DISTRIBUTION AND CORRELATES OF FERAL CAT TRAPPING PERMITS IN LOS ANGELES, CALIFORNIA

by

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LIST OF ABBREVIATIONS

AOI	Area of Interest
CPA	Cat Trapping Permit Application
gdb	Geodatabase
LAGDP	Los Angeles GIS Data Portal
NZDI	New Zealand Deprivation Index
TNR	Trap, Neuter, and Release
TOC	Table of Contents
GUI	Graphic User Interface
OLS	Ordinary Least Squares Regression

ABSTRACT

Uncontrolled populations of feral cats in urban settings have become of concern to public officials, wildlife scientists, animal rights advocates and the public in general due to the risks they pose to public health, urban wildlife, and esthetics. Solutions to the problem of unmanaged cat populations in cities have been limited in scope by the lack of actual data on feral cats and the urban geographic ranges they occupy. Full extent censuses and environmental analyses have not been collected or performed due to the resources allocations and costs involved. A method for collecting this data without the use of field crews and research summaries exists in the form of unused paper records. Past studies on the problem have used data mining of available records to model cat territories and densities (Aguilar and Farnworth 2012). This approach mitigates the cost while providing information regarding the distributions of these animals. This thesis investigates the spatial properties of feral cat populations in a large metropolitan area (Los Angeles, California) using a previously non-spatialized dataset as a proxy for concentrations of feral cats. The following case study explores two matters: 1) development of a workflow to create a spatial model of feral cat extents from geographic data brought into an analyzable format and 2) analysis of the model data to determine what, if any, variables are correlated with these distributions. The data used for the model were obtained from the City in the form of paper records and successfully imported into a Geographic Information System. Densities of applications were determined from the cleaned and geocoded records and concentrations of both raw density and patterns of clustering were mapped. Modeling of correlations found positive associations with population density and a weak negative correlation with median income. The analysis was assessed and future work on this type of data was considered.

CHAPTER ONE: INTRODUCTION

Statement of Problem

Feral cats, cats that have returned to or were born in an undomesticated state and do not rely on human care, thrive in urban environments. Most discussions of feral cats involve some estimate of their number, but the data used to support current nationwide estimate of 35 million are lacking (Loss et al. 2013). These concerns are often concentrated in urban/metropolitan environments. For example, the City of Los Angeles Animal Services estimates city wide feral cat population to be 3 million, slightly under 1/10 of the nationwide estimate (Feral Cat Caretakers' Coalition 2003).

Concerns are impacts to wildlife (Loss, Will and Marra 2013), impacts to public health (Gerhold and Jessup 2012, Roebling et al. 2013), public nuisance, and welfare of the animals. Population estimates in urban environments vary too widely and even less information is available on the geographic distribution of the animals despite their prevalence in human urban settings. Considerations in rural areas may differ because people involved in agricultural production may see free-roaming cats as a boon for the pest control they provide in barns, but rodent populations in urban environments are more controlled by food sources than cat populations (Glass, et al. 2009).

Since the cat was domesticated, it has been linked to humans and their environments as a companion animal, a form of pest control, and some would say, a pest in themselves. Debates over the best course of action in controlling burgeoning populations are complex in that euthanizing or eradicating wild cats foments opposition and may have unintended environmental consequences if not properly planned, while letting the populations run wild in urban settings poses risk to human health and quality of life. Undomesticated cats carry diseases, fleas, and leave waste behind them, in addition to the physical threat they may present to people and wildlife. Some jurisdiction pursue an alternative to euthanasia involving trapping, neutering, and releasing the animals (TNR), the idea being that less breeding will bring the populations. No such program has ever been shown to reduce free-roaming cat populations at the scale of a county because the proportion of sterilized individuals is not enough (Foley et al. 2005), although TNR programs have been shown to reduce the number of complaints received by local animal shelters (Hughes and Slater 2002).

The expense of money and time on a full-blown ground sampling of cat populations is not likely a priority topic for any city, so any investigation into distributions would have to be completed using data that are freely available and with methods that provide insight without major reconfiguration. To this end, spatialization and analysis of existing data using a Geographic Information System (GIS) could provide an inexpensive alternative to an actual census.

Goals and analysis focused on questions that may have relationships with each other and warrant more investigation. The goals of the thesis are:

1) Development of a workflow/methodology for spatializing a non-spatial dataset
2) Determination of areas of high (hotspots) and low (coldspots) trapping efforts
3) Examination of variables that may be associated with patterns of trapping requests

For the purpose of these investigations it was assumed that although the cat trap permits were not direct measurements of the density of feral cats, concentrations of permits could not occur without presence of cats or people willing to take the time to trap them. Analysis depends on these two factors — presence of free-roaming cats and presence of people sufficiently motivated to control their numbers to apply for a permit to trap them.

A methodology was developed and applied to a unique, "found" dataset to bring it into a digital format that can be used to answer questions about the desire to trap feral cats in a major city. These spatialized data were used to ascertain concentrations and clusters of applications and whether ancillary variables have effects on densities, or if more or different data are required. Exploratory analysis and summarization of this data show that it can serve as a proxy for concentrations of cats and that these areas will be associated with similar social and environmental factors.

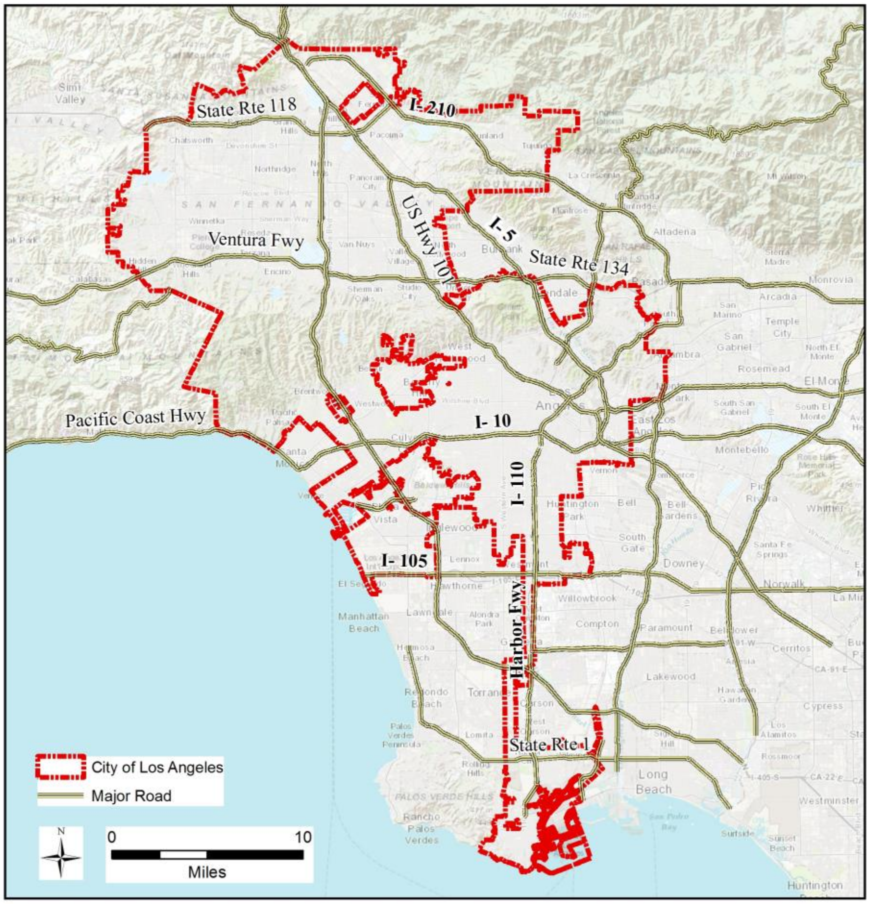
Proposed Solution

Available, yet previously unexplored, datasets might shed some light on either the concentrations of feral cats in urban environments or the resulting requests for municipal services associated with them, such as nuisance animal control and animal welfare efforts. A body of literature deals with "found" datasets in a geographic context (i.e. data which was not originally intended to be used for geospatial visualization or analysis). For example, Aguilar and Farnworth (2012) converted records of stray cat pickups for one year into geographically referenced information and then reconciled these locations with New Zealand census databases for global and local regression analyses (Aguilar and Farnworth 2012). They later developed the methods by encompassing a much larger dataset (unmanaged cat colony records from 1991 to 2011) and further exemplified how found datasets can be used to derive societal and administrative data and conclusions (Aguilar and Farnworth 2013). These studies showed not only the biogeography of feral or unowned cats in the Aukland region, but how a group of available records could be translated into a searchable database with space and time attributes.

This example speaks to the issue of unavailable data being made available as digital, searchable records and the advent of widespread use of mapping due to freely available computer applications (e.g. Google Maps). The ability for anyone with a computer and Internet access to create their own maps through a GUI allows future data collection in a searchable analyzable format, but creates a disconnect with data that has not been collected in this format. While digital record keeping is the *de facto* method in current times, masses of information are not available in this format, and are thus not searchable by officials or the public. What percent of these records that contain spatial data and could be of import to public, private, or government entities has not been estimated. This is not to say that every document in every file folder should be scanned and encoded into a searchable database, but that the possibility of using such non-digital information exists and could be encoded and used for scientific, government, and academic research purposes. Digitization and geo-coding of hard-copy records is a method of collecting and analyzing spatial data from a period in time that would otherwise be lost except in real world space. Creating these maps involves no georeferencing of legacy maps, since no legacy maps exist, and are true "data maps" of phenomenon observed from textual sources.

An example of the use of historic records being spatialized to an end includes the recording of archaeological site records, such as incorporation into a GIS database of the Anasazi Origins Project. In this work, a methodology was developed that "produced an invaluable dataset that was not fully published, analyzed, or properly preserved once fieldwork ended." (Plaza 2012). The project solved the problem of preserving, in a modern format, field work from archeological digs in the American Southwest as "living documents" by the manual transcription of the site records into a database with unique identifiers and then geocoding into a geodatabase. Once site records were encoded as such, the full analytical power of the GIS could be used to query the data, and the data were preserved in a readily accessible visual format for future researchers (Plaza 2012).

This thesis investigates the spatial properties of feral cat populations in a large metropolitan area Los Angeles, California, (Map 1) using a non-spatial dataset as a proxy for concentrations of feral cats. The unique data for the analysis have been provided in the form of applications for cat-trapping permits from various animal service centers in the City of Los Angeles from the period of 2004 to 2011. The applications in question contain various information, the most important being the addresses of the applicants or where the trapping is supposed to occur. To legally trap cats it is necessary to fill out a form documenting location, species type, and various reasons for wanting to trap. If a trap is needed, further forms for rental and deposit fees were required. While bureaucratic processes could be seen as deterrents to legal trapping, residents pursued trapping despite red tape and fees. Los Angeles Animal Service centers provided these documents to The Urban Wildlands Group pursuant to a lawsuit over an environmental analysis of the Trap-Neuter-Return program proposed by the City of Los Angeles. These documents present an unusual opportunity to demonstrate the benefits of extracting geospatial information from such records and to provide tools to understand distribution and impacts of feral cats in a major metropolitan area. While the documents contain the spatial and temporal information required for analysis, also included on the applications are many of the reasons that people gave for wanting to trap cats. Such reasons could further be spatially analyzed. For example, certain areas where people were reporting many instances of unchecked litters could be identified and this information passed on to animal service workers. What to do with the information would have to be ascertained, but efforts might include increased distribution of educational materials regarding feral cats, investigation of cat colonies, or deployment of ground teams to trap or neuter cats.



Map 1. Los Angeles AOI

In addition to the hard-copy paper applications, another set of data was made available after work had begun on the applications. This was a spreadsheet detailing phone calls regarding instances of feral, free-roaming, stray, or otherwise unowned cats from a similar period in time. Since this document contained many more records (>10,000) than the permit applications, it was decided to use the data in the analysis, but as a form of “ground truth” for the applications.

Methodology

The basic methodology was to enter the data into a spreadsheet, clean the data of outliers and remnants, geocode the points, and import into a geodatabase (GDB). In addition, other data were acquired to facilitate analysis, specifically data on populations and income in the City proper. A simplified diagram of the workflow for the study is shown below (Figure 1).

