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Using phone call reports to assess the relative abundance of urban mesopredators

Christine Alyssa Klinkowski
San Jose State University

USING PHONE CALL REPORTS TO ASSESS THE RELATIVE ABUNDANCE OF URBAN MESOPREDATORS

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Christine Alyssa Klinkowski

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APPROVED FOR THE DEPARTMENT OF BIOLOGY

Dr. Shannon M. Bros

Dr. Michael J. Kutilek

Dr. John O. Matson

APPROVED FOR THE UNIVERSITY

ABSTRACT

USING PHONE CALL REPORTS TO ASSESS THE RELATIVE ABUNDANCE OF URBAN MESOPREDATORS

By Christine Alyssa Klinkowski

I assessed relative abundance of raccoons, opossums, and skunks using nuisance phone call reports of wildlife made to Brevard County Animal Services and Enforcement, Florida over four years (2000, 2003, 2004 and 2005). I created quadrats in ArcGIS 9.1 and obtained land cover and mean human demographic information within quadrats. I used quadrat sampling to determine abundance from verified phone call reports per capita. I compared the results of verified reports to the results of all available calls (verified + unverified) to determine if all reports could be used. Raccoon abundance was high in residential and industrial categories, but low in wetland categories. Opossum abundance was high in residential areas, but low in areas with barren land. Skunk abundance was high in commercial, medium density residential, and upland non-forested categories, but low in high density residential areas. Techniques to remove bias appeared successful and results also showed mesopredators used habitats based on availability.

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Introduction

While the presence of wildlife in urban areas is often enjoyable and offers many benefits, encounters between humans and wildlife are often negative due to damage and costs associated with these interactions (Messmer 2000, Conover 2001). Urban wildlife may act as pests (nuisances), knock over garbage cans, become confined in buildings, cause property damage, and become involved in collisions with vehicles (Messmer 2000, Conover 2001, Prange et al. 2003). These conflicts are often costly for humans in terms of time and cost spent repairing damage and can be harmful for both humans and wildlife in terms of injury or death (Messmer 2000, Conover 2001).

The close proximity of mesocarnivores to suburban areas also creates a safety risk in the form of disease transmission to humans and domestic animals directly (Rosatte 1988) through bites and indirectly through contact with fecal material (Roussere et al. 2003). Common mesocarnivores include the raccoon (*Procyon lotor*), Virginia opossum (*Didelphis virginiana*), Eastern spotted skunk (*Spilogale putoris*), striped skunk (*Mephitis mephits*), coyote (*Canis latrans*), bobcat (*Lynx rufus*), red fox (*Vulpes vulpes*), and gray fox (*Urocyon cineroargenteus*). While other species may cause damage (Conover 2001), mesocarnivores are vectors for a variety of zoonotic diseases such as rabies, canine distemper, and parvovirus

(Rosatte et al. 1991, Riley et al. 1998, Broadfoot et al. 2001, Prange and Gehrt 2004). Indirect contact with fecal material from mesocarnivores such as raccoons may also lead to the spread of disease. Raccoons defecate in latrine sites, often located in residential areas (Roussere et al. 2003). Many different raccoons may use a single latrine, often leading to the presence of a large amount of feces (Rouserre et al. 2003, Page et al. 2005). Contact with feces from these latrines may lead to the transmission of raccoon roundworm (*Baylisascaris procyonis*) to humans, especially to small children who often put their hands in their mouths (Roussere et al. 2003, Page et al. 2005).

To manage populations of urban mesocarnivores to reduce predation risk and the spread of disease it is critical to know where these animals increase in abundance. Mesocarnivores thrive in urban areas without large predators (Crooks and Soulé 1999) and reduce populations of birds, small mammals, and herptofauna (Crooks and Soulé 1999, Mroziak 2000, Gehring and Swihart 2003). Locating where urban mesocarnivores are located may assist efforts to reduce predation on threatened species (Bruggers et al. 2002). Furthermore, this knowledge can also be used to identify areas where disease transmission is likely to occur and spread to other wildlife, domestic animals, and humans (Bruggers et al. 2002, Gehrt 2002), and identify areas to focus management efforts to reduce the spread of zoonotic diseases (Bruggers et al. 2000, Broadfoot et al. 2001). For example, vaccinating wildlife can be an effective option for reducing the spread of disease in urban areas (Hadidian et al. 1989, Olson et al. 2000, Broadfoot et al. 2001). Identifying areas where raccoons and skunks increase in abundance may enable managers to target certain areas more effectively (Broadfoot et al. 2001).

Current methodologies may not be suited for evaluating wildlife distribution in urban areas. Trapping and remote animal detection (e.g. scent stations and cameras) are common methods for estimating abundance in urban areas (Gehrt 2002, Locke et al. 2005). However, these methods are labor intensive, expensive (Gehrt 2002, Locke et al. 2005), and are difficult to use extensively throughout urban and suburban neighborhoods due the requirement of obtaining permission to sample on multiple private properties. If there was a sampling method that gave similar estimates of abundance as traditional methods, but was less expensive and allowed the sampling of multiple private residences, it could be used alone or together with radio-telemetry studies to reduce costs associated with estimating mesopredator abundance in urban areas.

Telephone call reports to animal control agencies (referred to as nuisance calls or reports of wildlife) can provide an appropriate and viable source of data to assess relative abundance of wildlife in urban areas. Members of the public make phone calls to local city, county, or state animal control agencies to report the point location of an animal that may be trapped in a cage trap, confined in a house, roaming around the neighborhood, or dead. In Brevard County, Florida (Fla.) Brevard County Animal Services and Enforcement (BCASE) records information from phone call reports of wildlife in a computerized database for raccoons, Virginia opossums, Eastern spotted and striped skunks, gray and red foxes, bats (non-specified species), and bobcats. A dispatcher records the date, the street address of the caller, the number and type of animal(s) reported, the address location of the animal(s), the action requested by the caller, and the resulting action taken by BCASE. These phone calls often result in the education of the caller about solutions to deal with urban wildlife problems. Solutions may include securing garbage cans or removing food sources (e.g. pet food) from areas where animals are causing problems, etc. Alternatively, an officer may go to a location where a problem occurred to remove an animal from a cage trap set by the property owner, dispose of a dead animal, or take an injured animal to a wildlife rehabilitation center.

Telephone calls are potentially useful for determining the relative abundance of species within urban areas if animals are visually confirmed (e.g. dead or alive) by an officer or captured in cage traps. Traditionally, habitat assessment uses trapped animals however, road-kill censuses or spotlight surveys may also be reliable for determining landscape use (Caro et al. 2000, Gehrt 2002, Prange and Gehrt 2004). As data from animal control agencies includes a combination of trapped animals within urban areas in addition to deceased animal locations, this source of data may also indicate animal presence in urban areas.

Using reports of wildlife to determine abundance may be a method that allows rapid assessment of relative abundance, is cost effective, easy to record and update over time, and allows easy sampling of these species in residential areas. Previous studies used information from animal control agencies to determine how calls about urban wildlife are handled (Curtis et al. 1993), to study how bait containing rabies vaccines are ingested by raccoons at different land use zones (Olson et al. 2000), and to find out how people respond to urban wildlife conflicts (Barden et al. 1995). Surveys given to animal control agencies report that complaint and nuisance calls about urban wildlife are increasing (Lord et al. 1998) and human-wildlife conflicts will likely increase in the future (Messmer 2000). Locating where these animals are abundant in urban areas allows the potential to determine where animals may encounter humans. Evaluating mesopredator abundance and habitat preference in residential developments may help reduce human-wildlife conflicts if these areas can be estimated.

There are several potential problems with using phone call reports to derive estimates of the distribution, abundance, and habitat preference of urban mesopredators. If an agency receives a large number of telephone calls about wildlife, this may lead to an overestimate of wildlife if the same animal is reported multiple times. The large number of calls an agency receives may restrict analyses if animals cannot be located or if the calls are biased with animal or address misidentifications. If a member of the public reports the wrong animal or address or the agency does not observe an animal, there is no way to know whether or not an animal was present. Sampling areas without people or telephones would lead to an underestimate of wildlife presence. Likewise, sampling rural areas might lead to an underestimate of abundance, as fewer people are present to report potentially fewer animals.

There are various difficulties associated with how data are recorded by agencies that can lead to problems interpreting analyses. If an agency does not record the exact species present at a location, information for several species may be grouped together. If trapped animals are relocated within the area, population estimates may not be possible due to potential recaptures unless animals are clearly marked before their release. This may also lead to an overestimate of the number of animals in an area in addition to problems with disease transmission associated with relocations (Rosatte and MacInnes 1989). There are no potential solutions to these problems currently.

It is important to look at human demographic influences within the study area to determine whether they may lead to biases in the dataset. Any encounter with wildlife or perceived conflict may result in a person requesting removal of an animal from their home (Messmer 2000, Conover 2001). However, due to differences in attitudes toward wildlife in urban areas and damage (Conover 2001), some people may call to report an animal while others do not. As an independent observer (e.g. animal control officer) cannot confirm some reports from members of the public, there is no way to know if the animal was present at that location. If higher numbers of people with certain demographic characteristics are correlated with high numbers of calls that cannot be confirmed (unverified), perhaps education of this demographic group may alleviate some of the problems with calls. If demographic information does not influence calls, agencies may be able to use the data directly to obtain estimates of wildlife abundance.

Examples of demographics that may affect calls include persons who are at home more than other people, people with children, and property owners. Retired persons, staying at home, may be at home more often than people at work, which could lead to an overestimate with this demographic group if animals are roaming around neighborhoods. People with children might report animals near their property more often than people without children out of worry about injury to their children from wildlife, leading to an overestimate of wildlife associated with this group. Homeowners may call more than renters out of concern for property damage leading to an overestimate with this group.

There are several strategies for dealing with bias associated with phone call reports from the public. While data from BCASE includes animals that may be verified for presence if animals are in cage traps, dead, or otherwise handled by an officer, there still may be some bias associated with reports by the public. Repeated call bias may be addressed using one telephone call per address per animal group per year. If a demographic factor (including the number of telephones) influences reports, a correction factor can be used to make estimates more reliable. If an animal control officer identifies the animal in a trap or dead on a street, the animal is present and verified at the location. If we know that an animal is present at a location, we can assess habitat characteristics in that area. Comparing the results of verified calls per capita to total calls per capita can determine whether calls have to be confirmed (verified) to determine relative abundance. In areas with a large number of people, weighting calls where verified animals are present by the mean human population size in that area will factor out some of the overestimation bias associated with calls and human population density. However, it is important to note this may actually underestimate preference in areas with high a human population such as residential areas. For example, if there were five verified raccoons in a quadrat with low human population density, taking the five raccoons divided by a mean human population of 400 and multiplying the result by 10,000 would lead to a testing value of 125 for this quadrat. However, for 20 raccoons in a quadrat with high human population density, taking the 20 verified raccoons divided by a mean human population of 12,000 and multiplying the result by 10,000 would lead to a testing value of ~16. This leads to a higher influence of verified phone call reports in areas with a lower human population density than areas with a higher human population density.

Geographic information systems (GIS) may allow the creation of models for abundant species. A GIS is a tool that is able to combine information from a variety of sources (Le Lay et al. 2001). Bruggers et al. (2002) state it is necessary to develop practical methods to survey abundant wildlife in urban areas. A GIS can be used to determine the centers of raccoon and skunk populations without the addition of a population model (Broadfoot et al. 2001). A GIS may also be useful for identifying areas for rabies vaccination programs for raccoons and skunks (Broadfoot et al. 2001) and for reducing costs associated with mesopredator related nuisance events in urban areas.

The focus of the present study was to determine the relative abundance of raccoons, opossums, and skunks using reports of wildlife by members of the public and assess potential human demographic influences on these calls. I assessed abundance of these mesopredators using animal reports verified by an officer. In addition, I compared results from using all available calls or total calls (officer-verified calls and calls that may or may not have been verified) with verified calls to determine whether verified calls were necessary for predicting animal distributions or if all of the calls could be used. Finally, I examined potential demographic bias on unverified calls reporting nuisance wildlife and determined whether animals were selecting certain habitats or using habitats based on availability. To examine these, I evaluated whether officer-verified phone call reports of wildlife can be used to assess abundance for raccoons, opossums, and skunks in urban areas. I also examined if potential biases and problems associated with nuisance calls can be addressed. If biases can be addressed, phone call reports may be a viable technique to assess relative abundance of mesopredators in urban areas. I measure success of this method if results from phone call reports match literature and the method is cheaper than traditional techniques.

Study area

Brevard County is located in eastern-central Florida between the coastal cities of Mims and Micco. By 1999, 50% of Brevard County, Fla. had been developed (T. J. Mallow, Coryi Foundation Inc., unpublished report). Land covers were defined using data from the most recent (2000) land use land cover layer (LULC) available from St. Johns River Water Management District (SJRWMD). Categories of land cover that would likely influence mesopredator distribution were selected for analyses: airport, agriculture, barren land, commercial, extractive, industrial, institutional, recreation, low, medium, and high density residential areas, upland forest, upland non-forested, transportation, communications, utilities, water, and wetlands. I combined communications and utilities into one category based on similar land cover codes. Upland non-forested areas contained rangeland, shrub, and brushland areas and consisted of native grasses and forbs, saw palmetto (*Serenoa repens*), wax myrtle (*Myrica cerifera*), coastal scrub, other shrubs and brush in addition to herbaceous cover such as sea purslane (*Sesuvium maritimum*). Upland forests included pine flatwoods such as slash pine (*Pinus elliottii*), longleaf pine (*Pinus palustris*) and sand pine (*Pinus clausa*) in addition to oaks and hardwoods such as bluejack oak (*Quercus incana*), turkey oak (*Quercus laevis*), and sand post oak

(*Quercus margaretta*). Upland forests also included other mixed upland coniferous/ hardwood stands including cabbage palm (*Sabal palmetto*), Australian pine (*Casuarina cunninghamiana*) and tree plantations. Institutional areas included military and use associated with the Kennedy Space Center at Cape Canaveral and often included large open grassy areas. Transportation included railroads, bus and truck terminals, roads and highways, port facilities, canals, and auto parking facilities. Communications and utilities included communications, electrical power facilities, electrical power transmission lines, water supply plants, sewage treatment plants, and solid waste disposal. Industrial areas included food-processing plants, light industry, and pulp and paper mills. Commercial areas contained cemeteries, oil and gas storage, and retail units. Recreational areas included swimming beaches, golf courses, and stadiums. Low density residential had less than two dwellings per acre, medium density residential had two to five dwellings per acre, and high density residential categories contained over five dwellings per acre (SJRWMD).

