

- The analysis portion of the study can be described in 6 individual steps:
  1. Explore all possible logistic regression models using Akaike's Information Criterion (AIC)
  2. Test for spatial autocorrelation
  3. Generate autocovariate and run autologistic regression models to generate new AIC values
  4. Calculate model-averaged parameter estimates
  5. Create predictive landscape model
  6. Assess validity of predictive map

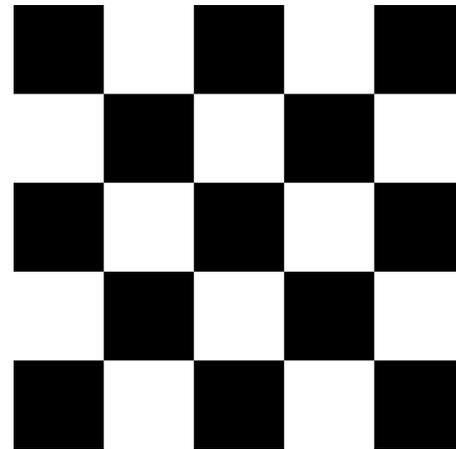
# STEP 1: EXPLORATION USING AIC

Spatial scale	Predictor variables	AIC	K	$\Delta_i$	$\omega_i$
2km radius	agri + devin + forest + manage	1255.424	6	0	0.105501794
2km radius	agri + devin + medhh + water	1255.452	6	0.028	0.10403506
2km radius	agri + devin + manage	1256.444	5	1.02	0.063353361
2km radius	agri + devin + manage + water	1256.801	6	1.377	0.05299661
2km radius	agri + devin + manage + medhh	1257.144	6	1.72	0.044644359
2km radius	agri + devin + imperv + water	1257.623	6	2.199	0.03513606
2km radius	agri + devin + imperv + manage	1257.918	6	2.494	0.030317586
2km radius	agri + devin + farm + manage	1258.022	6	2.598	0.02878136
2km radius	agri + bachel + devin + water	1258.063	6	2.639	0.028197349
2km radius	agri + bachel + devin + manage	1258.065	6	2.641	0.028169165
2km radius	agri + bachel + forest + manage	1258.327	6	2.903	0.024710493
2km radius	agri + devin + forest + medhh	1258.652	6	3.228	0.021004316
2km radius	devin + forest + medhh + water	1258.945	6	3.521	0.018141969
2km radius	agri + devin + forest + water	1258.946	6	3.522	0.0181329
2km radius	devin + medhh + water	1259.168	5	3.744	0.016227835

**Table 2.** The best models for predicting coyote sightings in Mecklenburg County, North Carolina, USA. Best models were those with the highest Akaike's Information Criterion (AIC) values and for which the sum of their weights ( $\omega_i$ ) equaled 0.75. The spatial scale is the distance from sighting or pseudo-absence locations within which predictor variables were measured. See Table 1 for predictor variable definitions. K = the number of estimated parameters;  $\Delta_i = \text{AIC}_i - \text{minAIC}$  for each model  $i$ ;  $\omega_i$  = Akaike weight or the probability of being the best model given the observed data and the set of variables considered.