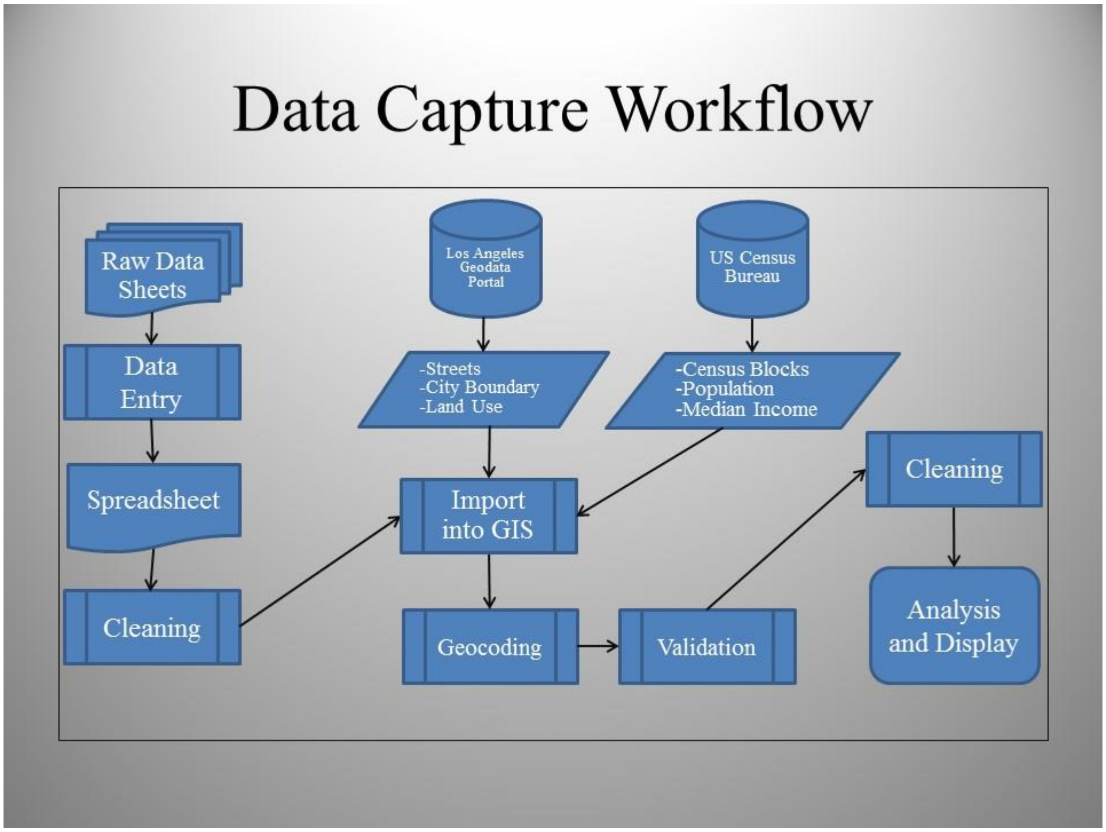


Figure 1. Workflow for spatialization of feral cat trapping applications

Structure of Thesis

The format of this thesis is that of a spatial analysis used to answer questions about a phenomenon fit within the overarching realm of the utility of digitization of unused data in applying modern approaches to analysis where it was not earlier possible. Given a problem (i.e. uncontrolled cat populations), possible solutions are examined through a novel methodology.

Chapter one establishes the setting and background for the problem, and outlines the methods proposed to deploy a solution. A brief review of related work is introduced, and goals are defined. A background in GIS, urban ecology, biogeography, and information technology is assumed for readers of this document.

Chapter two expands upon the related work that has been done on both the import of historical records into Geographic Information Systems and the spatially explicit studies related to feral cats. There is some basic information given about cats lives and how they live them that provides background for how cats impact their environments and how people have both incited and tried to solve the associated problems of unmanaged populations This section provides a basis for understanding the methodology used later, whether mirrored from the literature review or reached independently, and brings in key terms and concepts related to the work.

Chapter three describes the technology, methods, and datasets used to complete the thesis. Acquisition of base maps and datasets is described in detail and there is a large section dealing with the interpretation of the permit application records, including the rubric used to make decisions about what to include. The chapter concludes with in depth descriptions of the analysis tools used to examine the resulting database and the types of results that were produced.

Chapter four presents the results of the visual, tabular, and spatial analyses that were performed. This section contains the maps, graphs, and tables that were produced in hopes of better understanding the distribution of feral cats in Los Angeles by means of the proxy data produced from the acquisition phase.

Chapter five is the discussion of the results, detailing problems and successes found in the acquisition, import, and analysis of the data used. Questions about mathematical validity of the data are raised, and it is suggested that future work use a more robust set of data and variables for comparison.

Chapter six contains the references for the literature used in preparing this document.

CHAPTER TWO: RELATED WORK

Spatialization of Legacy/Unexplored Data

Most data with a spatial component collected in the modern world come in with all relevant attributes e.g. X/Y coordinates, projections, and dispositions. The advent of GPS technology, high-speed computers, and user-friendly applications, like Google Earth, allow the easy import and manipulation of records once data are downloaded from a device. This "spatial turn" in collection and record-keeping, where everyone with a computer can make a map, has generated a trend towards the spatialization of data that was recorded in earlier times and may still have value, but is not in a readily accessible scheme, such as a properly maintained geodatabase. This is of obvious use in disciplines having heavy historical components, like genealogy and archaeology, but is also used in the field of biogeography. While the use of georeferenced legacy maps is a typical process for the examination of data from different time periods, it is not the same in the case of tabular data or data that is not even in tabular form. However there are some examples of this type of data capture.

2.1.1 Case studies involving the use of legacy data

Mentioned earlier is the case of the Anasazi Origins Project, wherein the hard-copy paper from two archeological site survey campaigns were spatialized and imported into a GIS. Goals of the work were "the subsequent use of the database for research, to integrate with other datasets, and in part, to preserve the AOP collection." (Plaza 2012) The results of the project serve to not only achieve these goals, but to create a dataset from a raw state which has been brought into the modern digitally interconnected world, and is now available through the medium of the internet. Anyone seeking access to this collection before digitization would be faced with the task of finding where it resides, gaining permission to work with it, and then extracting the necessary facts. In addition to the preservation of the textual and visual data available, the collection now includes a spatial component allowing multiple maps to be created in any scale for the entire survey site. It is now accessible with many available commercial and non-commercial GIS applications with the advantages that format brings e.g. zooming, query by attribute and location, AOI delineation.

The original tables and field notes from the surveys, held at the Eastern New Mexico University (ENMU) curation facility, were manually keyed into a Microsoft Access® database, imported into ArcGIS® as a geodatabase and combined with terrain models and other databases and maps. Dividends are the base GIS for recursive research, the ability to expand and combine the database, and the case study itself as a methodology for this type of data mining and aggregation.

Re-examination and collation of old records into digital form also occurs in the field of conservation research and management. Aggregation of site-specific analyses for a certain time period into a larger dataset reveals patterns of wetland loss and use and where resources are best allocated for restoration efforts, such as the 2010 historical ecology analysis of California's San Gabriel River watershed (Stein, et al. 2010). Multiple disparate datasets (maps and supporting tabular and textual data) for the periods of 1850-1890 and 1769-1930 were interpreted, spatialized, and compared with current National Wetland Inventory polygons to reach conclusions about the health and coverage of wetlands within the basin. Primary data sources were maps from Mexican land grant sketches, General Land Office surveys, and soil surveys. Accompanying some of these sources were field notes, aerial photographs, and engineering reports that were used corroborate and ameliorate the mapping efforts for the longitudinal analysis. Additionally, herbaria records from the periods were interpreted using historic and current place names and habitat descriptions to characterize plant cover and wetlands, and the final database was translated into modern classification systems for clean comparison.

Feral Cats and Colonies: Definitions, life cycles, and past literature

Definitions: feral, free-roaming, and unowned cats

The common cat (*Felis catus*) is often described as the most popular companion pet in the world. Debate remains on when and where the animal was first domesticated; the Egyptians are commonly referenced in the history of the cat, but recent evidence from a small town in China indicates that cats and humans lived symbiotically as far back as 5300 years ago (Hu, et al. 2013). But before their status as pets, all cats were feral cats and it only takes one generation for them to revert to this state when deprived of human care (Bradshaw, et al. 1999). This fact is part of the reason feral cats have become a problem in urban communities when house pets are abandoned or allowed to breed unchecked with no consideration for the care of future generations. Whereas the ancient Egyptians regarded all cats as godlike beings, in the present day various countries have classified the unowned cat as an invasive species and pest (Farnworth, Dye and Keown 2010).

Literature about feral cats shows different views on what constitutes a cat being feral, free-roaming, unowned, or stray. Feral cats are generally regarded as having returned to a wild state and will be standoffish or aggressive toward humans, while stray, free-roaming, and unowned cats may have had human care and interaction in the past and can be brought back into a companionship setting. For the purposes of this thesis, each of these definitions were interchangeable since what was reported on the trapping permits lacked any fine semantic knowledge i.e. cats were reported, not necessarily whether they had collars, or exhibited particular behaviors.

Description and Life Cycle

Cats , whether owned, stray, or feral, are all semi-social animals which can live together in colonies or packs (clowders or glarings) at food sources, but hunt alone (Bradshaw, et al. 1999). They are carnivores and have evolved the tools of the active hunter; sharp claws and teeth, strong limbs, and remarkable speed and agility. Although all domestic or feral cats are of the same genus and species, there is wide variation in coloring and morphology for individual breeds. Average weights are between 6 and 10 pounds, though certain breeds can be much larger. Cats are fecund and may go into estrus five times in a year and produce up to three litters of four kittens on average (Liberg et al. 2000).

Lifespans of cats vary according to breed (e.g. Manx and Siamese tend to have longer lives) but more according to lifestyle. An average age for a “housecat” with consistent human care is between 12 and 15 years, but this is barring accidents, violent encounters, disease, etc. (Syufy 2014). Feral cats do not reach these ages generally unless they are part of a managed colony (a cat colony which is being cared for by volunteers/good Samaritans.) If a wild cat survives kitten hood it has an average lifespan of 2 years (ASPCA 2014). Given this short lifespan, it is difficult to see why feral cats have become a problem, but it must be remembered that this group also recruits from other sources besides nature. People abandon cats, cats wander off, and there are numerous individuals and agencies that actively care for feral cats, so populations are not solely controlled by natural birth and death cycles.

Effects on wildlife

Recently cats (owned and feral) have made the news as one of the top anthropogenic threats to native wildlife (mammals, reptiles, and birds) (Paramaguru 2013). The article cites a new study that vastly increases past estimates of wildlife death by cats. New estimates from a literature review and quantitative analysis are "that free-ranging domestic cats kill 1.4–3.7 billion birds and 6.9–20.7 billion mammals annually" and that feral or unowned cats are responsible for the bulk of these deaths (Loss, Will and Marra 2013). These estimates are for a large geographic range (the U.S.) and it is likely that these losses are concentrated in areas where cats do not face danger from other animals and are apex predators (e.g. urban environments.)

Since cats are largely introduced to new environments by humans either intentionally (e.g. rodent control) or unintentionally, they have been linked to extinctions of many species especially on islands where native wildlife have never been exposed to such a skilled hunter. A notable extinction is the Stephen's Island wren, improperly attributed to the lighthouse keeper's cat on its own, but the facts are that introduced cats killed off much of the island bird population (Galbreath and Brown 2004). Ecological imbalances and extinctions have prompted efforts to eradicate feral cats on island environments with mixed success (Campbell, et al. 2004). Eradication of feral cats on Macquarie Island (Australia) brought "trophic cascade", where the loss of one species brings changes in populations of other species and in this case, changes in the land cover of the island. The cats were introduced in the 1800s, and when a program to deplete the island's rabbit population (by disease introduction) was successful, the cats began feeding on the bird population. All the cats were exterminated which led to a boost in the rabbit population. The rabbits decimated vegetation necessary for protecting the native penguin population and radically altered the island's geography (Draper and La Canna 2009).

Cat-related Zoonoses

Not surprisingly one of the main fears of people when considering feral cats is the risk of infection or disease either from direct contact (e.g. cat bites) or an indirect vector (e.g. fleas, water contamination.) Diseases associated with free-roaming cats include rabies, toxoplasmosis, cutaneous larval migrans, tularemia, and (bubonic) plague (Gerhold and Jessup 2012). While domestic animals with access to proper veterinary care pose little risk of these infections/diseases, feral cats often do not have this advantage and pose a greater threat to humans and other animal populations (Gerhold and Jessup 2012).

Direct contact transmission is usually through a bite or scratch although simple handling of infected animals has been implicated for certain cutaneous infections. Of the animal bites treated annually in the U.S., cats account for between 3 and 15 percent of the bites with provocation being the reason 90% of the time. A cat bite or scratch has a high probability of infecting a victim (between 28% and 80% depending on the victim's constitution) due to the delivery method (Kravetz and Federman 2002).

Indirect concerns such as fleas and feces can also cause disease and infection. Of particular note are the parasites *Toxoplasma gondii* and *Toxocara cati* (which can be present in cat feces) whose eggs are hardy and can manifest months or years after exposure. Gerhold and Jessup write:

> "cat faeces-contaminated playgrounds, garden soil, sandboxes and other outdoor recreational areas may serve as a source of infection for humans." (Gerhold and Jessup 2012)

With this statement in mind it can easily be seen why cats, feral or otherwise, would be of concern to people in an urban setting.