Methods

For all aspects of the study, I used three data sources: reports of wildlife from Brevard County Animal Services and Enforcement (BCASE), demographics from the U.S. Census Bureau, and a land use land cover (LULC) layer from SJRWMD. From BCASE records, I selected three mesopredator groups for analyses: raccoon, opossum, and skunks. I examined a total of 17,053 calls in 2000, 2003, 2004 and 2005 including 10,069 calls for raccoons, 5,967 calls for opossums, and 476 calls for skunks (Appendix 1). Calls about skunks were lumped in the records, although both striped and spotted skunks were present in the study area (K. Earley, Brevard County Animal Services and Enforcement, personal communication).

Verified and unverified calls to BCASE report dead, sick, injured, confined, roaming, or nuisance wildlife. For verified calls, I only used those calls where an animal was seen, identified, and recorded by a BCASE officer (e.g. "trapped and relocated," "rehabilitated," or "dead on arrival") (Appendix 2-2d). When the same address made multiple calls, I only used one of these calls per address per animal group per year to determine conflict location for verified calls. Unverified calls were analyzed separately in a total calls database (officer-verified calls and unverified calls in the quadrats) to determine whether these could be used to determine relative abundance. Unverified calls included anonymous calls, repeated calls (over one call per address per animal group per year), and calls without a result (the animal was not seen by BCASE or was not recorded). I also included calls with ambiguous results ("Made Contact" or "Complied") and calls where the address could not be verified. If I was uncertain whether the animal was present at a location, I placed the call into the unverified database.

I matched each conflict location to the address of the caller using an address geocoding function within ArcGIS® version 9.1 (ESRI 2006). Address geocoding locates street addresses and converts them into x and y coordinates. I standardized street addresses from calls using the United States Postal Service (U.S.P.S) format to increase the likelihood of a correct match in the GIS. For analyses, I included only calls that were geocoded with a precision of 80% (90% of all verified calls and 79% of unverifed calls). I created an address locator using a dataset of roads created in 2000 from ESRI (Redlands, CA). Streets were defined using data from the most recent (2000) roads layer available at the time of analyses. However, using a dataset from the year 2000 means that some verified calls could not be located (geocoded) because roads built in 2005 were not present in the layer from 2000. However, this was the most recent information available at the time of analysis. The impact of this may lead to verified calls not being located where a verified report existed, but if one assumes a proportional increase in road density, the bias is minimal.

I obtained human census tract information from the U.S. Census Bureau and selected income, age, population and housing characteristics as a rough estimate of demographic influence. The Census Bureau provides demographic information about people throughout the country at an aggregated level (Rindfuss et al. 2004). Although the level of demographics should match the level of data collected (Rindfuss et al. 2004), ungrouped household level demographics are not available to compare with household level phone call reports. Census block data provides similar problems with grouped data. Without individual household information, it may not be possible to determine all bias that may be associated with telephone call reports. As such, census tract demographics are a rough estimate of the potential bias for unverified calls.

I combined the most recent demographic characteristics available at the time of analyses from the 2000 census. I included: human population (2001) and population per square mile (2001), the number of males and females, age groups (under 5, 5-17,18-21, 22-29, 30-39, 40-49, 50-64, over 65 years), median age, median age of females, median age of males, number of households, average household size, average family size, average number of housing units, number of vacant units, number of occupied units, owner occupied housing, renter occupied housing, per capita income, number of telephones, and income levels.

I assessed relative abundance for mesopredators by sampling from the geocoded verified locations and comparing these point locations against areas of land covers within quadrats. I created quadrats for analyses by creating a random raster in ArcGIS (ESRI 2006) for the extent of the county consisting of 2.0-km^2 grids. I selected this grid size to provide enough individuals per quadrat for analysis, allow for random sampling of non-adjacent quadrats, and ensure at least one call per quadrat. The use of non-adjacent quadrats for sampling is important to avoid spatial autocorrelation, which results in non-random sampling where areas that are closer together are more related than areas that are farther away; which often lead to artifacts within the data (O'Sullivan and Unwin 2003). For raccoons and opossums, 50 random non-adjacent quadrats were selected in which animals were present (Appendix 3, 4, 5). For skunks, I selected 35 random non-adjacent quadrats because there were fewer calls to sample (Appendix 6). When any quadrats contained ocean, I used the quadrat below and to the left.

Using ArcGIS (ESRI 2006), I used tools in ArcToolbox (ESRI 2006) to combine land covers within each quadrat sampled and calculate areas of land covers. The Intersect tool allows data from two different layers to be combined within one layer. In this case, the land covers were contained within the extent of the quadrat (Appendix 7), enabling areas of each land cover within the quadrat to be calculated within the GIS using the Calculate Areas tool. Finally, I exported the areas of each land cover within quadrats from the GIS into SPSS version 13.0 (SPSS Inc., Chicago IL) for statistical analyses.

I used Backwards Stepwise Multiple Linear Regression analyses (Zar 1996) to examine which land covers predicted abundance of each animal group. I tested the number of verified calls per quadrat and total (unverified and verified) calls separately against areas of land covers. I chose land cover (biophysical conditions) (Rindfuss et al. 2004) over land use (human uses) as a more specific indicator of habitat. I transformed areas of land covers using the square root of x + 1 where x was the total area for a land cover category within a quadrat. For raccoons and opossums, I removed airport, extractive, and recreation variables from the regression due to high leverage on the final model and only three instances where large areas of these land covers were present in any quadrat. Similarly for skunks, I removed airport and extractive land cover variables from the analyses. I computed loadings (correlations with significance at R > 0.300) of variables in the final regression model to interpret the relative impact of coefficients in the model. Using Pearson correlations, I tested the predicted values from the regression against significant coefficients in the model. To look at whether demographic factors influenced calls, I compared both unverified and total calls per capita against demographics using Pearson correlations to determine if there was demographic bias associated with these types of calls. To determine whether total calls led to the same predictions as verified calls, I compared the results of the Backwards Stepwise Multiple Linear Regression analyses.

To determine the relative influence of demographic factors on nuisance calls, I calculated the difference for the predicted values for total calls and those for verified calls to obtain the predicted values for unverified calls. I used Pearson correlation analysis to assess the relationship between demographic factors and the differences between the two models. To obtain demographic data for specific quadrats, I used GIS to intersect the census tract layer with the quadrats. As several census tracts often crossed through quadrats, the mean demographic values for the tracts passing through the quadrat were calculated, summarized, and exported the information into SPSS 13.0 as an estimate of demographics.

Since the number of calls an agency receives may be related to human population size, I sampled areas with people (Appendix 8) and telephones present to allow the potential for a telephone call from each quadrat. I used the number of verified sightings per capita for each animal group (the number of officer-verified animals divided by mean human population size in 2001 within the quadrat) multiplied by 10,000. According to the U.S. Census Bureau, human population increased in Brevard County, Fla. by 11.6 percent (476,230 to 531,250) from April 2000 to June 2005. Using mean human population in 2001 may not take into consideration changes in human population up to 2005, which may introduce a slight bias in this study. The impact is relatively insignificant and unlikely to change the results.

To determine whether animals were selecting habitats or using available habitats, I compared individual areas of land cover categories to total areas of land cover categories within the quadrats. To determine whether animals were selecting habitats, I compared the number of verified animals per capita per habitat type per quadrat to the total number of verified animals per capita for all quadrats. I tested the difference between selecting and availability using a Chi-Square Goodness of Fit test.

Results

The Backwards Stepwise Multiple Regression testing areas of land covers against the number of verified calls showed that raccoon abundance, estimated by verified nuisance calls per capita, can be predicted ($P < 0.001$) using habitat characteristics (Table 1). The final model included five land cover categories: medium density residential, high density residential, industrial, upland non-forested, and wetland and did not include agriculture, barren land, commercial, communications and utilities, institutional, low density residential, transportation, upland forest, and water. The model showed raccoons have higher abundance in medium density residential, high density residential, and industrial categories but lower abundance in wetland categories. The upland non-forested land cover categories was present in the final model, but not significant ($P = 0.060$). Loadings calculated using Pearson correlations on variables in the final model for raccoons included residential medium density (R = 0.449), wetland (R = -0.369), industrial (R = 0.245), and high density residential (R = 0.284) land cover categories (Fig. 1).

Table 1. Backwards Stepwise Multiple Regression analysis for assessing relative abundance for raccoons.[a]

Source	SS	DF	MS	F	*P*
Regression	3806.726	5	761.345	8.331	< 0.001
Residual	4020.997	44	91.386		

Model	Coefficient	*P*
Constant	15.896	0.015
Industrial	0.019	0.017
High Density Residential	0.009	0.010
Medium Density Residential	0.008	0.007
Upland Non-forested	-0.009	0.060
Wetland	-0.010	0.031

[a] The dependent variable was the number of verified reports of raccoons weighted by mean human population and adjusted for repeated calls in the quadrats. The significant independent variables in the final model were areas per quadrat of medium density residential, high density residential, industrial, and wetland land cover categories. The upland non-forested category was present in the final model, but not significant ($P > 0.05$).

The Backwards Stepwise Multiple Regression testing areas of land covers against the number of verified calls showed that opossum abundance, estimated by verified nuisance calls per capita, can be predicted ($P < 0.001$) using habitat characteristics (Table 2). The final model ($P < 0.001$) included three land cover categories: high density residential, medium density residential, and barren land, and did not include agriculture, commercial, communications and utilities, industrial, institutional, low density residential, transportation, upland forest, upland non-forested, water, and wetland. The model showed that opossums have higher abundance in high density residential and medium density residential categories, but lower abundance in areas with barren land. Loadings calculated using Pearson correlations on variables in the final model for opossums included high density residential (R = 0.533), medium density residential (R = 0.302), and barren land (R = -0.237) categories (Fig. 2).

Table 2. Backwards Stepwise Multiple Regression analysis for assessing relative abundance for opossums.[b]

Source	SS	DF	MS	F	*P*
Regression	3356.698	3	1118.899	15.378	< 0.001
Residual	3346.864	46	72.758		

Model	Coefficient	*P*
Barren Land	-0.023	0.022
High Density Residential	0.016	< 0.001
Medium Density Residential	0.009	< 0.001

[b] The dependent variable was the number of verified calls about opossums adjusted for repeated calls weighted by the human population per quadrat. The significant independent variables in the final model per quadrat were areas of high density residential, medium density residential, and barren land categories.

The Backwards Stepwise Multiple Regression showed that abundance for skunks, estimated by verified nuisance calls per capita, can be predicted ($P < 0.001$) using habitat characteristics (Table 3). The final model for skunks included five land cover categories: commercial, high density residential, medium density residential, upland non-forested, and institutional and did not include: agriculture, barren land, communication and utilities, industrial, recreation, low density residential, transportation, upland forest, water, and wetland. The model showed skunks have higher abundance in commercial, medium density residential, and upland non-forested categories but lower abundance in high density residential land cover categories. The institutional category was present, but not significant ($P = 0.070$) in the final model. Loadings calculated using Pearson correlations on variables in the final model for skunks included commercial (R = 0.533), institutional (R = 0.339), medium density residential (R = 0.245), high density residential (R= -0.130), and upland non-forested (R = 0.061) land cover categories (Fig. 3).

Table 3. Backwards Stepwise Multiple Regression analysis for assessing relative abundance for skunks.[c]

Source	SS	DF	MS	F	*P*
Regression	58.219	5	11.644	8.675	< 0.001
Residual	38.924	29	1.342		

Model	Coefficient	*P*
Commercial	0.003	0.001
Institutional	0.003	0.070
High Density Residential	-0.002	0.004
Medium Density Residential	0.001	0.021
Upland Non-Forested	0.002	0.032

[c] The dependent variable was the number of verified calls about skunks weighted by mean human population per quadrat. The significant independent variables in the final model were areas per quadrat of commercial, high density residential, medium density residential, and upland non-forested land cover categories. The institutional category was present in the final model, but not significant ($P > 0.05$).

The Backwards Stepwise Multiple Regression analysis for total calls per capita about raccoons (officer-verified per capita plus unverified calls per capita) (Table 4) led to a different model than verified calls per capita about raccoons (Table 5). The final model ($P < 0.001$) for total calls per capita about raccoons included two land cover categories: commercial and medium density residential categories, but did not include agriculture, communications and utilities, industrial, institutional, low density residential, high density residential, transportation, upland forest, upland non-forested, water, and wetland. Using total calls per capita, raccoons increase in commercial and residential medium density categories.

Table 4. Backwards Stepwise Multiple Regression analysis for assessing relative abundance for total calls about raccoons.[d]

Source	SS	DF	MS	F	*P*
Regression	13708.113	2	6854.057	18.751	< 0.001
Residual	17180.368	47	365.540		

Model	Coefficient	*P*
Commercial	0.051	< 0.001
Medium Density Residential	0.021	< 0.001

[d] The dependent variable was the number of total calls (officer-verified and unverified including repeated calls) about raccoons weighted by human population in the quadrat. The significant independent variables in the final model were areas per quadrat of commercial and medium density residential land cover categories.