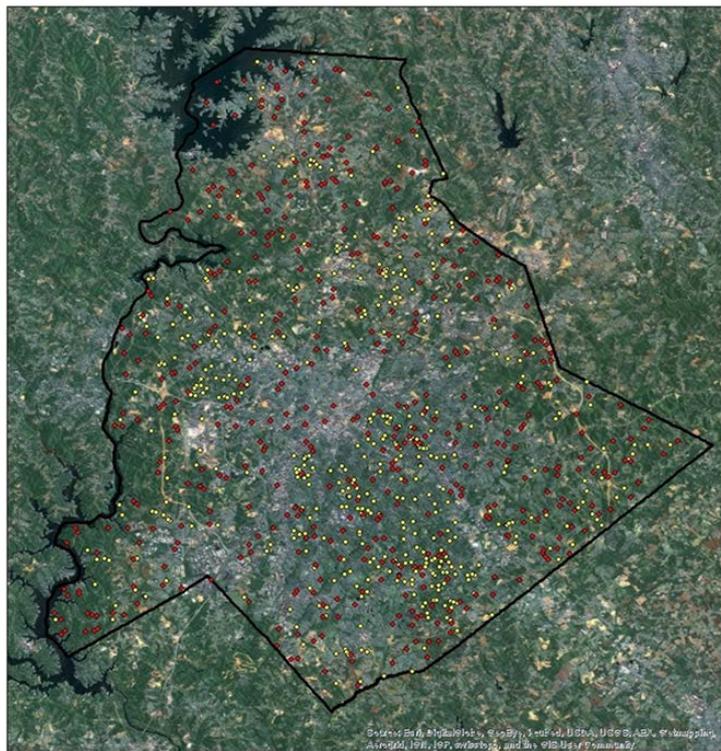
## STEP 2: TESTING FOR SAC

- Spatial autocorrelation (sac) is described as a correlation of characteristics among nearby locations in space
- Moran's  $I$  tests residuals for sac



- Every model tested as significantly or nearly significantly spatially autocorrelated

## STEP 3: GENERATE AUTO-COVARIATE



- Pseudo absences
- Coyote sightings



0 2.5 5 10 15 20  
Kilometers

- An autocovariate is a user-created predictor variable intended to explain unknown error in a spatially-autocorrelated model (Dormann et al. 2007)
- Used an inverse distance weight (IDW) calculation on the response variable
- Incorporated autocovariate and explored autologistic regression models using AIC

# STEP 3 CONT...

Variable Group	Variables	AIC	K	$\Delta_i$	$\omega_i$
2km radius	agri + devin + manage + autocov	1219.712	6	0	0.1050575
2km radius	devin + forest + manage + autocov	1220.58	6	0.868	0.0680681
2km radius	agri + devin + forest + manage + autocov	1220.633	7	0.921	0.0662879
2km radius	agri + devin + manage + medhh + autocov	1221.181	7	1.469	0.0504009
2km radius	agri + devin + manage + water + autocov	1221.287	7	1.575	0.0477992
2km radius	agri + devin + medhh + water + autocov	1221.328	7	1.616	0.0468293
2km radius	agri + devin + farm + manage + autocov	1221.354	7	1.642	0.0462244
2km radius	devin + medhh + water + autocov	1221.403	6	1.691	0.0451057
2km radius	agri + devin + imperv + manage + autocov	1221.554	7	1.842	0.0418256
2km radius	devin + forest + medhh + autocov	1221.572	6	1.86	0.0414508
2km radius	agri + devin + medhh + autocov	1221.592	6	1.88	0.0410384
2km radius	agri + bachel + devin + manage + autocov	1221.597	7	1.885	0.0409359
2km radius	agri + devin + forest + autocov	1221.874	6	2.162	0.0356414
2km radius	devin + water + autocov	1222.249	5	2.537	0.0295478
2km radius	devin + forest + imperv + manage + autocov	1222.317	7	2.605	0.02856