Three diseases are associated with fleas; cat-scratch disease (which is transmitted by a scratch but manifested by flea infestation and feeding), flea-borne typhus, and plague. Although cats may appear healthy, they may be infected with one or more of these diseases due to flea infestation (Gerhold and Jessup 2012).

Past studies on spatial distribution of feral cat populations

Major Contributions: Aguilar and Farnworth, Auckland, NZ

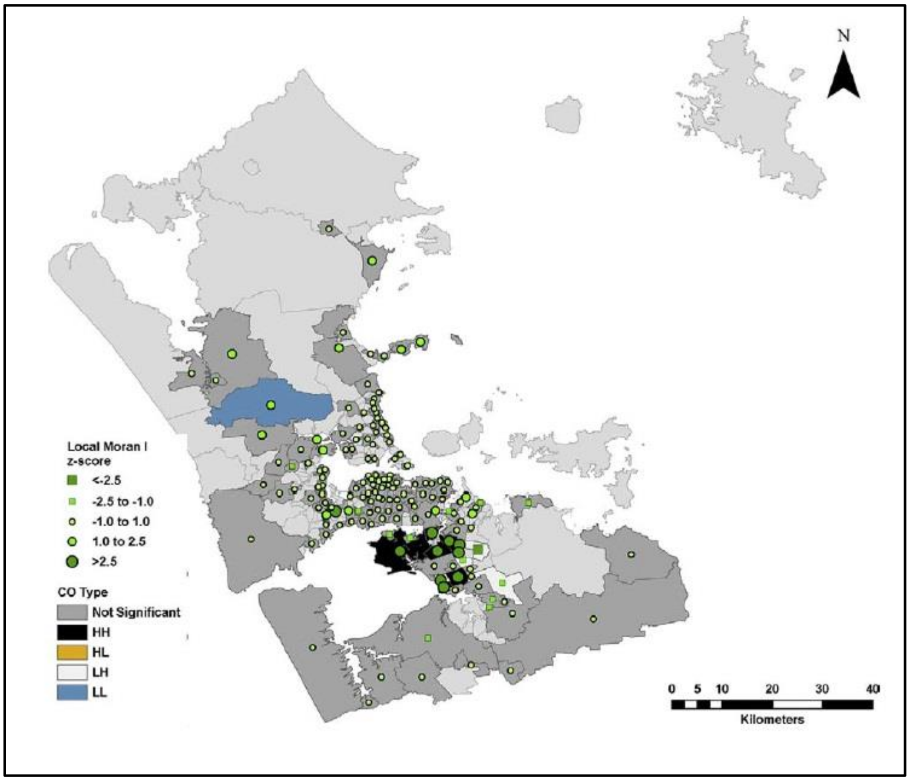
Already mentioned are the papers by Aguilar and Farnworth that directly dealt with using non-spatialized datasets to serve as proxies for the locations of feral cats and feral cat colonies. The first paper (Aguilar and Farnworth 2012) outlines a methodology to introduce non-spatial data into a GIS that would be suitable for use with the PDF files provided by the various Los Angeles Animal Service Centers, with some changes. Data about stray cat pickups (from public reports/trapping activity and drop-offs at veterinary clinics) were obtained from the Auckland Society for the Prevention of Cruelty to Animals from the period of March 2010 to March 2011. These data arrived in the form of a spreadsheet, cleaned (manually) and merged with a roads database layer yielding two GIS layers; one polygon shapefile used for determining density and one polyline file showing where stray cats were picked up or reported. Once the data were in the GIS, analysis included measures of global (Moran's I) (Moran 1948, 1950) and local (Anselin's Local Moran's I) clustering (Anselin 1995). Moran's I is an index of clustering/non-clustering for a whole area, but gives no indication of where clustering occurs. It is important in that it yields parameter values for further analysis such as Anselin's Moran's I and regression.

Using the derived density (cats/km^2) from the polygon layer for each New Zealand census area, Moran's I was calculated multiple times for distances beginning at 1 km and adding a 1km interval. The peak z-score occurred at 22 km (I=0.085; z=2.292; p=0.021) and this distance threshold was the cutoff for the local analysis. Spatial autocorrelation was positive indicating clustering of densities of stray or unowned cats.

Subsequently, a local analysis was performed using Anselin's Local Moran's I, a method of comparing a global mean with a mean derived from a smaller (local) area, in this case the New Zealand census areas. By this method, the contributions each area makes to overall clusterings (or non-clusterings) can be mapped out by comparing local (area) means of density with the overall density. Aguilar and Farnworth explain this as:

> "Groupings of positive *I* values with significant z-scores in close proximity provide evidence of clustering while groupings of negative spatial autocorrelation indices provides an argument for a lack of clustering…areas with statistically significant (0.05) indices are classified using the local and global means (local mean is the average stray cat density using the area's neighborhood while the global mean is the overall average.)"

By this method they produced a map of Greater Auckland with four different CO (cluster/outlier) types: areas that had local stray cat density averages higher than the global mean were designated HH, lower than the global mean LL; global stray cat density averages higher than the local mean were HL, and lower than the local mean were LH. (Aguilar and Farnworth 2012) This map is reproduced below and shows how Anselin's Local Moran's I can be used to delineate areas of significant stray cat activity:



Map 2. Example of spatial analysis of cat locations in urban context

Using this classification it can be seen that areas in South Auckland are the hardest hit by cat infestations, and the authors continue their analysis by looking into whether socioeconomic factors play a part in the profusion of stray or feral cats.

Since feral or stray cats have an interactive relationship with human populations (e.g. food sources, shelter), Aguilar and Farnworth continued the research by performing Ordinary Least Squares (OLS) regression between stray cat densities and a derived statistic called the New Zealand Deprivation Index (*NZDep2006*) which is based on several variables (e.g. home ownership, employment.) Weighted scores for *NZDep2006* were calculated for the Greater Auckland area and OLS showed positive correlation between stray cat densities and high *NZDep2006*. Moran's I was calculated on the residuals of OLS, and although spatial autocorrelation was not indicated (i.e. the model is adequately fit); Geographically Weighted Regression (GWR) was used to further investigate relationships. GWR takes into account spatial variances over distance (features/variables closer together will tend to be more similar) using a distance and interval decay function whereas OLS is a traditional statistical tool that assumes variable independence over spatial distances (Dark 2004, Mitchell 2005, Shi et al 2006). Results of GWR supported the OLS analysis (positive correlation between cats and deprivation) and Moran's I did not show autocorrelation. A comparison of the Akaike Information Criterion (AIC) scores for OLS and GWR showed that, as expected, GWR provided a better fit model.

Following the success of their method for importing and geocoding the reports of stray cats and drop-offs at clinics, Aguilar and Farnworth produced a complementary paper using a much larger dataset. The first paper provided the "proof of concept" background, methodology, and exploration of these unique datasets while the second paper uses data to support their hypothesis that unmanaged cats are a "persistent feature" of Auckland's urban geography (Aguilar and Farnworth 2013). Rather than focusing on individual cat reports, pick-ups, or drop-offs, the second paper utilized data (spreadsheets with locations and dates) on cat colonies collected by the Lonely Miaow Association Incorporated for the period of 1991–2011. For this study, a colony was defined as "Three or more individual cats and/or kittens reported to be permanently resident in a given location and with no discernible owner or caregiver." These locations were geocoded and spatially joined with census polygons for Auckland allowing for calculation of cat colony density/km^2, to be used as a dependent variable in further work. The data for this

20-year period were binned into four groups of years for a longitudinal analysis of how colony distributions changed over time. (Aguilar and Farnworth 2013).

Unlike the previous study, Moran's I was not initially used to determine if clustering was present. The Getis-Ord Gi* statistic was calculated to determine hotspots/coldspots in the AOI (Aguilar and Farnworth 2013) Positive statistically significant z-scores (at $p<0.05$) returned indicate "intense clustering of high values (hotspots)" (Aguilar and Farnworth 2013) and negative z-scores in the same analysis indicate more intense clustering of low values (Getis & Ord, 1992, Ord & Getis, 1995, 2001). Hotspots and coldspots were present, and coincided well with the initial mappings of density distributions (Aguilar and Farnworth 2013).

Anselin's local Moran I analysis was run also using the rating system for cluster/outlier types previously described in their first paper (HH, HL, LH, LL.) Results from this tool show the HH areas incident with the hotspots from the Getis-Ord Gi* (for the entire period.) They note that an occurrence of the LH type appears in a conservation area, showing how this type of data has predictive value from an environmental conservation standpoint (Aguilar and Farnworth 2013).

The method used to determine whether cat colony density is correlated with human population density or land use type was to generate a kernel density function for the colony locations and overlay this with the human density layers and the land use layer. This was done for visualization purposes, but the OLS tool was run for both the human population density and the NZDI at the $p < 0.01$ level. Both of these tests returned significant positive *t*-statistics (7.206 and 5.646 respectively) indicating an affirmative relationship between cat colony densities and these two measures. In the case of OLS for

NZDI, evidence of spatial autocorrelation (from a global Moran's I on the resuiduals) was present and further analyis using GWR was performed eliciting a better-fit model showing a weaker relationship between deprivation and colony density. The kernel density map overlayed with the land use map showed that high values for colony density were mostly found within the "Settlement" classification, and no further analysis was deemed necessary (Aguilar and Farnworth 2013).

From these results, Aguilar and Farnworth conclude that unmanaged feral cats are consistently present in the Greater Auckland area and that an integrated approach to population control (e.g. public education, compulsory registration) could better the situation since "The increasing density and persistence of cat colonies suggest current strategies may not be working" (Aguilar and Farnworth 2013). It is expected that this conclusion will be borne out from similar methods used on data from the Los Angeles area.

A subtle difference between the work of Aguilar and Farnworth and this project is that the records in question were furnished in the form of a spreadsheet in the beginning, allowing cleaning and geocoding to commence from that platform. In the examination of the cat trapping permit applications, the spreadsheet had to be created by manual entry of records into the spreadsheet, necessitating numerous choices regarding what data to include, and how to best represent the data in a GIS.

Related Contributions

Several studies and works have investigated quantifying home ranges for feral cats, information that was relevant to the geocoding validation of this project. The studies available are in a range of environments, from riparian reserves (Hall, et al. 2000) to inner cities of large metro areas (Natoli 1985). Cat ranges were determined by various methods such as radio telemetry, fixed motion-sensitive cameras, direct sampling/census, interviews, and trapping. Results varied depending on animal gender, environment, seasonality, and individual cat personality (e.g. subordinate or dominant) so a large spectrum of home ranges and densities were found in various studies (Liberg and Sandell 1988).

Liberg and Sandell conducted a review of the various studies with an eye toward the hypothesis that cat spatial organization and density will be determined by food abundance. They note that difficulties exist in testing this due to the various methods available for estimating density and the lack of data on food sources (Liberg and Sandell 1988). Their work includes a comprehensive table noting in what type of environment studies were performed as well as methods, food types and abundance, and proposed densities of animals/km^2. Regression performed on the data from the various studies (for both male and female cats) showed a negative correlation between home range size and density (as density increases, range decreases) attributed to the availability of food sources (i.e. urban cats tend to have centralized sources whereas true ‘wild’ cats subsist by hunting prey over larger areas.) Male cats were found to have roughly three times the home range of female cats (Liberg and Sandell 1988).

Due to the disparate nature of each urban environment where feral cats are found, it is difficult to settle on an average home range for cats as the variables are too numerous to pick apart. For example, Yamane, Ono, and Doi, in their study of cat ranges on an island off of Japan, found a mean home range of 0.78 ± 0.63 ha for males (non-estrous season) and 1.45 ± 0.81 ha (estrous season.) Female ranges were smaller and not affected by mating seasons (Yamane, Ono and Doi 1994). This finding contrasts with those of Hall et al. who found a mean home range of 31.7 ha for both sexes in the Putah Creek Riparian Reserve (California) which has an area of ~259 ha (Hall, et al. 2000). This disparity may be a function of food abundance, with greater local concentrations of food being available in urban environments while gathering food in rural environments entails travelling longer distances.

CHAPTER THREE: METHODS

Data Acquisition, Preparation and Import

Technology

Data for basemaps and existing data layers were downloaded from internet sources, most notably the Los Angeles County GeoData Portal (LAGDP). ArcGIS Online was used as a source for reference imagery. Initial data entry and cleaning were accomplished using Microsoft Excel which was also used for the preparation of some charts and graphs. All maps, images, spatial analysis were done on a home computer using ESRI's ArcGIS for Desktop 10.2. It is assumed that people reading, reviewing, or evaluating this document will have familiarity with geographic terms, theory, and concepts and will have knowledge of ArcGIS for Desktop and the tools therein.