Table 5. A comparison between Backwards Stepwise Multiple Linear Regression analyses for assessing relative abundance for officer-verified and total calls about raccoons.[e]

Raccoon (Verified)	Coefficient	*P*	Raccoon (Total)	Coefficient	*P*
Constant	15.896	0.015	Constant	8.002	0.105
			Commercial	0.051	< 0.001
Industrial	0.019	0.017			
High Density Residential	0.009	0.010			
Medium Density Residential	0.008	0.007	Medium Density Residential	0.021	< 0.001
Upland Non-Forested	-0.009	0.060			
Wetland	-0.010	0.031			

[e] The dependent variable was total calls about raccoons weighted by human population within the quadrat. The dependent variable for verified calls concerning raccoons weighted by mean human population and adjusted for repeated calls. The significant independent variables in the final model for total calls were areas per quadrat of commercial and medium density residential land covers. For verified calls, significant independent variables in the final model were areas per quadrat of medium density residential, industrial, high density residential, industrial, and wetland land covers.

The Backwards Stepwise Multiple Regression analysis for total calls about opossums per capita tested against areas of land cover category per quadrat led to a model of relative abundance. The final model for opossums ($P < 0.001$) included high density residential, medium density residential, and barren land categories and did not include agriculture, commercial, communications and utilities, industrial, institutional, low density residential, transportation, upland forest, upland non-forested, water, and wetland (Table 6). Using total calls per capita, opossums had higher abundance in high density residential and medium density residential categories, but lower abundance in areas with barren land. Models for opossums were similar for total calls and verified calls (Table 7).

Table 6. Backwards Stepwise Multiple Linear Regression analysis for assessing relative abundance for total calls per capita about opossums.[f]

Source	SS	DF	MS	F	*P*
Regression	11403.567	3	3801.189	22.189	< 0.001
Residual	7880.090	46	171.306		

Model	Coefficient	*P*
Barren Land	-0.040	0.010
High Density Residential	0.030	< 0.001
Medium Density Residential	0.015	< 0.001

[f] The dependent variable was the number of total calls (officer-verified and unverified including repeated calls) about opossums weighted by the human population within each quadrat. The significant independent variables in the final model were areas per quadrat of residential high density, residential medium density, and barren land categories.

Table 7. A comparison between Backwards Stepwise Multiple Linear Regression analyses for assessing relative abundance for verified and total calls about opossums.[g]

Opossums (Verified)	Coefficient	*P*	Opossums (Total)	Coefficient	*P*
Barren Land	-0.023	0.022	Barren Land	-0.040	0.010
High Density Residential	0.016	< 0.001	High Density Residential	0.030	< 0.001
Medium Density Residential	0.016	< 0.001	Medium Density Residential	0.015	< 0.001

[g] The dependent variable for total calls (officer-verified and unverified including repeated calls) about opossums weighted by mean human population within each quadrat. The dependent variable for verified calls about opossums weighted by the human population within the quadrat and adjusted for repeated calls. For verified calls, the significant independent variables in the final models for total calls about opossums were areas per quadrat of high density residential, medium density residential, and barren land categories. The significant independent variables in the final model for total calls about opossums were areas per quadrat of medium density residential, high density residential, and barren land.

The Backwards Stepwise Multiple Regression analysis for total calls per capita showed skunk abundance may be predicted testing areas of land cover categories against total calls per capita about skunks ($P < 0.001$). The final model for skunks included three land cover categories: commercial, high density residential, and medium density residential, but did not include agriculture, barren land, communications and utilities, industrial, institutional, low density residential, recreation, transportation, upland forest, upland non-forested, water, and wetland (Table 8). Using total calls per capita, skunks have higher abundance in commercial and medium density residential areas, but lower abundance in high density residential categories (Table 9).

Table 8. Backwards Stepwise Multiple Linear Regression analysis for assessing relative abundance for total calls about skunks.[h]

Source	SS	DF	MS	F	*P*
Regression	685.775	3	228.592	8.026	< 0.001
Residual	882.962	31	28.483		
Model	**Coefficient**	***P***			
Commercial	0.013	0.001			
High Density Residential	-0.005	0.027			
Medium Density Residential	0.005	0.011			

[h] The dependent variable was the number of total calls (officer-verified and unverified calls including repeated calls) concerning skunks weighted by mean human population per quadrat. The independent variables in the final model were areas per quadrat of commercial, medium density residential, and high density residential categories.

Table 9. Backwards Stepwise Multiple Linear Regression analyses for assessing relative abundance for verified and total calls about skunks.[i]

Skunks (Verified)	Coefficient	*P*	Skunks (Total)	Coefficient	*P*
Commercial	0.003	0.001	Commercial	0.013	0.001
Institutional	0.003	0.070			
High Density Residential	-0.002	0.004	High Density Residential	-0.005	0.027
Medium Density Residential	0.001	0.021	Medium Density Residential	0.005	0.011
Upland Non-Forested	0.002	0.032			

[i] The dependent variable for total calls (officer-verified and unverified including repeated calls) concerning skunks included total calls weighted by the human population per quadrat. The dependent variable for verified calls concerning skunks was the weighted by mean human population within the quadrat and adjusted for repeated calls. For verified calls, the significant independent variables in the final models for calls about skunks were areas per quadrat of commercial, high density residential, medium density residential, and upland non-forested land cover categories. The significant independent variables in the final model for total calls about skunks were areas per quadrat of commercial, medium density residential, and high density residential land cover categories.

The Chi-Square Goodness of Fit tests indicated that none of the three mesopredator groups are selecting specific habitat types. The proportional distribution of nuisance calls for raccoons weighted by mean human population size was not significantly different ($P = 0.9997$) from the proportional distribution of available habitat land covers. The same was true for opossums ($P = 0.9999$) and skunks ($P = 0.9999$). This demonstrates that mesopredators in Brevard County, Fla. do not select certain land covers, but use habitats based on availability in the landscape.

Unverified calls for raccoons, opossums, and skunks were weakly related to several demographic characteristics (Table 10). Bias for unverified calls per capita for raccoons ($R = 0.521$, $P < 0.001$) and opossums ($R = 0.534$, $P < 0.001$) were positively correlated with renter occupied housing. For skunks, unverified calls were negatively correlated with median age of males ($R = -0.522$, $P = 0.001$). Demographic characteristics that were not correlated with these animal groups included: the number of males and females, age groups (under 5, 5-17, 18-21, 22-29, 30-39, 40-49, 50-64, over 65 years), median age, median age of females, number of households, average household size, average family size, average number of housing units, number of vacant units, number of occupied units, owner occupied housing, per capita income, number of telephones (imputed and non-imputed), and income levels. The results of the *a posteriori* Backwards Stepwise Multiple Linear Regression analyses on significant demographics for raccoons (renters) against all land covers showed commercial areas were correlated ($R = 0.563$, $P < 0.001$) with an increased number of renters.

Table 10. Pearson correlations on demographics testing the unstandardized predicted values for unverified calls from the multiple regression.

Demographics	**Raccoon**		**Opossum**		**Skunk**	
	R	***P***	**R**	***P***	**R**	***P***
Number of Males	0.080	0.582	0.190	0.187	0.078	0.655
Number of Females	0.068	0.638	0.240	0.093	0.035	0.843
Age under 5	0.193	0.180	0.176	0.220	0.238	0.168
Age 5 to 17 years	0.119	0.411	0.096	0.509	0.234	0.176
Age 18 to 21 years	0.263	0.065	0.191	0.184	0.242	0.161
Age 22 to 29 years	0.384	0.006	0.321	0.023	0.279	0.104
Age 30 to 39 years	0.141	0.327	0.157	0.276	0.188	0.280
Age 40 to 49	0.061	0.674	0.062	0.670	0.139	0.427
Age 50 to 64	-0.125	0.386	0.124	0.392	-0.134	0.442
Age over 65 years	-0.171	0.236	0.248	0.082	-0.348	0.041
Median Age	-0.312	0.028	-0.103	0.476	-0.428	0.010
Median Age- Female	-0.231	0.106	-0.038	0.791	-0.317	0.064
Median Age- Male	-0.386	0.006	-0.163	0.259	**-0.522**	**0.001**
Households	0.028	0.848	0.280	0.049	-0.126	0.471
Average Household Size	-0.026	0.860	-0.227	0.113	0.228	0.188
Number of Families	-0.055	0.705	0.157	0.276	-0.067	0.701
Average Family Size	0.153	0.289	-0.063	0.663	0.376	0.026
Number of Housing Units	0.008	0.955	0.277	0.052	-0.177	0.309
Vacant Housing Units	-0.101	0.486	0.110	0.447	-0.375	0.027
Owner Occupied Housing	-0.188	0.191	0.086	0.554	-0.186	0.285
Renter Occupied Housing	**0.521**	**< 0.001**	**0.539**	**< 0.001**	0.177	0.309
Household Total Income	0.030	0.835	0.281	0.048	-0.123	0.481
Income under $10,000	0.279	0.050	0.366	0.009	0.006	0.972
Income $10,000 to $14,999	0.248	0.082	0.288	0.043	0.029	0.869
Income $15,000 to $19,999	0.184	0.200	0.268	0.060	-0.334	0.050
Income $20,000 to $24,999	0.222	0.121	0.321	0.023	-0.071	0.684
Income $25,000 to $29,999	0.175	0.225	0.223	0.120	-0.080	0.648
Income $30,000 to $34,999	0.149	0.303	0.302	0.033	0.114	0.513
Income $35,000 to $39,999	0.059	0.686	0.258	0.071	-0.096	0.582
Income $40,000 to $44,999	0.204	0.155	0.328	0.020	0.116	0.505
Income $45,000 to $49,999	-0.056	0.701	0.077	0.594	0.002	0.991
Income $50,000 to $59,999	-0.011	0.940	0.129	0.373	-0.042	0.811
Income $60,000 to $74,999	-0.148	0.306	0.077	0.596	-0.029	0.866
Income $75,000 to $99,999	-0.187	0.192	0.075	0.602	-0.162	0.352
Income $100,000 to $124,999	-0.216	0.133	0.061	0.676	-0.160	0.358
Income $125,000 to $149,999	-0.105	0.469	0.068	0.638	-0.158	0.365
Income $150,000 to $199,999	-0.110	0.449	0.178	0.217	-0.239	0.167
Income over $200,000	-0.187	0.192	0.055	0.704	-0.184	0.291
Household Median Income	-0.355	0.011	-0.293	0.039	-0.187	0.281
Per Capita Income	-0.373	0.008	-0.214	0.136	-0.427	0.010
Telephones (Imputed)	-0.022	0.837	0.121	0.402	-0.042	0.810
Telephones (Not Imputed)	0.030	0.837	0.283	0.046	0.129	0.460

The results for total (officer-verified plus unverified) calls per capita showed no bias associated with raccoons, opossums, or skunks was above $R > 0.500$. Demographic characteristics that were not correlated with these animal groups included: the number of males and females, age groups (under 5, 5-17, 18-21, 22-29, 30-39, 40-49, 50-64, over 65 years), median age, median age of females, median age of males, number of households, average household size, average family size, average number of housing units, number of vacant units, number of occupied units, owner occupied housing, renter occupied housing, per capita income, number of telephones (imputed and non-imputed), and income levels.

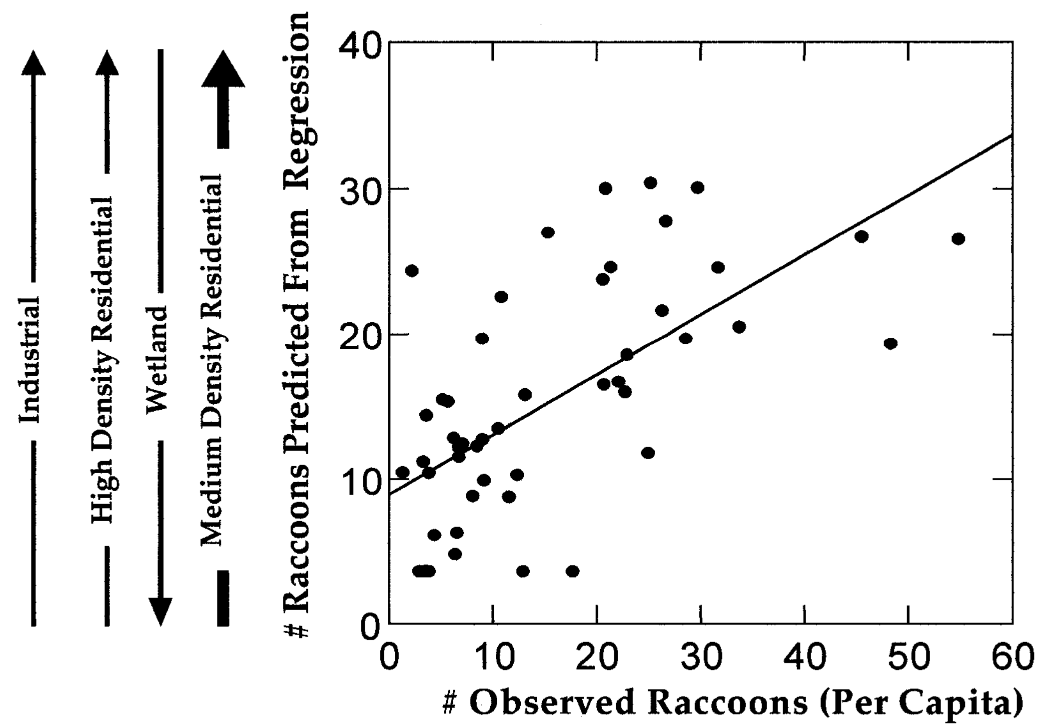

Figure 1. Habitat preference for raccoons using verified calls, was predicted using Backwards Stepwise Multiple Linear Regression ($P < 0.001$). The x-axis indicated the number of raccoons per capita within the quadrat. The y-axis indicated the unstandardized predicted number of raccoons from the regression. Loadings (shown as weighted directional arrows) calculated using Pearson correlations on variables in the final model for raccoons include residential medium density (R = 0.449), wetland (R = -0.369), high density residential (R = 0.284) and industrial (R = 0.245) land cover categories.