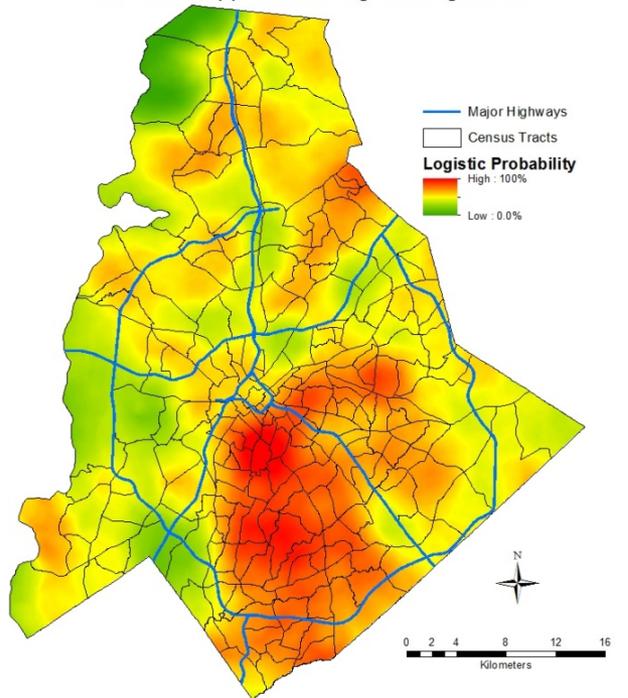
# STEP 4: AVERAGE PARAMETER ESTIMATES

Predictor	Estimate ( $x_2$ )	Upper 95% CI	Lower 95% CI
agri_2	0.306852535	0.730717	-0.11701
autocov_2	1.686237084	2.230681	1.141793
bachel_2	0.003861193	0.017875	-0.01015
devin_2	0.17806559	0.304014	0.052117
farm_2	-1.101976411	2.847107	-5.05106
forest_2	0.960442803	2.592639	-0.67175
imperv_2	-0.311410272	1.874939	-2.49776
manage_2	4.751031201	10.25697	-0.75491
medhh_2	4.2852E-06	1.09E-05	-2.3E-06
water_2	-1.436577472	1.366077	-4.23923
Intercept	-2.080143585	-1.03704	-3.12324

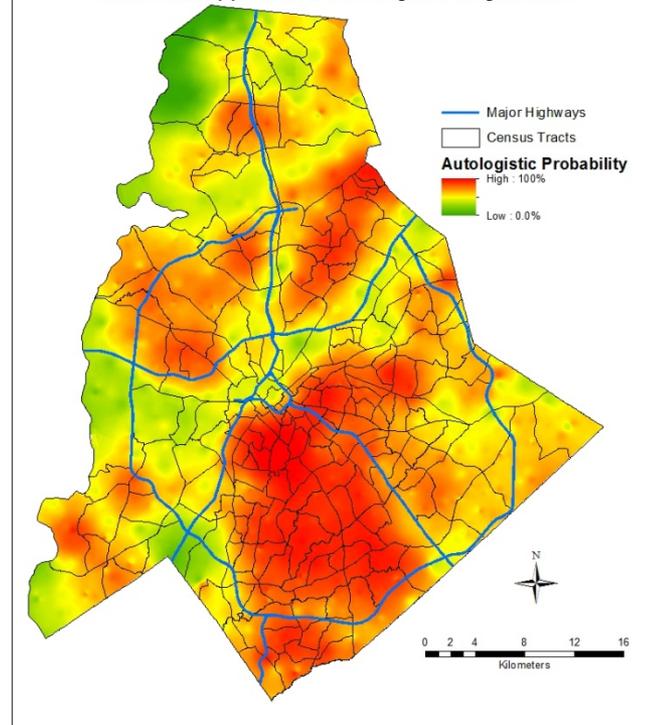
**Table 5.** Model-averaged estimates of the coefficients of predictors in the best models (Burnham and Anderson 2002) of coyote sighting prediction in Mecklenburg County, NC after accounting for spatial dependence. Upper and lower 95 % confidence intervals (CI) were calculated using unconditional variances (Burnham and Anderson 2002)

# STEP 5: PREDICTIVE LANDSCAPE MODEL

Probability Distribution of Coyote Sightings in Mecklenburg County, NC Using a Multi-Model Inference Approach to Logistic Regression