Geodatabase Design and Creation

A file system was created in Windows to store the various files, folders, and objects for the project. Folders containing data were given descriptive names (e.g. "Xcel files" or "LA GIS Data".) A file geodatabase (gdb), **LAFeralCatGDB,** was created as a repository for data layers, tables, tools, etc. The structure of the gdb is straightforward; it contains an address locator, the feature classes, tables, and raster layers, upon which the analysis was conducted. Because the data for the permit applications would have to be entered and then geocoded, base-map layers for the City of Los Angeles would be necessary, as well as the layers to be used as dependent variables in analysis (i.e. population, land use, and socioeconomic status.) These layers were researched, downloaded, and edited as necessary to compile the information for the final maps and analysis.

Basemap Layers

Boundary Layer

The boundary of the City of Los Angeles was obtained from the Los Angeles County GIS Data Portal (LAGDP) (http://egis3.lacounty.gov/dataportal/2011/07/19/census-tracts-2010/.) This shapefile (**City.shp)** was downloaded and imported into a geodatabase for editing. The layer contained extraneous polygons which had to be removed to obtain the final city boundary layer named **LA proper.**

The data points in the study were limited to those that fell within the limits of the City of Los Angeles and some outlying areas included to mitigate edge effects during analysis. This data layer was obtained from the LAGDP (http://egis3.lacounty.gov/dataportal/) downloadable as the .zip file City-Boundary from http://egis3.lacounty.gov/dataportal/2013/01/03/city-boundaries/. The layer is in NAD_1983_StatePlane_California_V_FIPS_0405_Feet with a Lambert Conformal Conic projection, which was the system that was used for all future work. The unzipped shapefile included all of Los Angeles county and artifacts. The city proper was selected out by using **Select by Attributes > Select from City WHERE: "CITY_NAME" = 'Los Angeles' AND "FEAT_TYPE" = 'Land'**. In this fashion the breakwaters, piers, three nautical mile buffer, and communities other than Los Angeles were eliminated from the AOI. The resulting layer, City of Los Angeles, was shown before in Map 1, Section 1.3.

Streets Layer

A layer of the Los Angeles street network would be necessary to create an address locator in ArcMap. This was also available from the LAGDP as the shapefile **Streets.shp** and this was imported into the gdb as **LAstreets.** In order to preserve outlying areas where permit applications may fall close to the boundary, the layer was clipped to a 5-km buffer of the **LAproper** layer. The clipped layer included areas for geocoding outside the boundary as some permit records may have fallen in these areas, but might be included in analysis to mitigate edge effects. Using a clipped layer also speeded up the geocoding tool.

Cat Trapping Permits Data

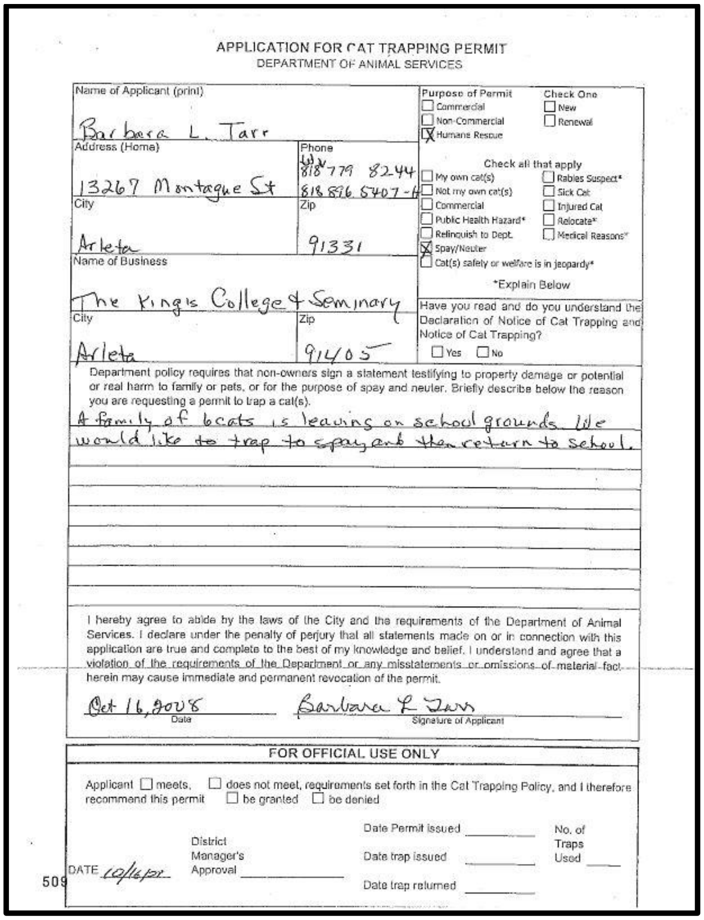
Acquisition

The City of Los Angeles has a permit process required to trap cats or other species. The procedure is for the resident to apply for a cat trapping permit from the Department of Animal Services, to pay a deposit for any trap being obtained from the City, to post the area to be trapped with a public notice before any trapping is done. The application to trap and the permit issued are records maintained by the City. These documents contain information about the location where trapping is desired and about the reasons cited for wanting to trap the cat. An initial batch of permits was available as part of the documents compiled for a lawsuit by a group of conservation organizations challenging the City of Los Angeles' implementation of a Trap-Neuter-Return program for unowned cats prior to doing the required environmental review (*The Urban Wildlands Group et al. v. City of Los Angeles*). A second batch of permit records was obtained by The Urban Wildlands Group in response to a California Public Records Act request to the City of Los Angeles for cat trapping applications and permits that were then made available to interested parties for research purposes.

Data Entry

One set of data for the analysis has been provided in the form of applications for cat-trapping permits from various animal service centers in Los Angeles (LA.) from the period of 2004 to

2013. The records for the ending years did not encompass full years, so these records were recorded but not necessarily used in the analysis. These were hard copy, hand-written applications with various check boxes to indicate certain information about why an application was being sought. These forms were scanned and delivered to the author in .pdf file format. An example of a typical form is shown in Figure 2.


APPLICATION FOR CAT TRAPPING PERMIT
DEPARTMENT OF ANIMAL SERVICES

Name of Applicant (print): Barbara L. Tarr

Purpose of Permit: ☐ Commercial ☐ Non-Commercial ☒ Humane Rescue

Check One: ☐ New ☐ Renewal

Address (Home): 13267 Montague St

Phone: (W) 818 779 8244; 818 896 5407-H

City: Arleta

Zip: 91331

Check all that apply: ☐ My own cat(s) ☐ Not my own cat(s) ☐ Commercial ☐ Public Health Hazard* ☐ Relinquish to Dept. ☒ Spay/Neuter ☐ Cat(s) safety or welfare is in jeopardy* ☐ Rabies Suspect* ☐ Sick Cat ☐ Injured Cat ☐ Relocate* ☐ Medical Reasons*

*Explain Below

Name of Business: The King's College & Seminary

City: Arleta

Zip: 91405

Have you read and do you understand the Declaration of Notice of Cat Trapping and Notice of Cat Trapping? ☐ Yes ☐ No

Department policy requires that non-owners sign a statement testifying to property damage or potential or real harm to family or pets, or for the purpose of spay and neuter. Briefly describe below the reason you are requesting a permit to trap a cat(s).

A family of 6 cats is leaving on school grounds. We would like to trap to spay and then return to school.

I hereby agree to abide by the laws of the City and the requirements of the Department of Animal Services. I declare under the penalty of perjury that all statements made on or in connection with this application are true and complete to the best of my knowledge and belief. I understand and agree that a violation of the requirements of the Department or any misstatements or omissions of material fact herein may cause immediate and permanent revocation of the permit.

Oct 16, 2008 — Date

Barbara L Tarr — Signature of Applicant

FOR OFFICIAL USE ONLY

Applicant ☐ meets, ☐ does not meet, requirements set forth in the Cat Trapping Policy, and I therefore recommend this permit ☐ be granted ☐ be denied

District Manager's Approval ______

DATE 10/16/08

Date Permit Issued ______

Date trap issued ______

Date trap returned ______

No. of Traps Used ______

509

Figure 2. Example cat trapping permit application for the City of Los Angeles.

The forms were delivered asynchronously, with the first roughly 500 being sent in the spring of 2013. The data from this set of forms were entered, cleaned and geocoded. Further data for applications were sent later in the fall of 2013. The data were entered into separate spreadsheets according to the Animal Service Center region the records were delivered from (e.g. East Valley), and were combined into one Excel® spreadsheet

The final product contained the following fields. Short explanations for these fields are given:

Trapping Location – Address given on the application. Used for geocoding locations of feral cat reports.
City – Los Angeles unless the city was included as part of a buffer process..
State – California
Zip – Used for geocoding and validation.
Latitude and Longitude – Addresses that were unmatched using the LA_AddressLocator (see Chapter 3) were geocoded using a free web geocoder and coordinates were reported in Lat/Lon
Date – Dates were taken first from the application, secondly the permit issued (if present), and lastly any other source (e.g. correspondence, notes.) Applications with no date were not entered.

The following fields were added to the spreadsheet as binary (1= yes, 0=no) values since they were in the form of check boxes that were either checked or left blank by the applicant:

- New Permit?
- Rescue?
- Owned Cats?
- Relinquish to Dept.?
- Relocation
- Public Health
- Desire Spay/Neuter (TNR)
- Cat Safety/Welfare
- Rabies suspect
- Sick/Injured cat
- Medical reason (e.g. allergy)

Several fields were created from reading the explanations people gave in the space provided for commentary. These fields were additional complaints and concerns or explanations of situations:

- Damaging property
- Fear of Aggression
- Unchecked Litters
- Other

Four more fields that held ancillary or derived information were also added:

- # Reasons
- Approx. # Cats
- Application Accepted?
- Comments

This form provided the basis to create the spreadsheet. Some of the fields in the spreadsheet were obvious in whether they should be included, the most important being the location where the trapping was to occur. In all cases where a trapping address could not the determined, the data were not entered.

Information detailed on the forms fell into various categories such as personal data, reason for trapping, and general administrative information. In addition, some forms included other photocopies/scans that were sometimes helpful in clarifying information that was unclear from the basic form. These data might include driver's licenses, correspondence, or trap rental forms.

While the check boxes included most of the common reasons why someone might want to trap cats, the space provided for explanation often included information that was not present in the check boxes alone. In fact, in some cases no boxes were checked at all and all the information had to be gleaned from these explanations. For this reason a rubric was developed to facilitate the collection of textual information.

Rubric for data delineation

Given the wide spectrum of possible interpretation of the applications, a rubric was developed so that given a choice of two or three interpretations there would be a hierarchy of what information to enter, and that this would give some constancy to the data. Some of the rules are common sense and some rules seemed to point themselves out as similar instances arose. For example, an applicant may have complained about cats soiling flower beds, which is an esthetic reason for trapping, but this reason also speaks to the larger issue of public health, and could also be considered to be property damage.

Basic Information

- Name of Applicant(s): This information was not used in the sheet since it had no bearing on the question and to protect confidentiality of permit applicants.
- Home Addresses: This information is essential to a spatial analysis of cat trapping/feral cat population. Care had to be taken to make sure the address given was for the area where traps were to be set, and not the applicants home address. This included street number, street, city, and zip code.
- Business Address: Like the home addresses, if this was the area where traps were to be set, this would be the field entered into the spreadsheet.
- Phone: This was not included for the same reasons as the name of the applicant.

Check Boxes-General

- Commercial/Non-commercial: If the permit application was for a commercial venture (e.g. a pest removal business) or personal endeavor had no relevance to the questions being investigated, so this was not included as a field.

- New/Renewal: This information is likely for record keeping, and was included in the interest of future analysis.
- Humane Rescue: Whether people were trapping for the purpose of eliminating the cat problem or for humane reasons seemed relevant. This was included as a field.
- Owned Cats: In the initial data entry, this data was recorded but later filtered out using Select by Attributes. Subsequent data entry did not include this information.
- Relinquish to Dept.: This would mean that the applicant wanted the cats handled by the shelter, either for adoption, TNR, or euthanasia. This was noted for statistical purposes.
- Relocation: Indicates that the intent was to move cats to a new location. It was noted.