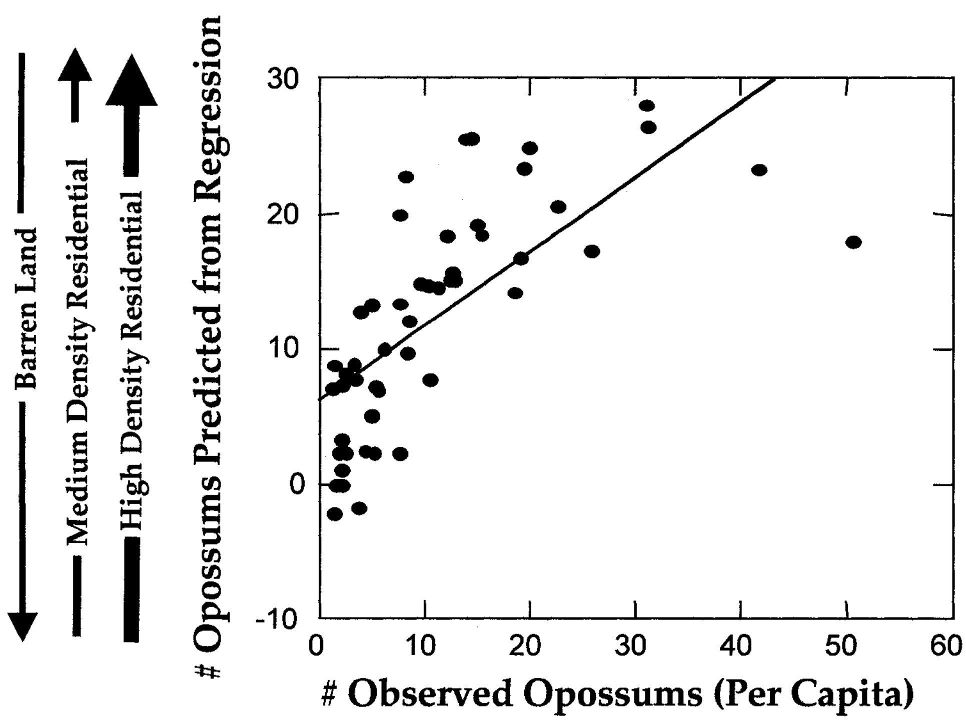

Figure 2. Habitat preference for opossums using verified calls, was predicted using Backwards Stepwise Multiple Linear Regression ($P < 0.001$). The x-axis indicated the number of opossums controlled for human population within the quadrat. The y-axis indicated the unstandardized predicted number of opossums from the regression. Loadings calculated using Pearson correlations on variables in the final model (shown as weighted directional arrows) for opossums include high density residential ($R = 0.533$), medium density residential ($R = 0.302$), and barren land ($R = -0.237$) land cover categories.

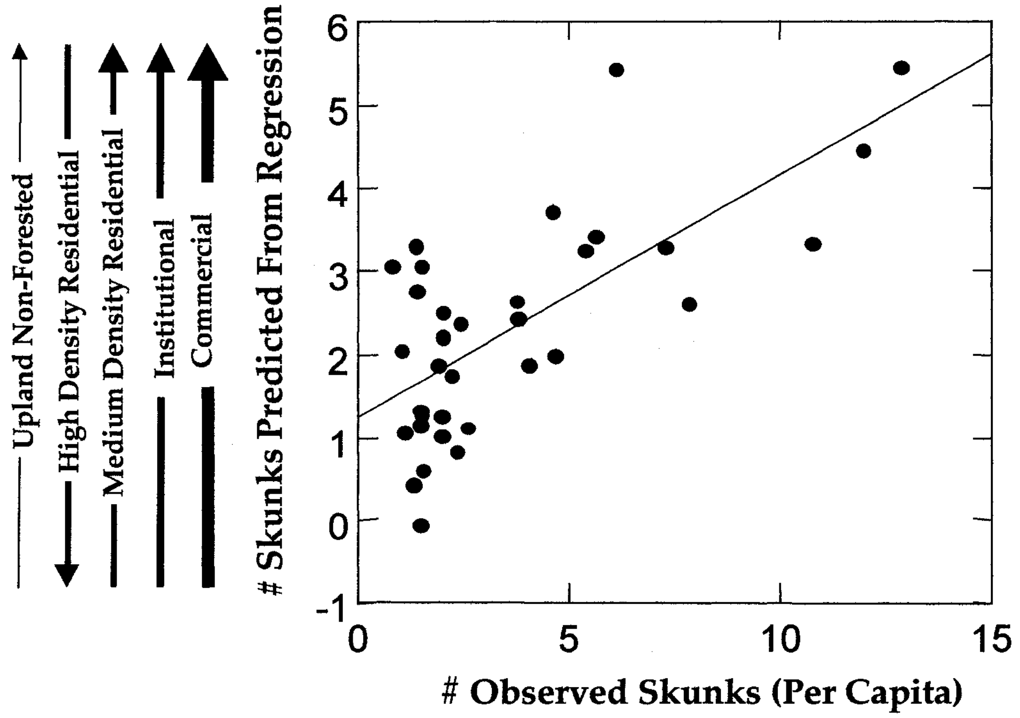

Figure 3. Habitat preference for skunks using verified calls per capita, was predicted using Backwards Stepwise Multiple Linear Regression ($P < 0.001$). The x-axis indicated the number of skunks per capita within the quadrat. The y-axis indicated the unstandardized predicted number of skunks from the regression. Loadings calculated using Pearson correlations on variables in the final model for skunks (shown as weighted directional arrows) include commercial ($R = 0.533$), institutional ($R = 0.339$), medium density residential ($R = 0.245$), high density residential ($R = -0.130$), and upland non-forested ($R = 0.061$).

Discussion

The analyses of verified nuisance telephone call reports per capita to estimate relative abundance showed results similar to studies using other sampling techniques. Surprisingly, verified phone call reports were a cheap and successful method to estimate relative abundance. The analyses of verified calls per capita showed that raccoon abundance is higher in medium density residential, industrial, and high density residential land cover categories, but lower in wetland areas. Rosatte et al. (1991), using radio-telemetry and cage trapping, found high trapping densities of raccoons for residential and industrial areas. In the present study, the analyses showed that opossum abundance was higher in high density residential and medium density residential, but lower in areas with barren land. Similarly, Crooks (2002) found high opossum density in areas less than 50 meters from human development. Using verified calls per capita, skunk abundance was higher in commercial, medium density residential, and upland non-forested categories, but lower in high density residential areas. As in the present study, Rosatte et al. (1991), using radio-telemetry and cage trapping, found high skunk capture rates in commercial and field areas. Gehring and Swihart (2003) used trapping and scent station techniques and found that among others, striped skunks were associated with human dwellings and grasslands.

However, there were also several studies where habitat preference for raccoons appeared to differ from the present study, although these differences may potentially be related to differences in population density. For example, Hoffman and Gottschang (1977) and Broadfoot et al. (2001) concluded in urban areas, raccoons prefer wooded areas and avoid industrial areas. Rosatte et al. (1991) also initially found high numbers of raccoons in forested and residential areas. However, at the same site two years later Rosatte et al. (1991) found high capture success in industrial and groomed grass areas in addition to forest and residential areas. Rosatte et al. (1991) hypothesized that the apparent change in habitat use for raccoons may have been related to increases in population density.

Another explanation for the differences in results among studies may be although the animals had higher densities in some areas, it does not necessarily mean that they were selecting habitats. Using regression models to evaluate differences in abundance among sites where animals are present might mean that animals select certain land cover categories, but only if increases in abundance were not proportional to habitat availability. In the present study, the regression analyses indicated that mesopredators appear to prefer certain land cover categories. However, examination of the availability of habitats indicated that differences in abundance among different land covers can be explained by the relative availability of land covers. Therefore, raccoons, opossums, and skunks in Brevard County appear to be generalists using habitats opportunistically.

Ultimately, land cover classifications may not adequately reflect food or shelter availability (Prange and Gehrt 2004) and habitats that offer garbage, food, and shelter may allow mesopredators to achieve high densities in urban areas (Hoffman and Gottschang 1977, Riley et al. 1998, Crooks 2002, Smith and Engeman 2002). Residential developments offer a constant supply of food and garbage (Conover 2001, Crooks 2002, Prange and Gehrt 2004) and the presence of garbage may lead to increased human-wildlife conflicts. For example, Barden et al. (1995) found raccoon-human conflicts often occur at dumpsters with easy raccoon access. Ultimately, evaluations of true resource allocation for mesopredators in urban areas should include percent cover associated with urban housing (including access to attics and basements), the number of people feeding wildlife directly or indirectly, and estimates of the number of easily accessible garbage cans and dumpsters in an area.

It is interesting to note that the results of the Pearson correlations for the relative impacts of each land cover in the final model of the regression (loadings), may indicate minor habitat partitioning between raccoons, opossums, and skunks. Results of the verified models show skunks have a higher correlation with commercial areas, but a lower correlation with areas of high density residential land covers. However, opossums have a higher correlation with high density residential while raccoons show a higher correlation with medium density residential land covers. While some of the land covers in the final verified models are similar for raccoons, opossums, and skunks, some form of habitat partitioning may be occurring in Brevard County, Fla. Unfortunately, it is difficult to entangle whether the grouping of spotted and striped skunks has an effect on this result.

Surprisingly, bias associated with calls was relatively minor. An increased number of renters was weakly positively correlated with the number of unverified calls about raccoons and opossums. As the number of renters is also correlated with commercial land covers, this suggests that the areas with high numbers of renters and commercial areas may overestimate the number of calls. This may potentially be due to businesses (especially restaurants and supermarkets) that may report wildlife near their establishment more often than others due to health concerns. Also, unverified calls about skunks were negatively correlated with the median age of males. According to the U.S. Census Bureau, at the 2000 census the median age of males in Brevard County, Fla. was 46 years old indicating that a large number of males in this age group may not be leading to an overestimate of calls. In addition, a large number of people or telephones in an area did not lead to an overestimate of wildlife, if the number of animals per capita was used. Persons of retirement age (over 65) did not make more unverified calls than people of working age. Homeowners did not make more calls than people who rented and the number of children present in an area did not lead to an increase in calls. Also, the impact of human population density on telephone calls appears to be controlled by weighting call frequency by the mean number of people, but this may still have underestimated the influence of high and medium density residential areas.

Some of the apparent lack of bias identified by evaluating the difference between verified and unverified calls may be the result of types of reports that were included in the unverified category (K. Earley, Brevard County Animal Services and Enforcement, personal communication). In some situations, it was unclear whether the officer saw an animal at a location. These cases were evaluated as unverified and were included in the total call database separately. As such, a potentially high number of verified calls placed in the total call database could contribute to the minimal bias observed. Likewise, calls with incorrect addresses could often not be geocoded with a high precision and could not be mapped or analyzed (a total of 2,041 calls could not be geocoded). In addition, repeated calls often led to multiple verified reports indicating that areas with repeated calls may also be targeted for urban wildlife education.

The results of this study indicated that certain restrictions need to be included in the use of phone call reports. For total calls per capita, there appeared to be little bias for verified calls about opossums which suggested they may be used in rare cases for a crude relative estimate of where to trap opossums in an urban area when measures are taken to reduce bias. While total calls for opossums appeared to be adequate for evaluating crude abundance changes, total calls for raccoons and skunks cannot be used to estimate relative abundance. This is due to differences in raccoon and skunk model predictions of relative abundance using verified calls. As a result, it is important for officers to clearly specify whether or not an animal was seen (verified) on site. In addition, while the use of phone call reports requires that people with phones be located within the study area, phone call reports should not be used in rural areas to assess changes in relative abundance of mesopredators. Like road-kill estimates of abundance or spotlight surveys, this method may potentially give differing results in rural areas with different mosaics of habitats, areas with low population densities of animals or people, or if data are not recorded in a standardized format (Gehrt 2002). To minimize overestimation of mesopredator abundance, calls need to be per capita per quadrat, and calls from the same location need to be analyzed separately. To identify "repeat wildlife offenders," animals that are relocated within a study area should be marked (Smith and Engman 2002). Officers should also specify species (e.g. spotted or striped skunk) to prevent grouping of animals.

Analysis of nuisance calls requires much less time and resources than trapping studies. Trapping studies in urban areas provide the most reliable data however, there are some advantages to using nuisance call data to evaluate changes in relative abundance of mesopredators. As trapping studies require time to set up, in cases when an immediate response to a rabies outbreak in raccoons or skunks is required, using verified animal control data may be a relatively good alternative to quickly identify areas for rabies baiting.

The present method could also be used as a preliminary study to rapidly assess, justify, and indicate where trapping studies should be concentrated. Combining information from reports of wildlife (trapped animals and deceased animal locations) with radio-telemetry studies would allow access to multiple private residences, maximize catch, and reduce costs associated with these studies in urban and suburban areas. Finally, to identify areas where wildlife-human conflicts may occur, using habitat characteristics available in GIS format and verified reports allows large areas to be sampled relatively quickly when on-the-ground efforts are not possible.