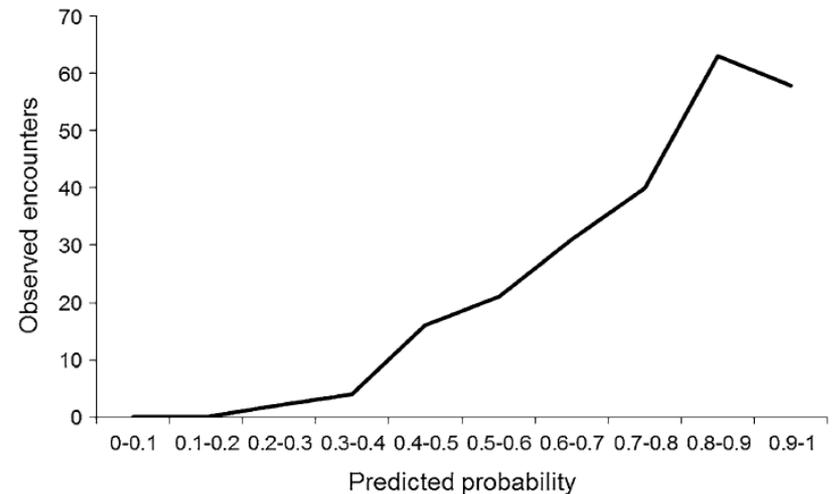


Probability Distribution of Coyote Sightings in Mecklenburg County, NC Using a Multi-Model Inference Approach to Autologistic Regression



# STEP 6: MODEL VALIDATION

- I classified the probability of sighting a coyote into 10 equal-interval classes categories ranging from 1 ( $0 < \text{probability} \leq 0.1$ ) to 10 ( $0.9 < \text{probability} \leq 1$ )
- To assess the validity of the predictive map, I calculated the correlation between the proportion of observed sightings in each probability class and the value of each probability class (Weckel et al. 2012).
- The correlation was greater using the results of the autologistic regression models ( $r = .96$ ) than the results of the logistic regression models ( $r = .54$ )



# DEVELOPMENT INTENSITY (+)



Higher development intensities may result in more supplemental resources for urban coyotes



# OUTDOOR EMPLOYMENT (+)

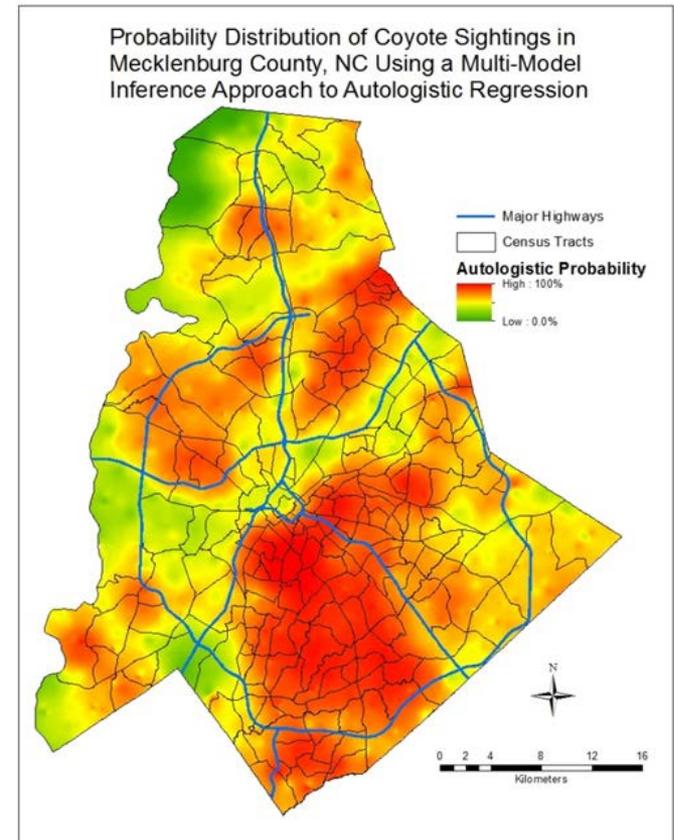
Intuitively, the more time a person spends outdoors, the greater is the likelihood that they will see a coyote.

Farmers may be more inclined to report these nuisance coyotes in the hopes that they be removed or eliminated.



# MED HOUSEHOLD INCOME AND EDUCATIONAL ATTAINMENT (+)

- Possible link to golf courses.



# MANAGEMENT IMPLICATIONS

Mecklenburg County Division of Nature Preserves and Natural Resources staff can use our results to target educational efforts to communities in areas where we predict particularly high encounter probabilities.



THANK YOU!

# Any questions?