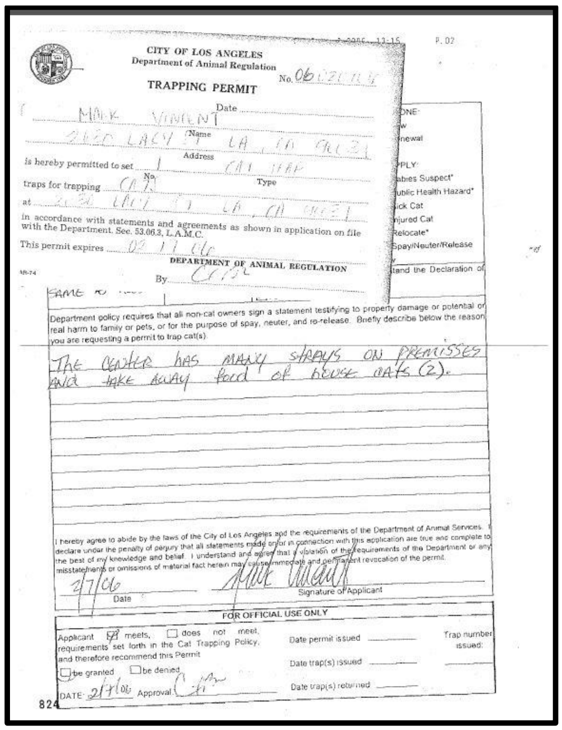
Check Boxes-Purpose of Permit

Specific reasons for wanting to trap cats were also listed in the check boxes and these were obvious choices for noting. It was asked that reasons with an asterisk be explained in a space provided. All of these reasons were included in the final spreadsheet.

- Public Health Hazard*
- Cat safety and welfare is in jeopardy*
- Sick/Injured Cat
- Spay/Neuter (TNR)
- Rabies Suspect*
- Medical Reasons (e.g. allergies, pregnancy)*

Date

The date field was included to allow for the future longitudinal analysis of the dataset. In all cases possible the date used was the date the application was filed, that is the date shown by the applicant's signature. Sometimes this date was not visible due to the fact that it was covered up by other documents which were scanned with the application. In some of the applications scanned this occurred frequently, like the application below in Figure 3:



P. 02

CITY OF LOS ANGELES
Department of Animal Regulation

TRAPPING PERMIT

No. 06

Date

Name

Address

is hereby permitted to set 1 CAT TRAP

No. Type

traps for trapping CATS

at

in accordance with statements and agreements as shown in application on file with the Department. Sec. 53.06.3, L.A.M.C.

This permit expires 02 17 06

DEPARTMENT OF ANIMAL REGULATION

By

AR-74

SAME

Department policy requires that all non-cat owners sign a statement testifying to property damage or potential or real harm to family or pets, or for the purpose of spay, neuter, and re-release. Briefly describe below the reason you are requesting a permit to trap cat(s).

The center has many strays on premisses and take away food of house cats (2).

I hereby agree to abide by the laws of the City of Los Angeles and the requirements of the Department of Animal Services. I declare under the penalty of perjury that all statements made on/or in connection with this application are true and complete to the best of my knowledge and belief. I understand and agree that a violation of the requirements of the Department or any misstatements or omissions of material fact herein may cause immediate and permanent revocation of the permit.

2/7/06

Date

Signature of Applicant

FOR OFFICIAL USE ONLY

Applicant ☑ meets, ☐ does not meet, requirements set forth in the Cat Trapping Policy, and therefore recommend this Permit

☐ be granted ☐ be denied

DATE: 2/7/06 Approval

Date permit issued

Date trap(s) issued

Date trap(s) returned

Trap number issued:

824

Figure 3. Example of permit application where date is not visible.

In these instances, the date used was the "next best", ideally the date from the trapping permit, but if this was not available, any date associated with the application. By this method, all entries were associated with a date that could be reasonably assumed to be within the month of filing.

Text information entry

After entering this information, it was necessary to read any text included in the document. These entries ranged from nothing at all to explanations continuing on to other pages. Reading these statements showed that there were more reasons people might not want ferals in their neighborhoods/areas. After reviewing these reasons, several new fields for the spreadsheet were added. Some complaints were not common, and these were noted along with a notation in the "Comments" field. By this fashion, if noise complaints were to be investigated someday, there would be a way to filter the comments by text.

A "Fear of aggression" field was added for people who complained that they had been scratched, bitten, or were otherwise intimidated by aggressive animals. This was entered as true for these reasons and also if it were mentioned that their own pets' safety was in danger. The field "Damaging Property" was added since some people reported that the cats were causing damage, generally with some monetary value, but sometimes for cosmetic reasons. Entries such as "scratching screens", "spraying", or "soiling flower beds" fell into this category. An "Unchecked Litters" field was added when people reported cats breeding and it was clear that they were not owned by any one. Mention of "a mother and three kittens", "having babies all the time", "dead kittens on my doorstep", etc. were coded positively.

"Approximate number of cats" was a field used to report if people had some type of count noted in the text. This may have evidenced itself with reports such as "A large grey Tabby" or "Hundreds of cats." The intent of this field is not to gain an estimate of actual population, a virtual impossibility, but as a possible factor in gauging severity of infestation for future analysis.

An “Other” field was added to account for miscellaneous complaints, largely about noise at night, but might say that cats were climbing on the roof, fighting each other, or mating. The nature of this field was usually explained in the “Comments” section, which might say what the “Other” complaint was, a side note of possible interest, status of the application, or a note to the author that the text may serve well as an example of the problems encountered when entering the data (e.g. application in Spanish.)

Any information obtained from text included was entered into the spreadsheet. For example, if the check box for “Public Health Hazard” was not checked on the form, but fleas, feces, or disease were mentioned in the text, then the mention was entered as positive for public health concens in the spreadsheet

An initial spreadsheet was created for the first sets of data delivered. This “proof of concept” sheet was geocoded by the addresses given in the “Trapping Location” field. This sheet was refined and ameliorated before the final product emerged. At this point, the addresses were geocoded again in order to produce a final dataset.

Spreadsheet Creation

The spreadsheet created from the cat trap application documents went through several iterations before a final sheet was produced. The spreadsheet was created from the cat trap application documents consisting of ~800 applications viewed, the initial omissions being detailed in the previous Data Entry section. The final file went through several iterations before completion due to the data being supplied asynchronously.

The scanned PDF files were entered into separate Excel files and then cut and pasted into one large file with the records as the rows and the headers discussed in the Data Entry section as the columns. A second set of data was delivered and entered in the same fashion, and fields were added to the sheet producing the final sheet for cleaning and geocoding. This sheet was also used to produce graphs and tables summarizing the data regarding the number of applications over time, the number of applications in municipal districts, and the reasons given for wanting to trap cats.

Cleaning

Removing *Duplicates*

The Excel file produced, contained duplicates due to human error in data entry or entry of data with the same information from different PDF files. A new field was added by concatenating the **Trapping Location** field with the **Date** field to create a unique identification for the records. Conditional formatting was applied to this field to locate records filed on the same day for the same location. These two duplicate records were removed manually.

Removing Owned Cat Records

People wishing to trap their own (non-feral) cats were included in the first set of data entered but were not relevant to the study. A filter was applied where **Owned Cat =1** and these records were deleted and the field omitted. Further cleaning of non-relevant records would have to be performed in ArcMap during the geocoding.

Geocoding

Geocoding in ArcMap

The geocoding function in ArcMap requires an address locator be created to match the given addresses from the spreadsheet to known addresses from a reference layer. The address locator was created in **FinalFeralGDB** using the parameters of US-Dual Ranges and the **tigerroads.shp** file (downloaded from the LAGDP, and clipped for the AOI) as a reference style, all other parameters being default. The clean spreadsheet with addresses was then added to the Arcmap document as a table. The addresses from the *Trapping Location* field were then geocoded using the native geocoding tool in Arcmap. The *Trapping Location* field was selected to geocode, the XY output field box was checked in the Geocoding Options dialog and the tool was run. Only a part of the addresses were returned as positively geocoded. While ArcMap allows for manual editing and researching of the unmatched addresses, it was decided to extract these unmatched addresses and input them into the online batch geocoder.

First, the new geocoded layer was exported to **FinalFeralGDB** to preserve integrity in case of errors. The unmatched and tied records were selected from the layer using **Select by Attributes > Status = 'U' OR Status = 'T'**. These records were then copied and pasted back into a spreadsheet. The Trapping Location, City, State, and Zip fields were then selected from this file and pasted into the online geocoder. The geocoder was developed by David B. Zwiefelhofer and is operated by pasting a .txt or .xlsx file into the input field, setting the parameters, and retrieving the output field, which can easily be imported back into the spreadsheet (Zwiefelhofer 2008).

Latitude and Longitude were set as output fields and the tool was run (see Figure 4) resulting in a .txt file with latitude and longitude that could be pasted back into the Excel file in the same order and the resulting Lat/Lon values moved into the appropriate columns. The results also included an accuracy value ranging from 0 to 9 (9 being most accurate) so unmatched addresses could be deleted. 238 records were processed with no failures and only 8 records with an accuracy of below 8.

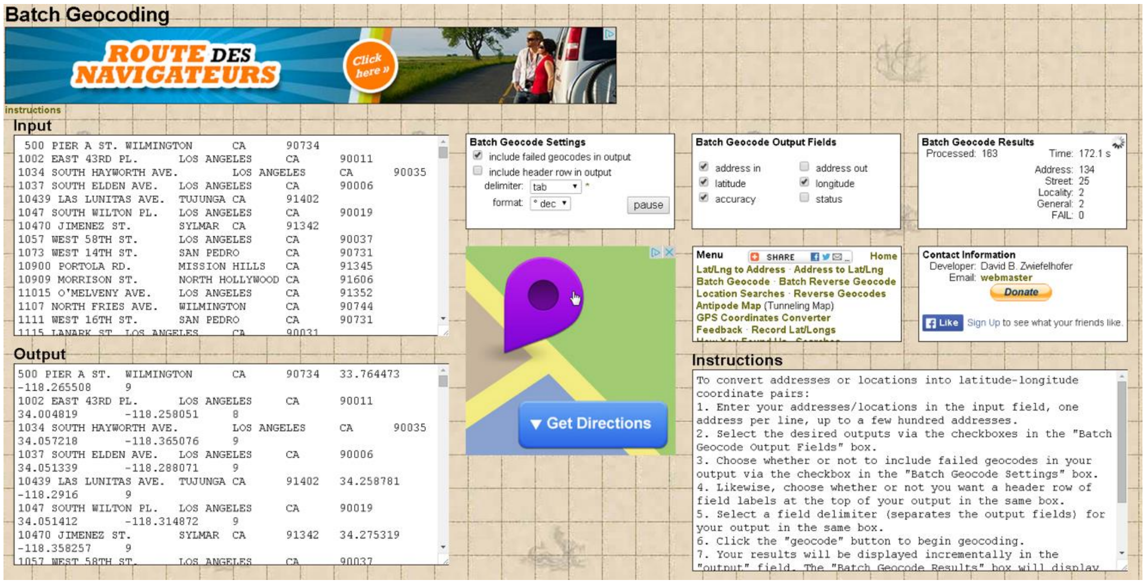
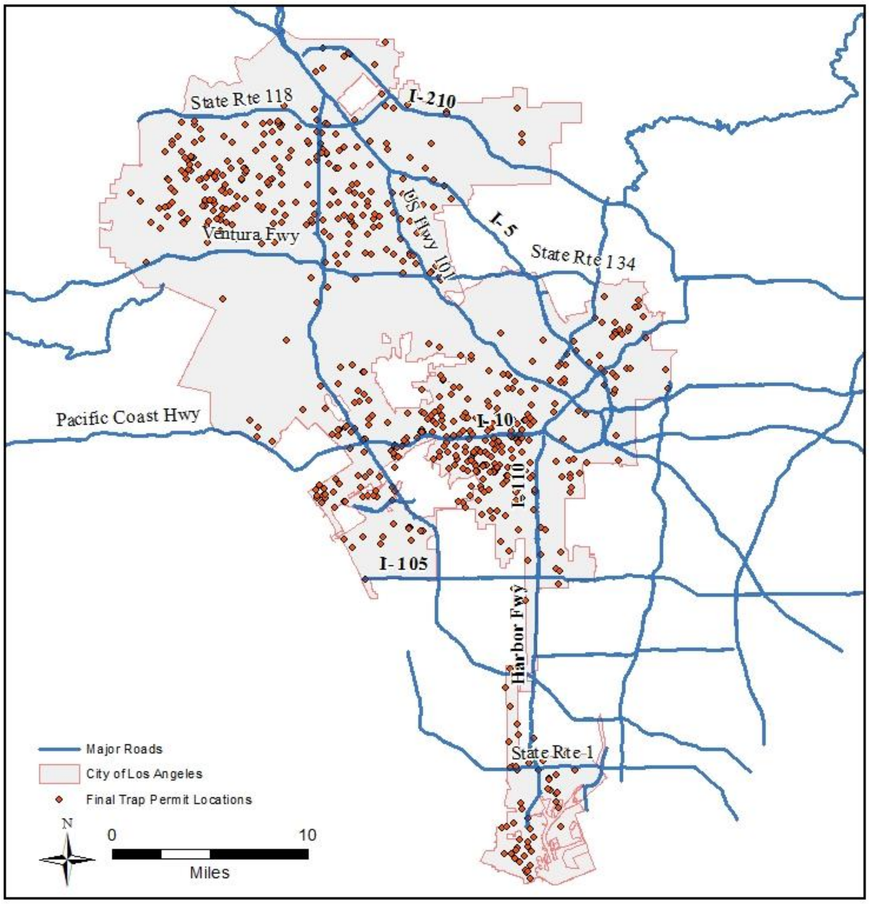


Figure 4. David B. Zwiefelhofer's Online Geocoder page.