Management implications

The use of verified nuisance calls per capita is an opportunistic passive sampling method that provides a reasonable tool for measuring relative abundance of mesopredators in urban areas. This technique allows the trapping of urban mesopredators on residential properties with relatively low cost. These data may then be used to evaluate the health of the population or perform a rapid assessment of abundance. Moreover, the presence of an animal control officer provides an independent confirmation of animal presence at a location in addition to an opportunity to educate the public regarding wildlife conflicts.

These types of data need to be recorded in a computerized database uniformly throughout the state and potentially throughout the country. Reports should be investigated and verified to determine the number and species of wildlife present in urban areas. Verified reports should be combined in a database with information from pest control (vector) agencies, humane societies, and other animal services agencies responsible for responding to wildlife reports and deceased animal locations. These types of data need to be recorded in a standardized format so data may be easily retrieved and used by managers to solve wildlife problems. Currently this data is recorded differently at different agencies. Furthermore, creating a deceased animal database would allow easy access for researchers to access available data within an area and allow data to be compared between counties with relative ease. In addition, increased funding should be allocated to local animal control agencies to facilitate the collection of this important data about urban wildlife.

When members of the public call agencies to report animals, several items should be included in GIS compatible databases (Appendix 9) to enable future analyses. These include the date, number and species present, location (address or intersection), whether or not the animal was verified at the location, and whether the animal has been trapped previously (e.g. by the presence of ear tags or other marking). Determining how many times an animal was trapped will assist with population estimates and whether the same animals are creating nuisances at other locations. In addition, animal control agencies should provide officers with a list of common names for wildlife species if they are not known. While officers at Brevard County Animal Services and Enforcement are able to identify species present, personnel at other agencies may not be able to identify all animals they encounter to the species level. If agencies obtain GPS locations (UTM locations and error) almost immediate results would be possible. If this information is recorded, analyzing where deceased animals are located may show where wildlife are moving unsuccessfully in urban areas (Appendix 10).

This data may also be used to understand where impounded animals, suspected of rabies are located (Appendix 11) or to improve and validate corridor models (T. M. Diamond, San Jose State University, unpublished data).

Agencies can use verified nuisance calls per capita to determine relative abundance of mesopredators in urban areas because it is less expensive and provides similar results to other techniques with a minimum of bias. While animal reports per capita act as relative measures of abundance in urban areas, these reports should not be used for population estimates in areas where animal relocations occur or in rural areas where few people are present. Lacking direct population studies in urban and suburban areas, the primary method that an agency has to assess the abundance of urban wildlife in an area is to use telephone call reports from the public. This method provides managers information that is necessary to manage mesopredator species in urban areas.

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Appendicies

Appendix 1. Geocoded total telephone calls (verified + unverified) for skunks, opossums, and raccoons in 2000, 2003, 2004, and 2005.

Appendix 2. Geocoded verified telephone call reports for skunks, opossums, and raccoons in 2000, 2003, 2004, and 2005.

Appendix 2a. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2000.

Appendix 2b. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2003.

Appendix 2c. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2004.

Appendix 2d. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2005.

Appendix 3. Verified raccoon locations in 2000, 2003, 2004, and 2005.

Appendix 4. Quadrats used for sampling raccoons and opossums in Brevard County, Fla.

Appendix 5. Verified opossum locations in 50 non-adjacent quadrats in 2000, 2003, 2004, and 2005.

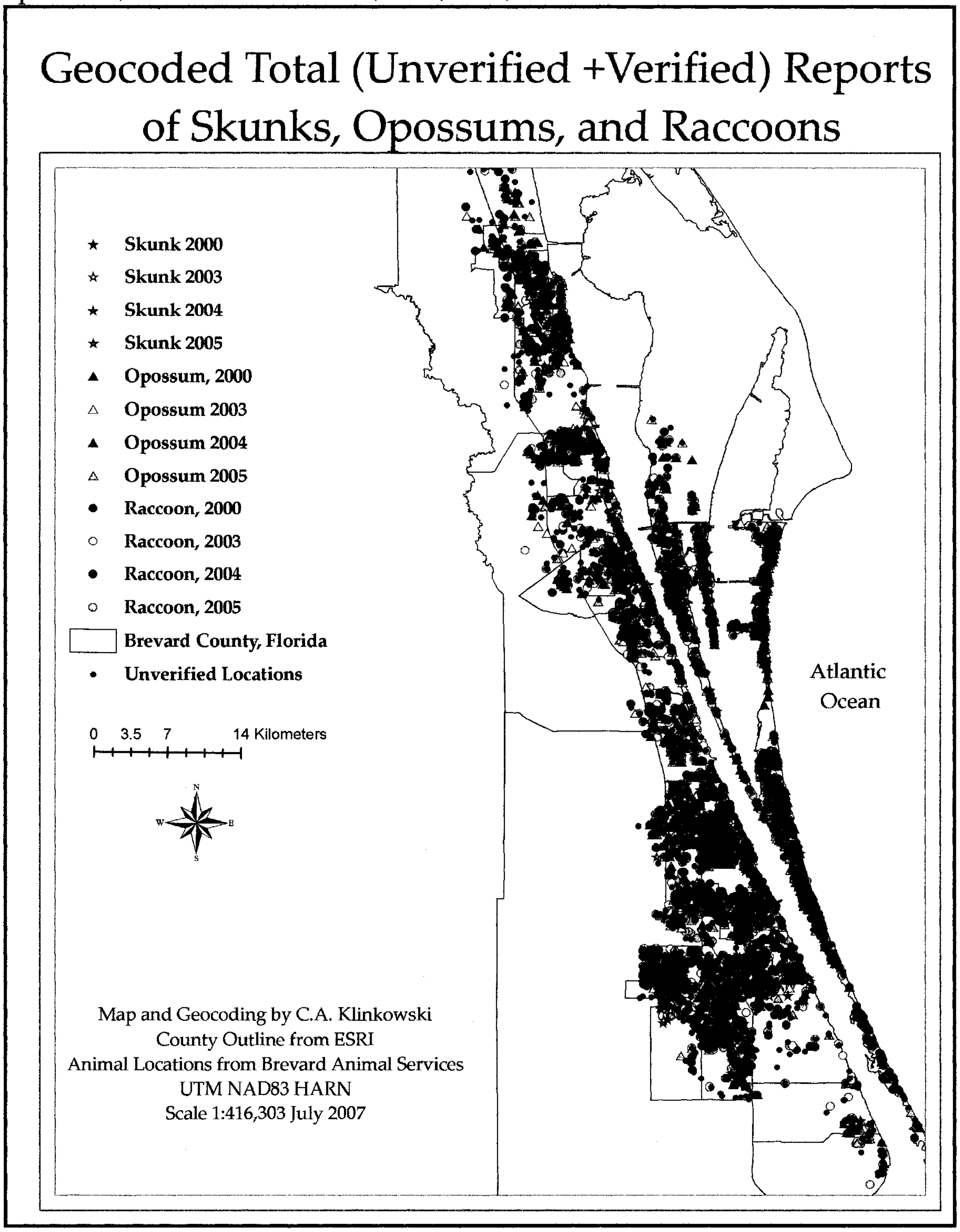
Appendix 6. Verified skunk locations in 35 non-adjacent quadrats in 2000, 2003, 2004, and 2005.

Appendix 7. Quadrats intersected with land covers for sampling opossums and raccoons.

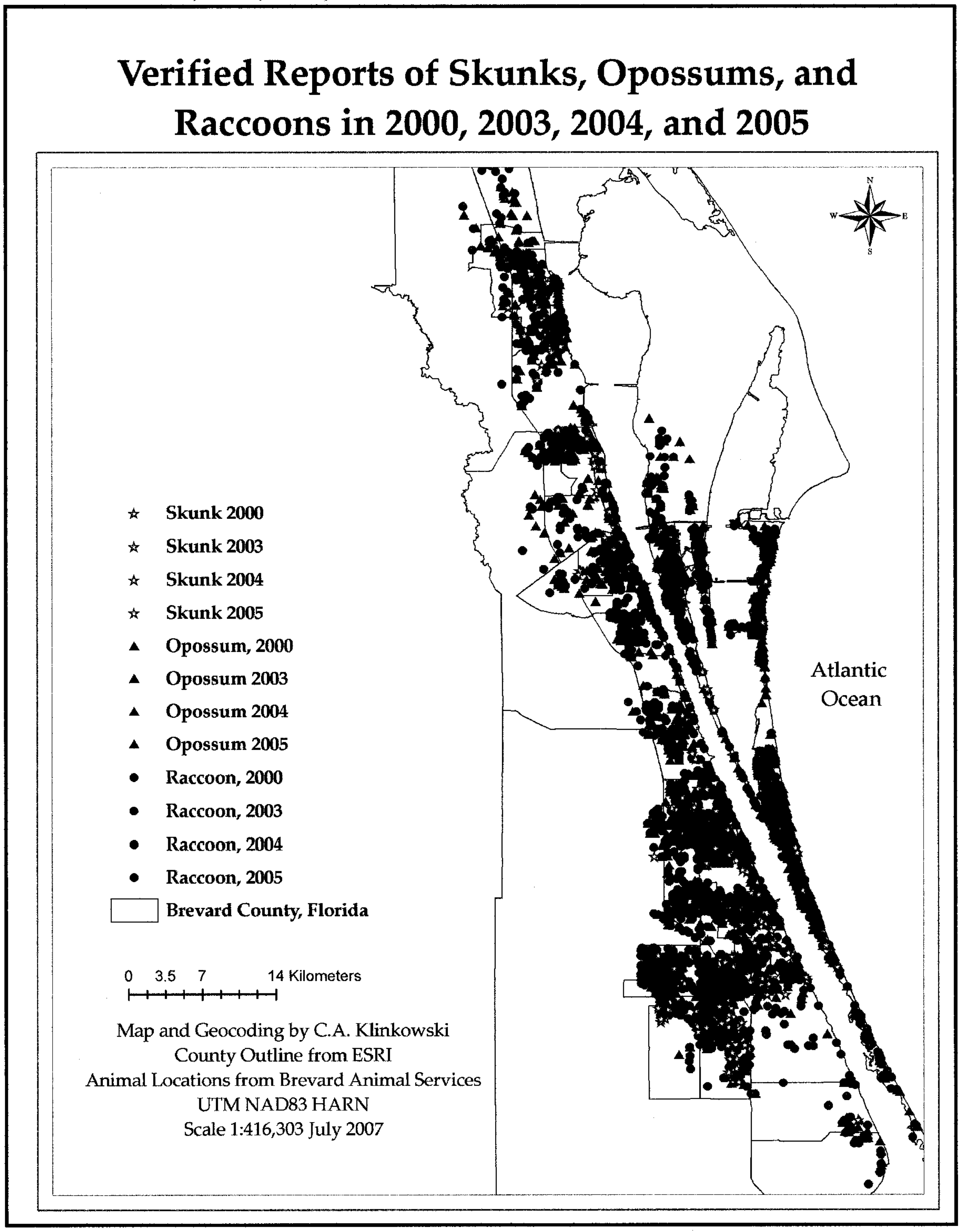
Appendix 8. Location of human population by census tract in Brevard County, Fla.

Appendicies (Continued)

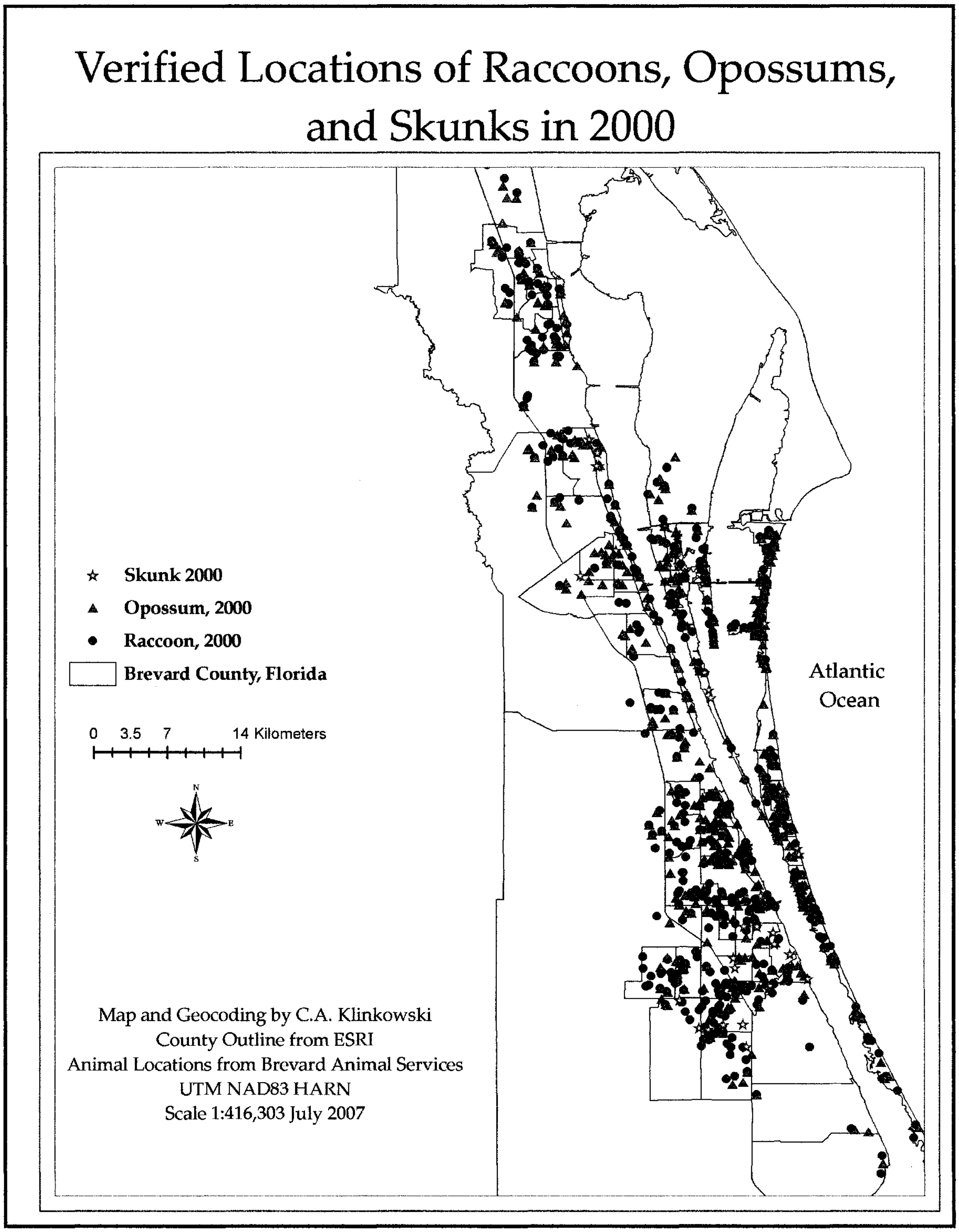
Appendix 1. Geocoded total telephone calls (verified + unverified) for skunks, opossums, and raccoons in 2000, 2003, 2004, and 2005.