The Excel file was then added back into Arcmap as a table and compared with the geocoded layer in preparation for a **Merge** operation. The new shapefile was created with the **Add XY Data** function, using the geographic coordinate system WGS 1984 since Lat/Lon were in decimal degrees, and the resulting layer exported to the geodatabase. The two layers were merged with unnecessary fields (e.g. Status, extra ObjectID's) deleted in the field map dialog. Further operations included reconciling coordinates since the merged layer contained both X/Y fields (from geocoding in ArcMap, expressed in US feet) and Lat/Lon fields (from geocoding online, expressed in decimal degrees.) Using the Calculate Geometry function from the field context menus, all null values for these fields were populated. The layer was then projected into the document's native system (NAD_1983_StatePlane_California_V_FIPS_0405_Feet.) The resulting point feature class, **FinalTrapPermitLocations (FTPL),** showing Cat Trapping Permit Locations (CPAs) is shown in Map 3.



Map 3. CPA locations derived from geocoding in Arcmap and using the online geocoder

A final step was taken in the cleaning process by using Select by Location to locate points that did not fall within a 2 km buffer which returned only one record that was deleted.

Validating Geocoding

This method of geocoding eliminates the step of re-matching addresses manually and has not been tested for accuracy or precision. Lacking the time, tools and resources to create a perfect ground-truth map with which to validate the points meant relying on available internet resources. Google Earth©, a freely available online mapping tool, was used to validate the geocoding. 30 random points were selected interactively from the map document by moving in a counter-clockwise direction and selecting points from various areas on the map to avoid concentrating on particular areas. The **Select by Attributes** function was then used to select the points from the online geocoding that had geocode accuracies of less than 8, which produced 8 more records, and these were checked to see if they were doubles of the random selection, which they were not. This selection was separated from the original layer by the **Create layer from selected features** function, yielding a layer for conversion into a .kml file suitable for viewing in Google Earth© layer. The selection was copied to a new spreadsheet and the addresses from the *Trapping Location* field were then copied into Google Earth manually, and saved to the TOC. The TOC was then saved as a .kmz file and imported into ArcMap using the **KML to Layer** tool. Both layers were turned on in ArcMap and **Select by Location** was used to determine if any of the points were identical. 13 out of 30 records were identical and the selection was run again to see if points were within a 2 kilometer distance to account for variation in coordinates. 28 of the 30 records fulfilled this parameter. Discrepancies in geocoding may have resulted in similarities in field entries (e.g. Marietta Avenue vs. Murietta Avenue) and confusion over cardinal directions in street names (e.g. West 122cd Street vs. East 122cd Street.) The decision to proceed with the records in this form was made. The two records were edited in the **FTPL_prj** layer, and analysis was continued. A screenshot of central Los Angeles, to visualize the validation process, is shown below in Figure 5, with geocoded entries as red dots and Google Earth entries as green stars.

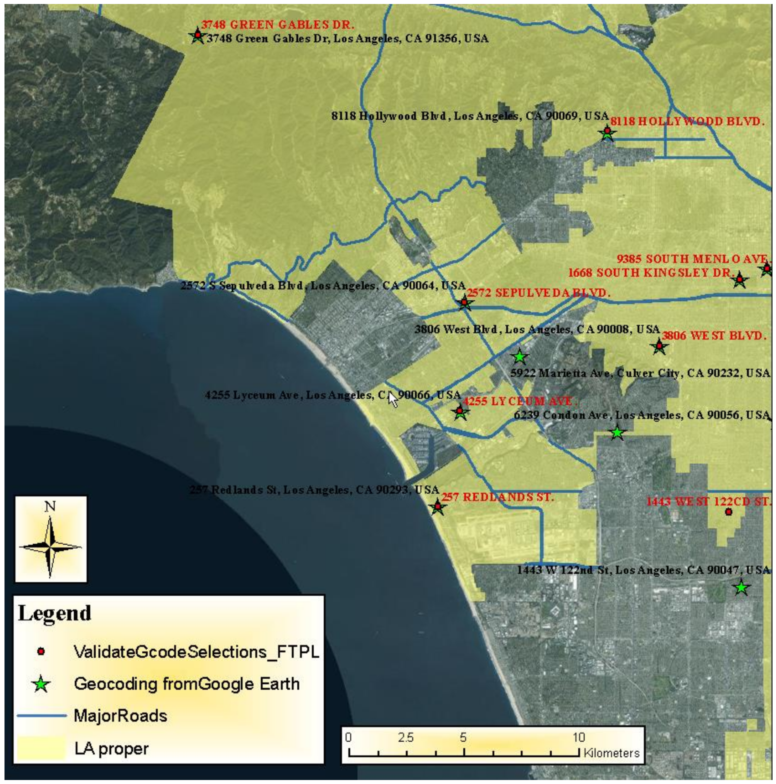


Figure 5. Results of validating geocoding mash-up using Google Earth.

Demographic, Municipal boundary, and Land Use Layers

Data from the U.S. Census Bureau were used to define variables for analysis. Data for city population and median income by census block would be used for comparison with CPA densities per census block. A geodatabase containing Census Block group data was downloaded from the U.S. Census Bureau's websites (http://www.census.gov/geo/maps-data/data/tiger-data.html.) This .gdb contained the feature class **2011_ACS_5YR_BG_06_CALIFORNIA**, which are census block polygons with selected demographic information. This layer was for the whole state of California and was missing information, necessitating selection and cleaning.

Total population and median income for each block were contained in the fields *B1001e1* and *B190013e1* respectively. A **Select by Location** was made to limit polygons to those that fell within a distance of 2000 feet of the **LAproper** layer. This distance was chosen so that the selection would include polygons within the buffer distance used for including CPAs. This intermediate layer was then manually cleaned of outlying polygons that would not figure into analysis (specifically water areas and 38 heavily outlying polygons) and exported as the layer **ACS_5YR.** Exporting the data projected the layer from the geographic projection system (in decimal degrees) to the native projection system of the document, resulting in fields with square feet as units that would have to be converted.

Population layer

The raw population field *B01001e1* was used to calculate the density of people per square mile in the AOI. Since the *Shape_Area* field of the block polygons was given in square feet, the new field *AREA_SQMI* was added to **ACS_5YR** and this was calculated by dividing the field by the number of square feet in a square mile (27,878,400). The new field *PPL_SQMI* was then added and calculated by dividing *B01001e1* by *AREA_SQMI.* This field would figures into the exploration of correlates between population density and CPAs.

Poverty Status

Noted earlier in the study by Aguilar and Farnworth is the use of the NZDI as a dependent variable in regression analysis of feral cats in Auckland, New Zealand. Poverty status in the United States is linked to the Consumer Price Index and individuals or families applying for governmental aid are assessed for certain criteria as to whether they qualify as below poverty status. US census data contains no comparable figure like the NZDI, so the analogous measure of Median Income (Median Household Income In The Past 12 Months- 2011 Inflation-Adjusted

Dollars – Universe-Estimate), *B19013e1*, was used as a proxy for poverty status. The new field *MEDINC_PERSON* was added to the attribute table of **ACS_5YR** and calculated to equal *B19013e* for clarity. The median income value has already been normalized for population and no further calculations were needed for it. This measure was used in the scatterplot created assessing correlates between poverty status and density of trapping applications.

Land Use

As part of the methodology for the study, land use was a possible factor in determining distributions of cats. LAGDP provided this layer in a zipped file and the file **Landuse.shp** was extracted and imported into **FinalFeralGDB.gdb.** The schema for this layer contained the standard fields and a field describing what type of land use was present in each polygon.

With 48 types of land use to review, it was decided to simplify the classification scheme of the land use layer. A Look Up Table (LUT) was created and joined to the land use layer. To bring the number of classes down from 48 to 5, the created table was given a *Land Use Score* field running from 0 to 4. Essentially the scale ran from 0 (Open Area/Green Space) to 4 (Heavy Industry/Manufacturing) in an approximation of where the literature indicated that feral cats were most likely to be found (Liberg and Sandell 1988). The LUT was created manually in Excel.

Once this table was joined to the LA land use layer, the land use map was re-symbolized using the new *LandUse Score* field in a simplified form by dissolving the boundaries based on the new land use score. Finding how many permits occurred in each class of the newly simplified land use layer presented with a problem resulting from the geocoding process. Some records did not fall within a specific land use polygon since some of the point places fell directly on streets. These records were selected and a new layer was created from the selection for editing. The non-coincident records were deleted from a copy of **FTPL_prj** in preparation for a later merge operation. The **Snap** tool in the editing toolbox was then used to snap the non-coincident points to the land use layer with the parameters of EDGE and a 100 feet threshold. The snap process was validated by selecting by location whether all the points now fell within the land use layer. This produced a better result, and the few points that fell outside the layer were manually moved within the layer. Three of the points were deleted since they fell outside of the relevant study area. The edited layer was exported to the geodatabase and then merged with the copy of **FTPL_prj** (containing the points that did not need editing) and the resulting layer, was exported as a new layer. By determining the number of points falling within each land use type, a graph was created showing the number of CPAs in each type.

Municipal boundaries

A further breakdown of the data by time was performed using the council districts of Los Angeles, a layer downloaded from the LAGDP. These districts are arbitrary administrative areas of the city functioning as a method of aggregating the data. By performing a spatial join between this layer and the **FTPL_prj** layer (where the CPAs are within the districts with a one-to-one relationship) and binning the dates in 6 month intervals, a table was produced showing numbers of applications per district per interval. The intervals used were from May to October and from November to April, approximating Summer and Winter months for this area. Records at the ends of the intervals were left off since certain intervals were incomplete.

Density Calculations

Any type of statistical analysis will require a range of values, and for regression analyses the values should be in ratio data format (Mitchell 2009). An essential problem with the permit locations data was that it contained no index upon which to base examinations. The *Approximate # Cats* field was considered, but since this data was neither complete (i.e. most of the applications did not have exact numbers of cats reported, and the default value of 5 would skew the mean) nor necessarily relevant this idea was not pursued. Lacking interval or ratio values for analysis, the next step was to aggregate points and calculate densities for each census block.

The Spatial Join tool creates a new feature class with the attributes of the input layers and two new attribute fields, the *Target FID* and the *Join_count.* The *Join_count* field is based upon the desired user input spatial relationship in the Match Option dialog (e.g. contains, within, within a distance of) between the target features and the join features.

The layers **ACS_5YR** and **FTPL_prj** were spatially joined using the following parameters:

Target Features: ACS_5YR
Join Features: FTPL_prj
Output Feature Class: ACS_FTPL_SPJO
Join Operation: ONE_TO_ONE
Match Option: CONTAINS

The field **Density_Apps_per_Block** was added to the resulting **ACS_FTPL_SPJO** layer and the field calculator was used to calculate the density of number of applications within each block by dividing the *Join_count* field by the *AREA_SQMI* field. The **ACS_FTPL_SPJO** layer was subsequently used for several of the other analyses performed.

Average Nearest Neighbor

While the initial visualization of the permit data points indicated that the points were likely clustered, the Average Nearest Neighbor tool was run to show that this was true. The area of the **LAproper** layer had an area of ~13,187,296,732 square feet, and this was used as the optional **Area** parameter for the tool. The **FTPL_prj** layer was input and the tool was executed with the following parameters:

Input Feature Class: FTPL_prj
Distance Method: EUCLIDEAN_DISTANCE

Generate Report: Enabled
Area: 13,187,296,732

The Average Nearest Neighbor tool is in the Spatial Statistics toolbox and the operation is shown below in Figure 6.

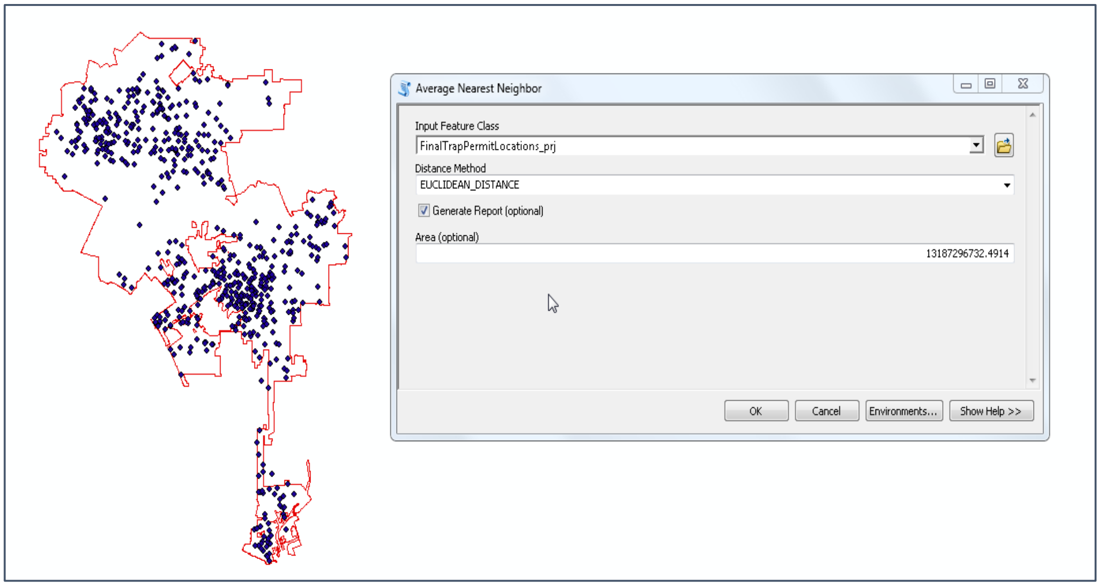


Figure 6. User interface for Average Nearest Neighbor tool.

Kernel Density Estimation (KDE)

Kernel Density Estimation is a method particularly suited to this type of dataset in that it is useful for data with no associated index value (e.g. population, frequency.) The method returns a raster surface with intensity values based on proximity alone. The tool moves a “kernel” of cells across an AOI and weights centrally located points more heavily than those at the edges of the kernel. As the kernel moves across the area, points will accrue weight as their proximity increases. The equation for the KDE function is:

$$\hat{\lambda}(s) = \sum_{i=1}^{n} \frac{1}{\tau^2} \kappa\left(\frac{s - s_i}{\tau}\right)$$

where $\widehat{\lambda}(s)$ is estimated intensity at location s; s_i is observation I, κ is the kernel weight function and τ denotes bandwidth (search radius). As an investigative tool, KDE produces continuous surfaces that readily show clustering and intensities without the need for index values and avoids the pitfalls of areal aggregation techniques such as quadrat counts. (Kloog, Haim and Portnov 2008).

This tool was operated on the **FTPL_prj** layer and a raster surface created showing relative densities of CPAs in the Los Angeles AOI. While the number of records used for this study is well within bounds for most statistical analyses, it is still relatively small given the time period over which it was collected and the area it covers. It was decided to use a dataset in the early stages of cleaning and geocoding preparation for comparison. This dataset was comprised of phone records from various animal service centers between 2011 and 2013, and has the advantage of containing over 10,000 records. This lends credence as a proxy measure for cat complaints, the logic being that cat problems multiplied by people equals the beginning of the next step, applying for a permit to trap. This data was supplied in the form of a spreadsheet that was cleaned of empty fields only and quickly geocoded, keeping only records that came back positive. KDE was run on this dataset, **PCCL_prj** (Preliminary Cat Call Locations) for comparison with the KDE from **FTPL_prj**. The tool was run using the default parameters. Search radius in this case is calculated from the input points and the configuration of points, accounting for outlying points very far from the bulk of points (Esri ArcGIS Desktop Help 10.2 2013).

Hotspot Analysis (Getis-Ord Gi* statistic)

Drs. Arthur Getis and Keith Ord are credited with developing both the General G and the Getis-Ord Gi* statitistics which are measures of high and low concentrations of values within distances Both methods compare neighboring features to a target feature, the difference being that Gi* includes the value of the target feature in the calculations. This is useful in identifying hotspots and coldspots in that the target feature contribute to any clustering that is present (Mitchell 2009).

The Gi* statistic is calculated by summing the values of the target feature's neighbors (either by adjacency or by distance if a likely value is available, using binary weighting) and dividing by the weighted sum of all the values in the AOI. Since the weights of non-adjacent/non-neighbor features will be zero when computing the score for a target feature, these values will not affect the target's score. The formula for the Gi* statistic is:

$$G_i^*(d) = \frac{\sum_i w_{ij} \ (d)x_j}{\sum_i x_j}$$

where i is the value for a feature, d is a distance variable, and j is the binary weighting factor.

The Optimized Hotspot Analysis tool Figure 7) was used for the operation. This script analyzes the data and sets parameters based on the analysis, including checking for distance outliers and incremental spatial autocorrelation using valid locations. The Gi* statistic was calculated for the **ACS_FTPL_SPJO** layer with the following parameters:

Input Feature Class: **ACS_FTPL_SPJO**
Output Feature Class: C:\[...]\FinalFeralGDB.gdb\ACS_FTPL_OHS
Analysis Field: CPA_DENSITY

This information has value for future use if one wanted full control over the parameters using the non-optimized version of the tool.

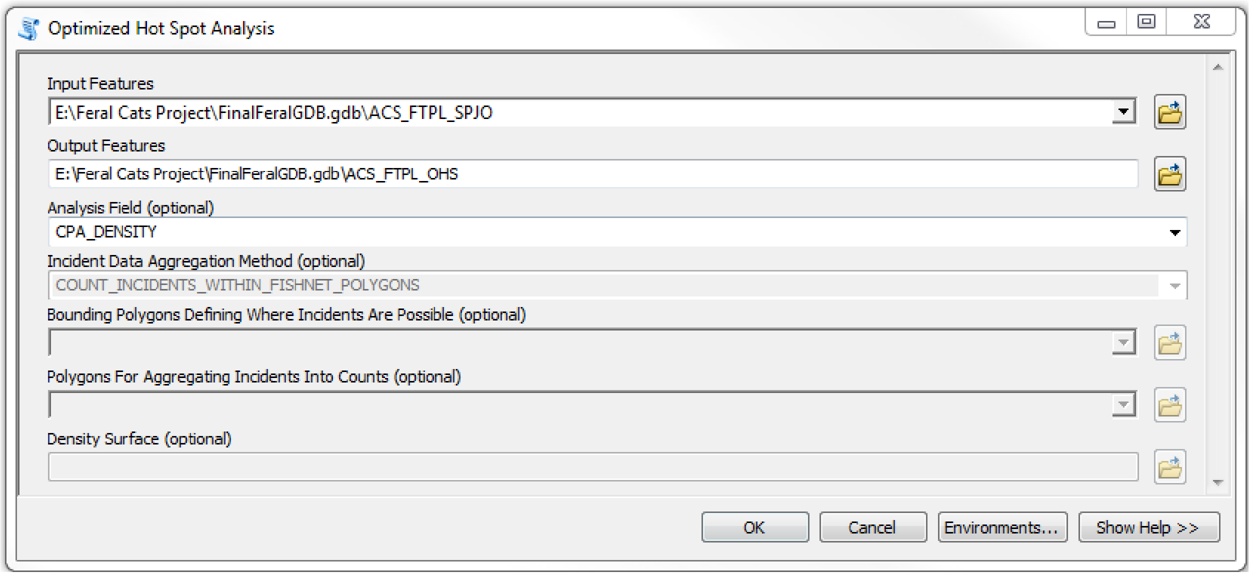


Figure 7. User interface for Getis-Ord Gi* calculation (Optimized Hotspot Analysis).

The outputs of the tool are the new feature class layer containing the standard fields and the results of the computation: the p value, the z score, and an ordinal bin number to allow easy grouping of confidence levels. The p value indicates the probability that the pattern is the result of random processes, and is used to establish confidence levels. Very low p values associated with high absolute z values indicate areas that are significantly different from the theoretical random distribution.

Three maps were produced for the **ACS_FTPL_SPJO_OHS** layer . A cold to hot color ramp was used using the default classification scheme (Jenks). The map themes were:

1. Confidence levels from the Gi Bin score
2. Z-score of aggregated CPAs per census block
3. Selected CB/gridcell where $p<0.05$ and $z> 1.96$

Local Anselin Moran's I

While Moran's *I* is useful for determining whether a spatial pattern is clustered, it does little to pinpoint where it is clustered since it accounts for all features in the AOI whether they are proximal or not. Like the Gi* statistic, Local (Anselin) Moran's *I* takes into account a target features neighbors only, and uses binary weighting. The target features and its neighbors are both compared to the mean. The equation for Local Moran's *I* is:

$$\mathrm{I}_i = \frac{(x_i - \overline{x})}{s^2} \sum_i w_{ij} \, (x_j - \overline{x})$$

where I is the index of the target feature, x_i is the value of the target feature, $\overline{x}$ is the mean of the data, s^2 is the variance, w_{ij} is the weight of the target/neighbor pair, and x_j is the value of the neighbor.

Local (Anselin) Moran's *I* (Cluster/Outlier Analysis) was calculated for the **ACS_FTPL_SPJO** layer. The following parameters were used in the calculation:

Input Feature Class: **ACS_5YR_FTPL_SPJO**
Input Field: CPA_DENSITY
Output Feature Class: C:\[...]\FinalFeralGDB.gdb\ACS_LMI_IDW2
Conceptualization of Spatial Relationships: INVERSE_DISTANCE_SQUARED
Distance Method: EUCLIDEAN_DISTANCE

All other parameters were left at default settings.

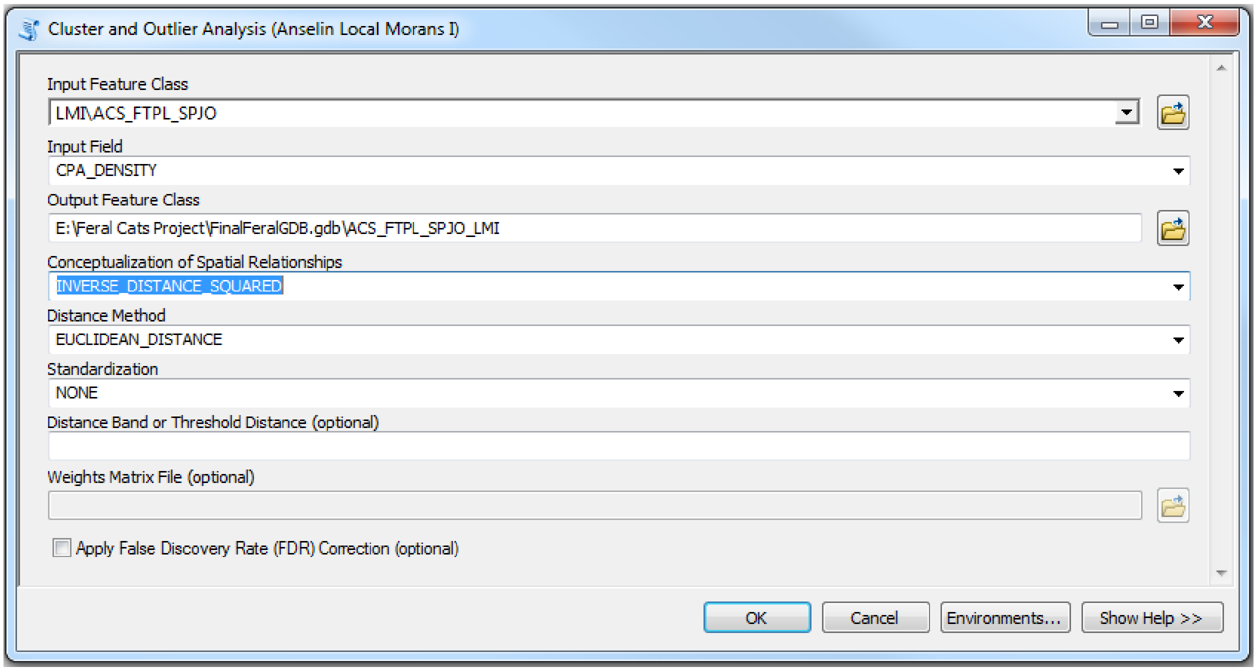


Figure 8. User interface for local Moran's I calculation.

The outputs for Local Moran's *I* are the new feature class containing the standard attribute fields and four new fields: the *LMiIndex* field, the *LMiZScore* field, the *LMiPValue* field, and the *COType* field. The LMiIndex is the raw calculation with high values showing that the target feature is has neighbors with similar values that can be high or low. A target feature surrounded by similar values (i.e. large highs or small lows) will have a high *I* score. Negative values show that the target is surrounded by neighbors with values unlike the target. Because Local Moran's *I* is dependent on the differences in values between the target and its neighbors, a single neighbor with a very different score could have strong effects on the *I* value for a target feature (Mitchell 2009).

The z-score for *I* is an indicator of statistical significance for the dataset and the p-value is the confidence level and can be used in conjunction with the z-score to determine which values are significant within a certain probability level. The CO(Cluster/Outlier) value is a reclassification/selection of the z-scores and I values where areas with high or low I values are surrounded by significant z-scores, high or low. The software takes care of this selection by location and attributes.