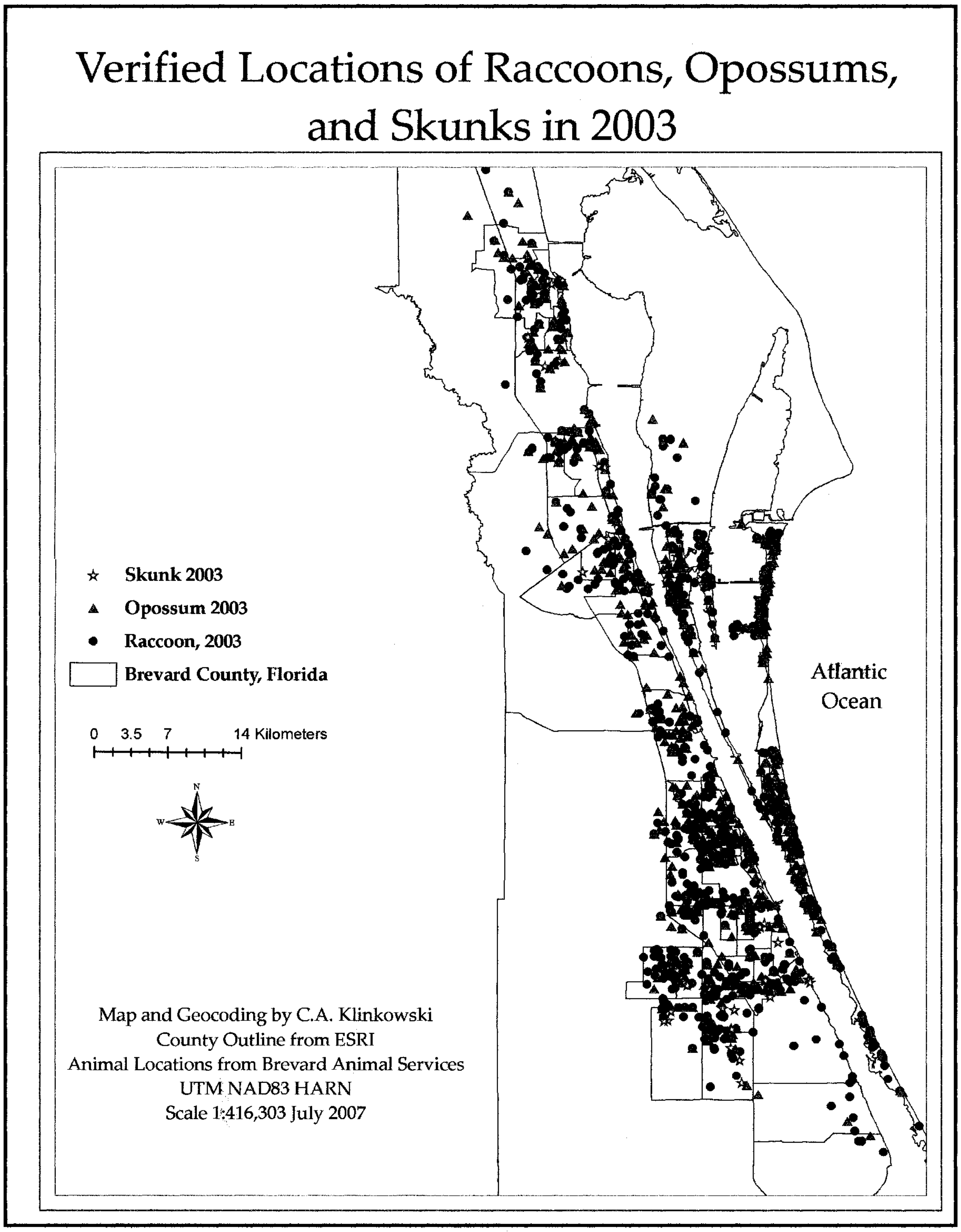
Appendix 2. Geocoded verified telephone call reports for skunks, opossums, and raccoons in 2000, 2003, 2004, and 2005.



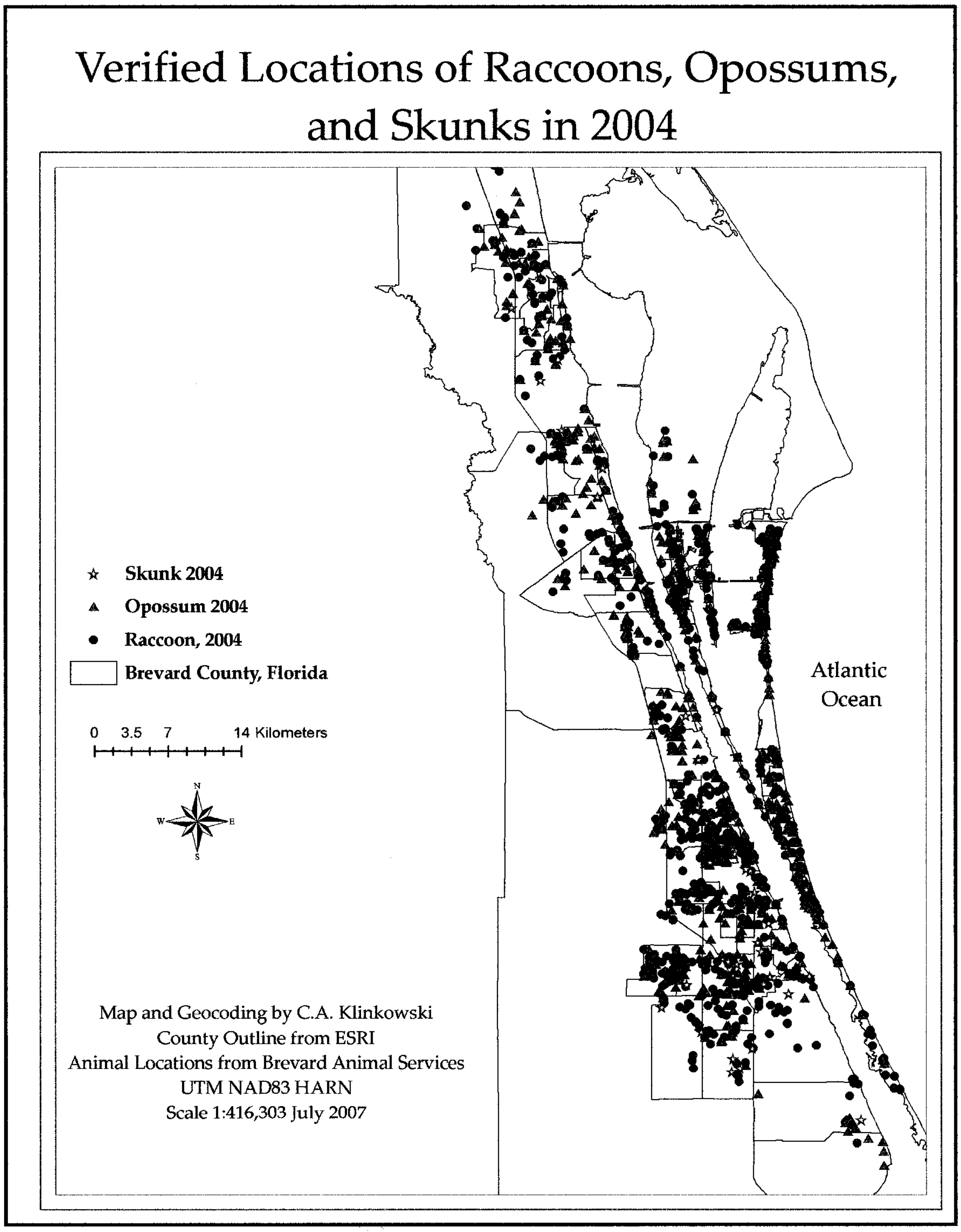
Appendix 2a. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2000.



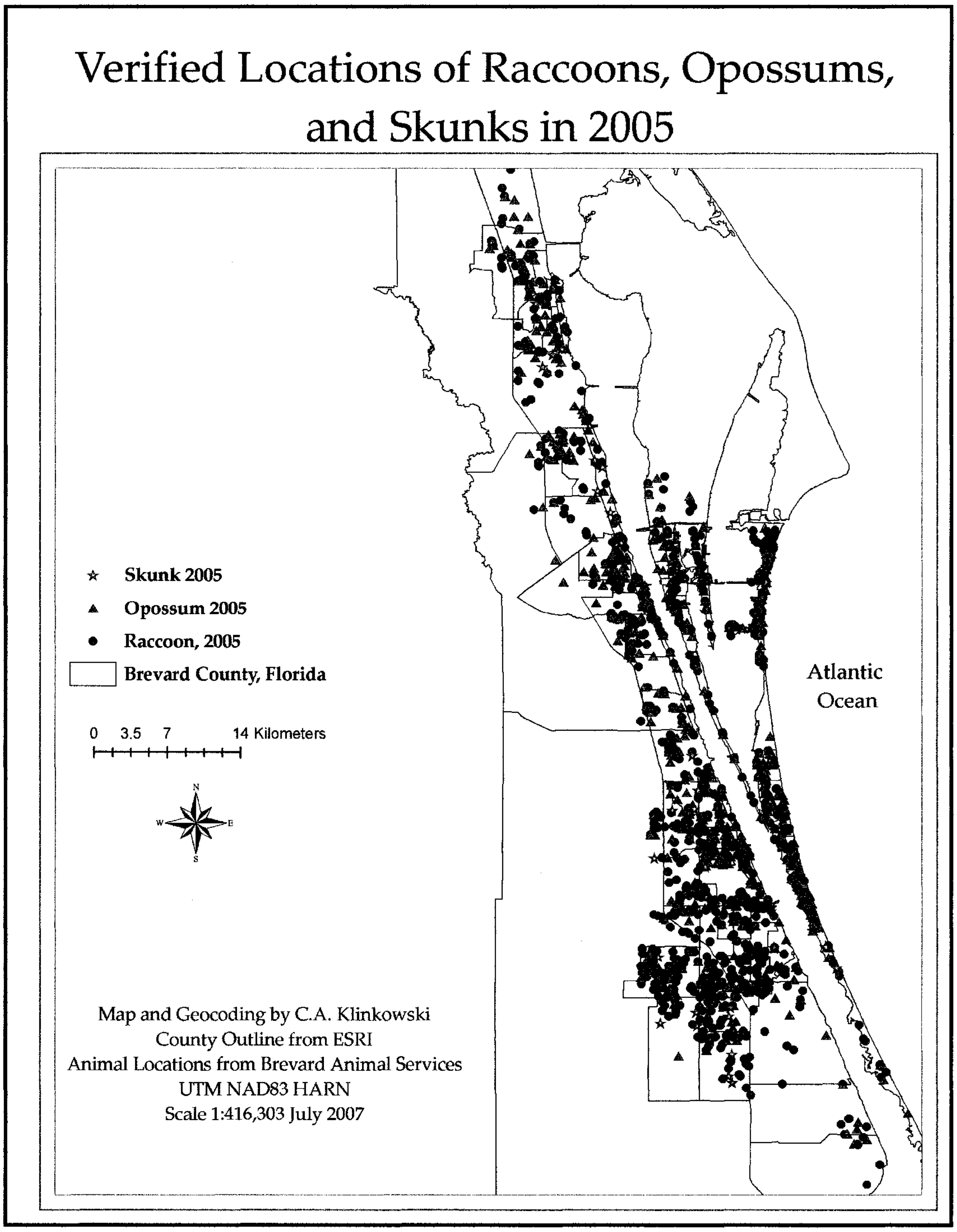
Appendix 2b. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2003.



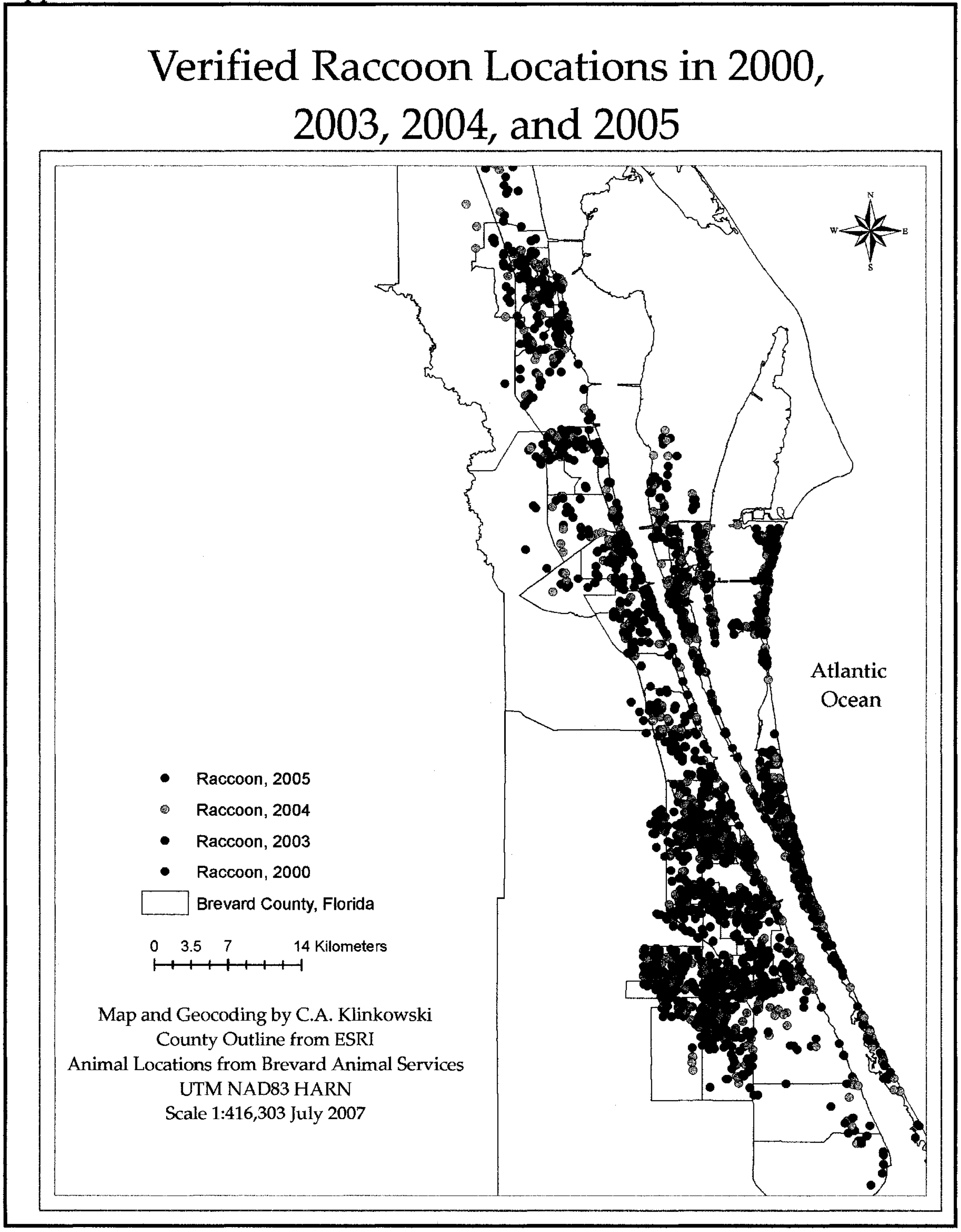
Appendix 2c. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2004.



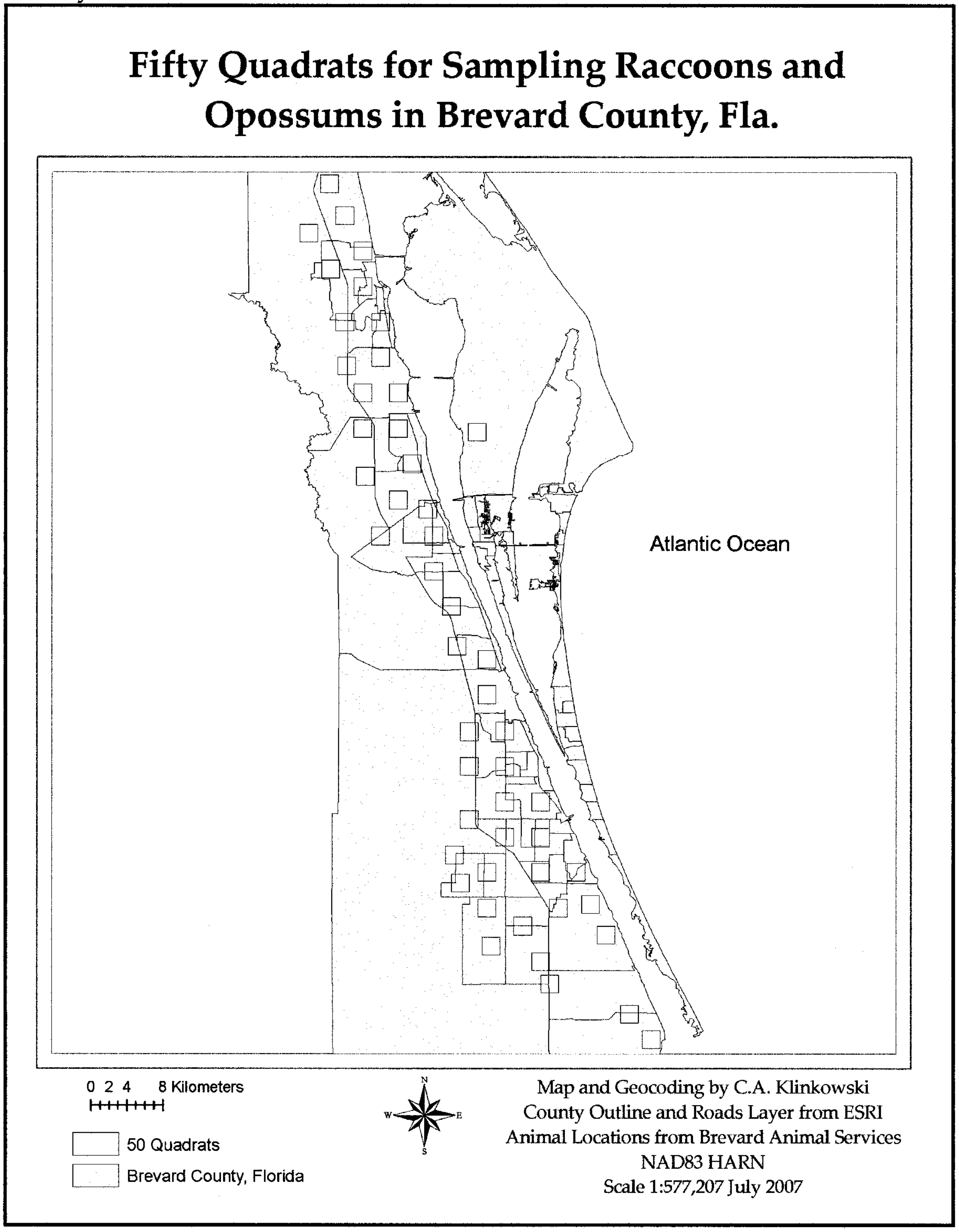
Appendix 2d. Geocoded verified telephone call reports for skunks, opossums, and raccoons from 2005.



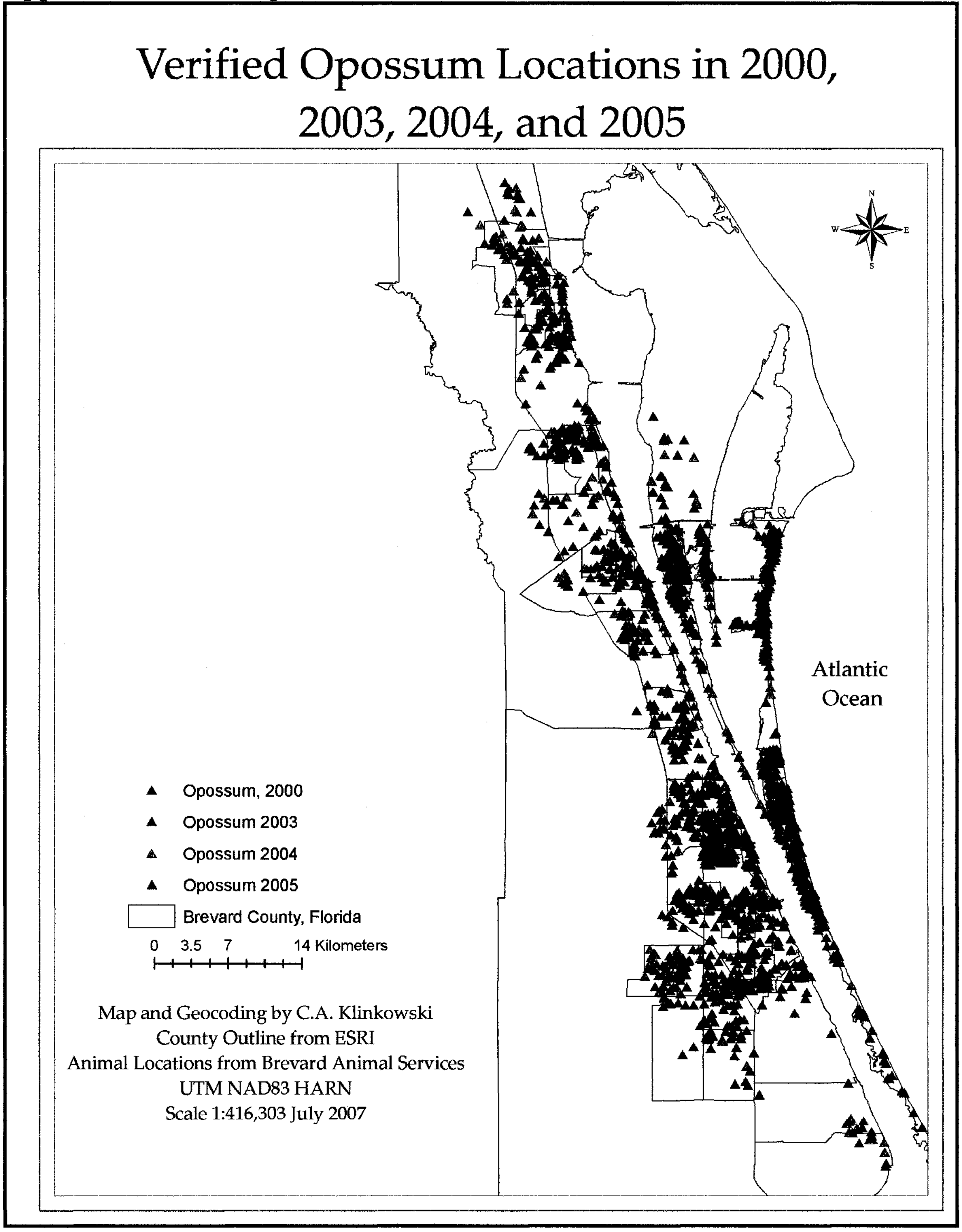
Appendix 3. Verified raccoon locations in 2000, 2003, 2004, and 2005.



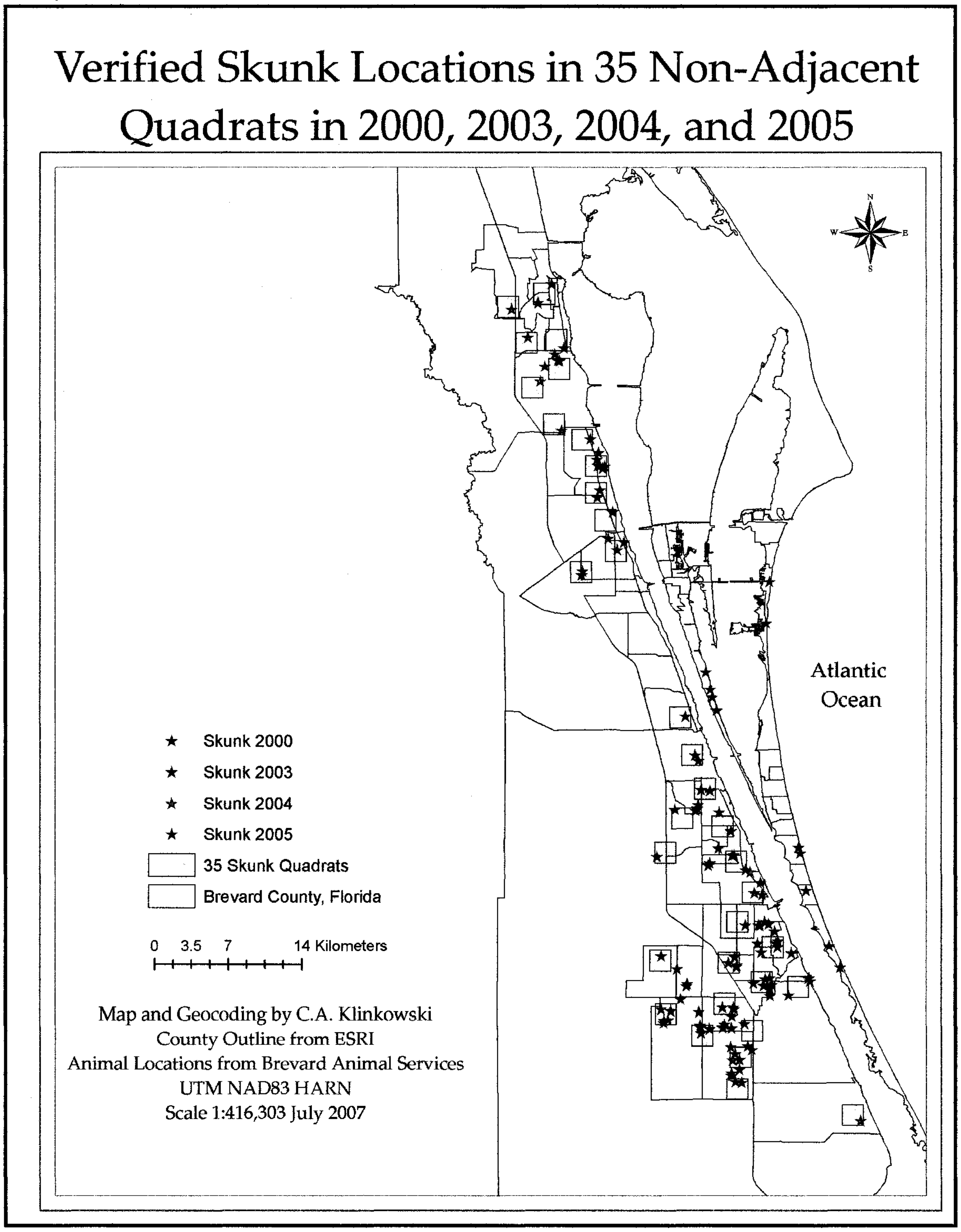
Appendix 4. Quadrats used for sampling raccoons and opossums in Brevard County, Fla.



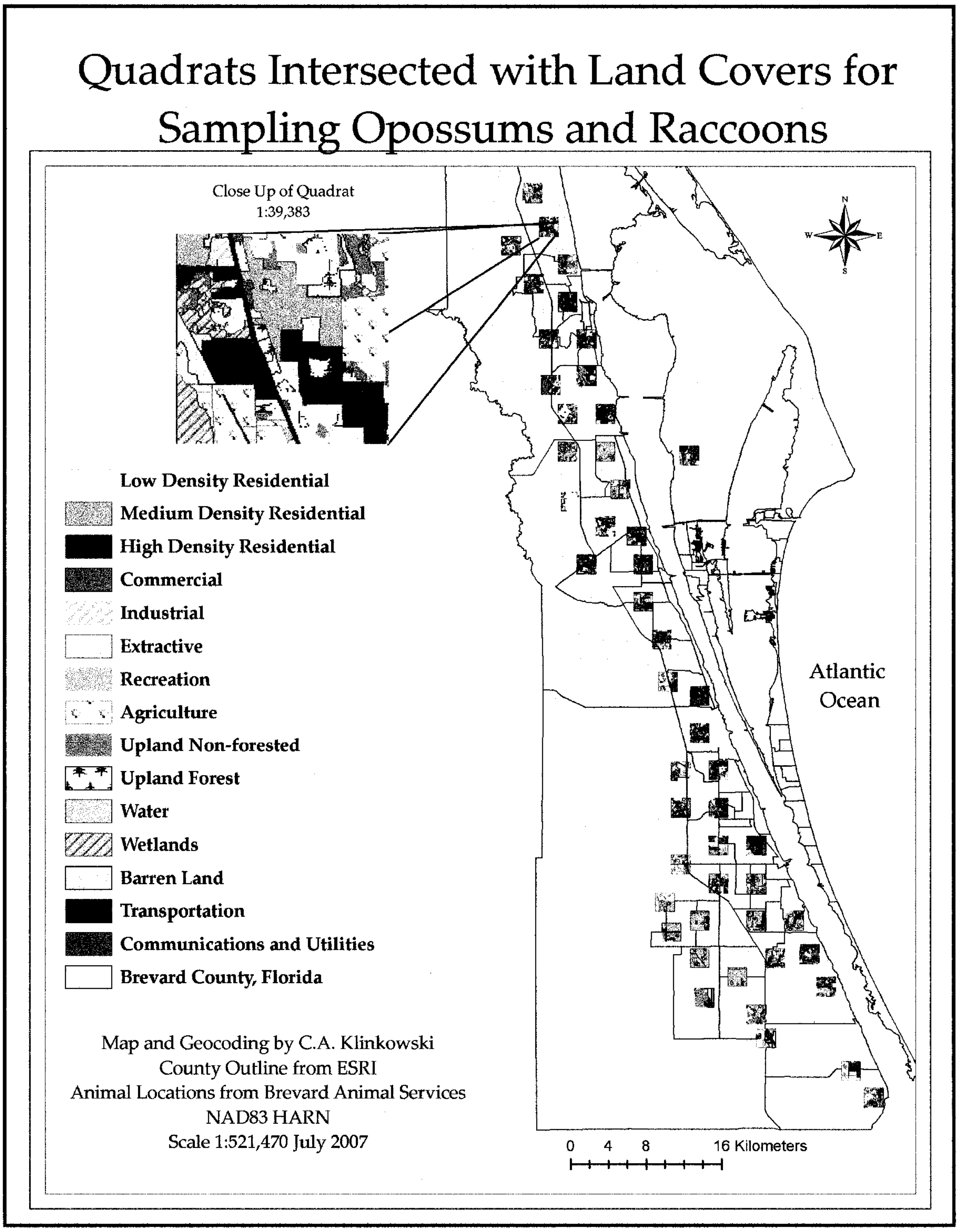
Appendix 5. Verified opossum locations in 2000, 2003, 2004, and 2005.



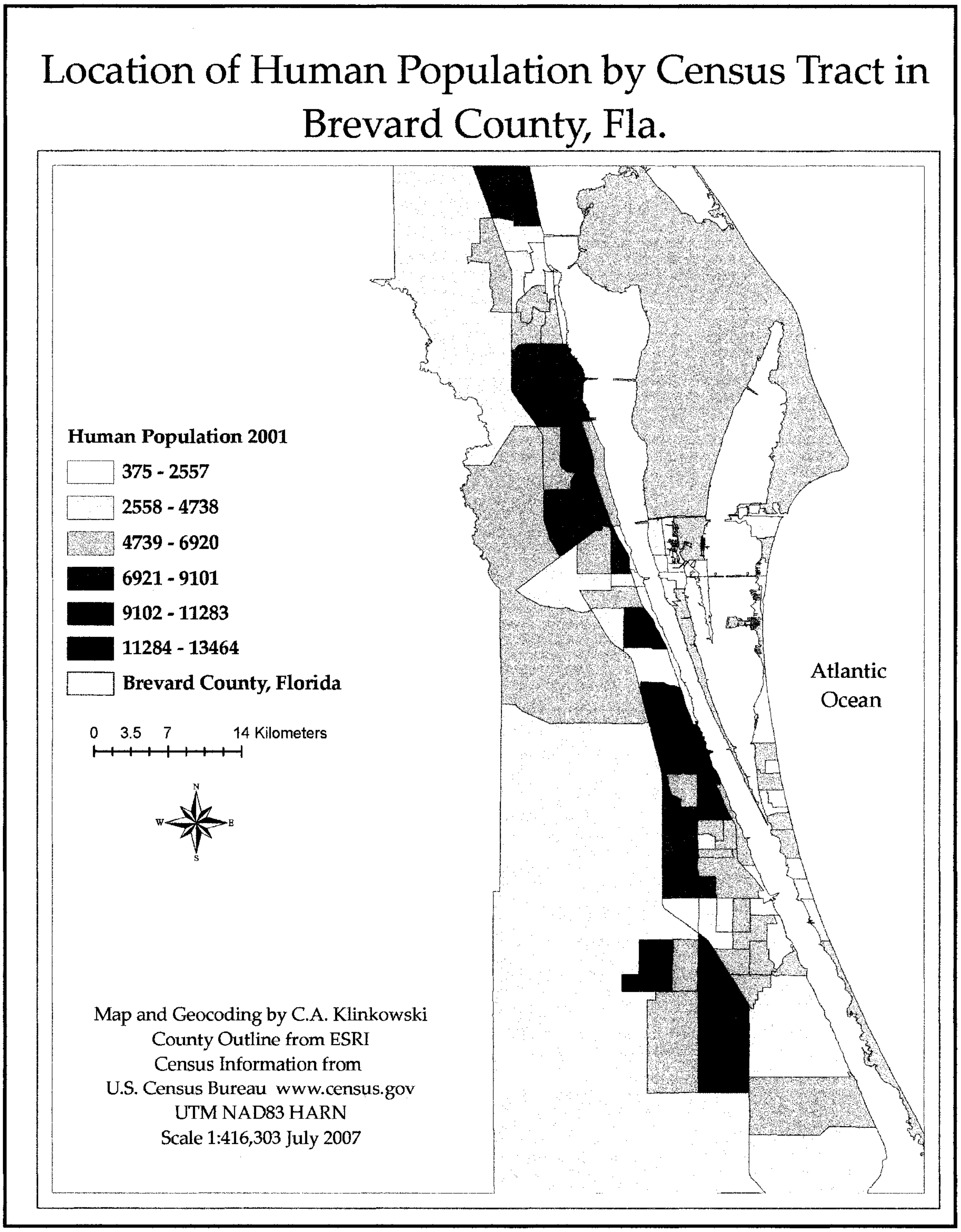
Appendix 6. Verified skunk locations in 35 non-adjacent quadrats in 2000, 2003, 2004, and 2005.



Appendix 7. Quadrats intersected with land covers for sampling opossums and raccoons.



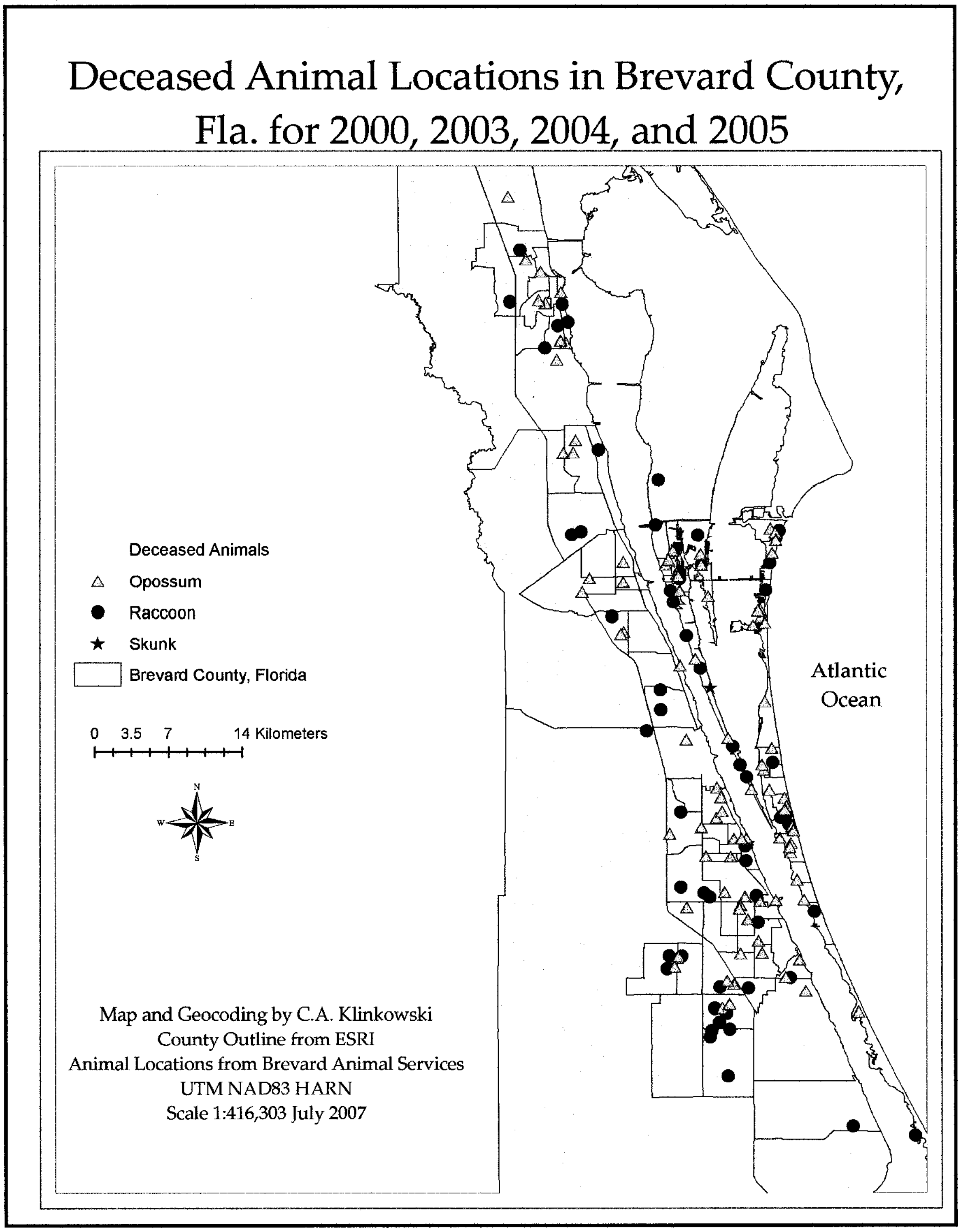
Appendix 8. Location of human population by census tract in Brevard County, Fla.



Appendix 9. Suggestions for a data collection form for Animal Control.

Accession number	
Date (day, month, year)	
Season (Winter, Spring, Fall, Summer)	
Animal Type	
Common Name or Species of Animal (e.g. Spotted Skunk or *Spilogale putoris*)	
Sex (if known)	
Number of Animals Reported, Number Present	
Requestor's Name	
Address of Requestor (with zip code)	
Address location of Animal (with zip code) (or nearest street intersection)	
Animal seen (presence verified by officer)?	
Request (e.g. Confined, Dead, Bite, etc.)	
Action taken (e.g. Trapped, Rehabilitated, Impounded, etc.)	
Animal Tagged? What number?	
Recapture? Tag number	
GPS location (Easting, Northing, +/- error)	
Date Entered into Database	
Officer on Duty	
Notes:	

Appendix 10. Deceased animal locations in Brevard County, Fla. from 2000, 2003, 2004, and 2005.



Appendix 11. Impounded animal locations in Brevard County, Fla. (2000, 2003, 2004, and 2005).