Two maps for each input layer were produced from the tool: 1) the COtype for density of CB's in the AOI, and 2) Z-scores for density of CB's in the AOI. Statistics and frequency distributions were also output from the values calculated.

Scatterplot Matrix

Determining likely variables that may contribute to the distribution of CPAs in Los Angeles is best accomplished by graphing the variables of interest against each other using the Scatterplot Matrix function available in ArcMap©. This tool allows for multiple fields to be entered into a GUI and having all possible plots represented in a single window. This is valuable in deciding whether further analysis is warranted for certain variables. The function returns only general trends: no metrics are computed e.g. a fitting (regression) line or residuals.

Since a preponderance of the dataset contained no data for certain polygons, it was decided, after consultation, to eliminate the polygons for which the field *CPA_DENSITY* was zero. A selection was performed and an interim analysis layer, was exported to the geodatabase and evaluated with the Scatterplot Matrix function.

The function was opened and 3 fields from the **ACS_FTPL_SPJO** layer were selected and labeled for plotting:

1) CPA_DENSITY (Apps/SQMI)
2) MEDINC_PERSON (Median Income per capita)
3) PPL_SQMI (People/SQMI)

Ordinary Least Squares Regression

While the scatterplots of income and population versus density of applications indicate some pattern in each of the distributions, quantifying these relationships and modeling these relationships simultaneously can be done using Ordinary Least Squares regression (OLS), a global method allowing for multi-variate analysis. This is a well-documented statistical method that results in a number of diagnostic values and requires a few formatted parameters. The equation used for the OLS is:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

where y is application density, $\beta_0 \ldots \beta_n$ are the computed coefficients showing strength and relationship with explanatory variables, and ϵ are the residuals, over and under predictions showing the unexplained proportion of the dependent variable (Esri ArcGIS Desktop Help 10.2 2013). The GUI for OLS is shown below in Figure 11.

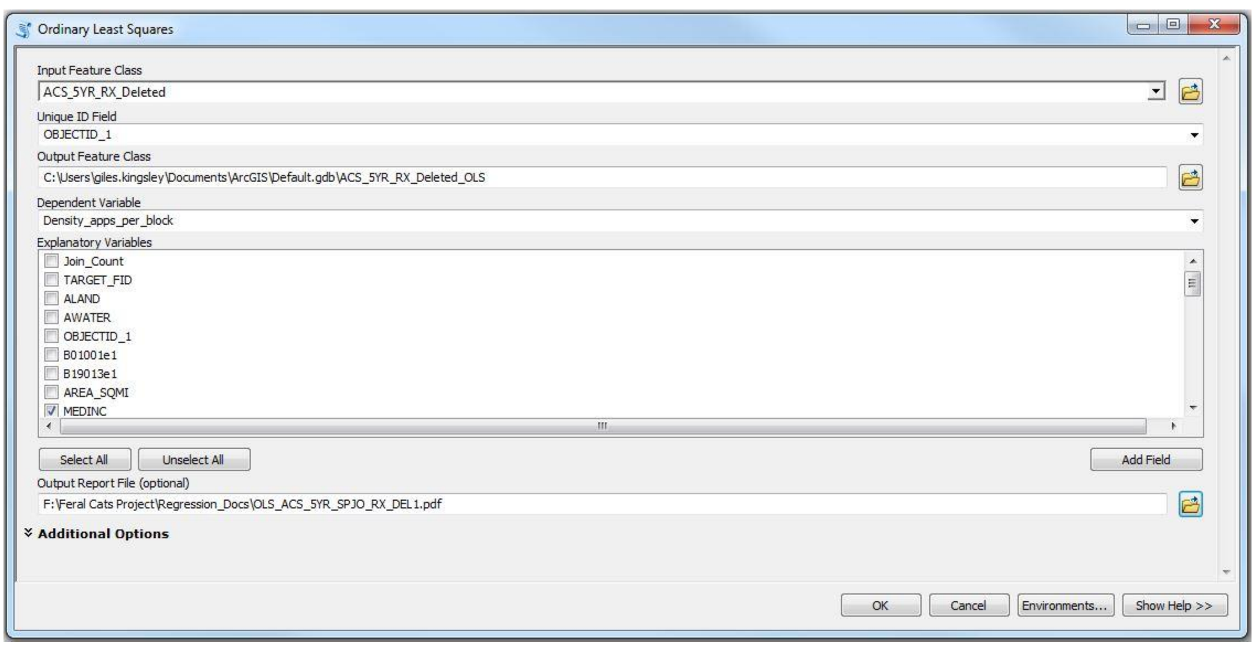


Figure 9. GUI and parameters for OLS

Outputs from OLS are a new feature class containing the attributes of the variables, and the standard and estimated residuals of the analysis. In addition, there are optional tabular outputs that show various diagnostic values for the test. Assessment of these outputs indicates model performance, whether the model is properly specified, and can give some indication of missing variables or model bias.

CHAPTER FOUR: RESULTS

Initial Analysis, Visualization, and Data Summary

One of the unique features of the **FTPL_prj** layer was the ancillary information regarding the reasons people were applying to trap cats. The graph below shows percentages of these reasons for trapping for the entire dataset.

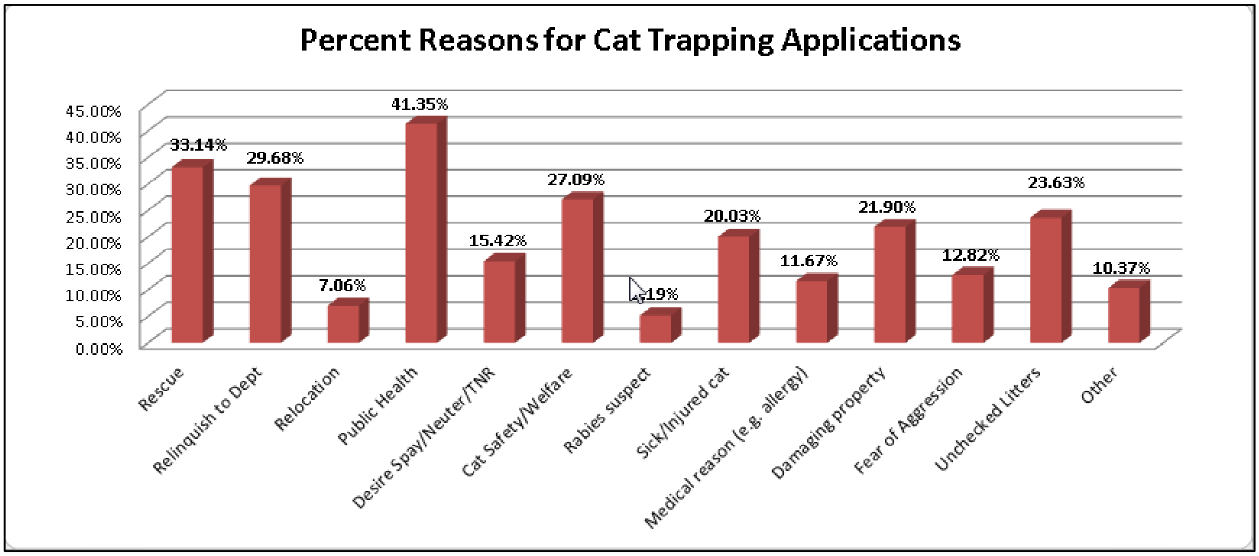
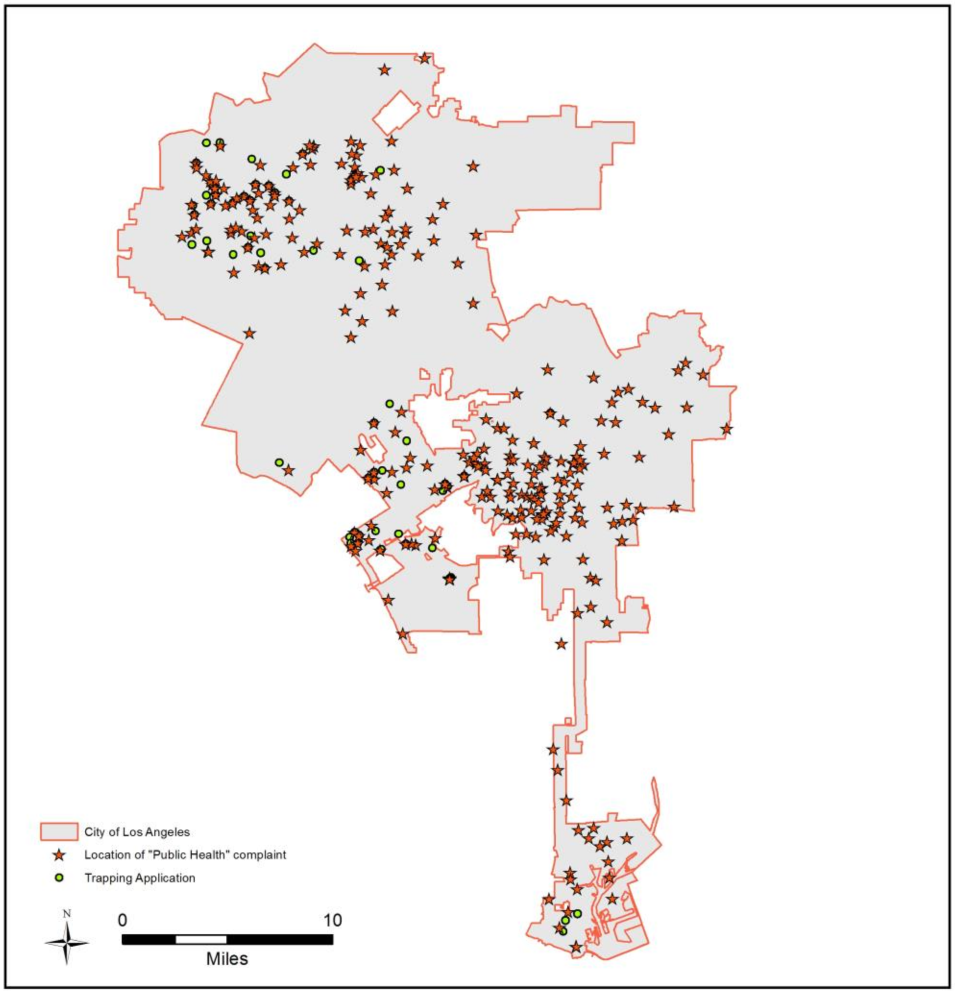


Figure 10. Prevalence of reasons given for applying to trap cats by percent of applications

The reason of most concern to LA’s citizenry is that of public health (Figure 10). A third of people had no desire to deal with ferals by lethal means (evidenced people who wished to rescue the cats.) This information could be of use to municipal services (such as those working in animal service centers or public health agencies). The applications where public health were of concern to people were visualized for the entire area (Map 4) and by visual inspection did not differ from the distribution of permit applications overall.



Map 4. "Public Health" complaints compared to all permit locations

Other permutations of this map are possible using other SQL queries. Relating (using a relationship class) this data layer to other data layers (e.g. census block, neighborhoods) could be useful in identifying areas with certain attributes that might relate to prevalence of various reasons for trapping cats. For example, the cultural make-up of a neighborhood could have an effect on whether or not people were interested in TNR activities rather than taking trapped cats to the shelter.

Binning the data by year shows the some of the limitations of the data, since some years (i.e. 2004 and 2013) contained only records for part of the year. Table 1 below shows how many applications (that were ultimately entered into the database) were received for particular years by district.

	DISTRICT															
6-MONTH INTERVAL	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Grand Total
10/2004-4/2005			3		2	1					6	5				17
5/2005-10/2005			8		3	2	1			1	10	10			2	37
11/2005-4/2006	2		5	2	3	1				1	5	4	1		6	30
5/2006-10/2006	10		18	4	6	3				5	9	16	11	10	22	114
11/2006-4/2007	4	7	1	2	5	4	4				5	11	2	2	6	53
5/2007-10/2007	7	7	7	8	12	8	4			5	19	7	3	4	7	98
11/2007-4/2008		4	7		3	2	1	4	2	8	1	6			1	39
5/2008-10/2008	6	5	11	6	10	6	4	17	5	27	6	10		1	3	117
11/2008-4/2009	1	1	3	2			6	10	10	6	5	8				52
5/2009-10/2009	3				1	1		10	5	30						50
11/2009-4/2010	1			1	1	1		4	3	8						19
5/2010-10/2010							1	5		1					1	8
11/2010-4/2011		4	1	2		7	2			1						17
5/2011-10/2011		8		1		8	11									28
Grand Total	34	36	64	28	46	44	34	50	25	93	66	77	17	17	48	679

Table 1. CPAs recorded by Council District over the period 2004-2011.

The number of applications received by year and provided in the dataset varied substantially (Figure 11). The lack of applications for the years 2004 and 2013 indicate incomplete records for those years.

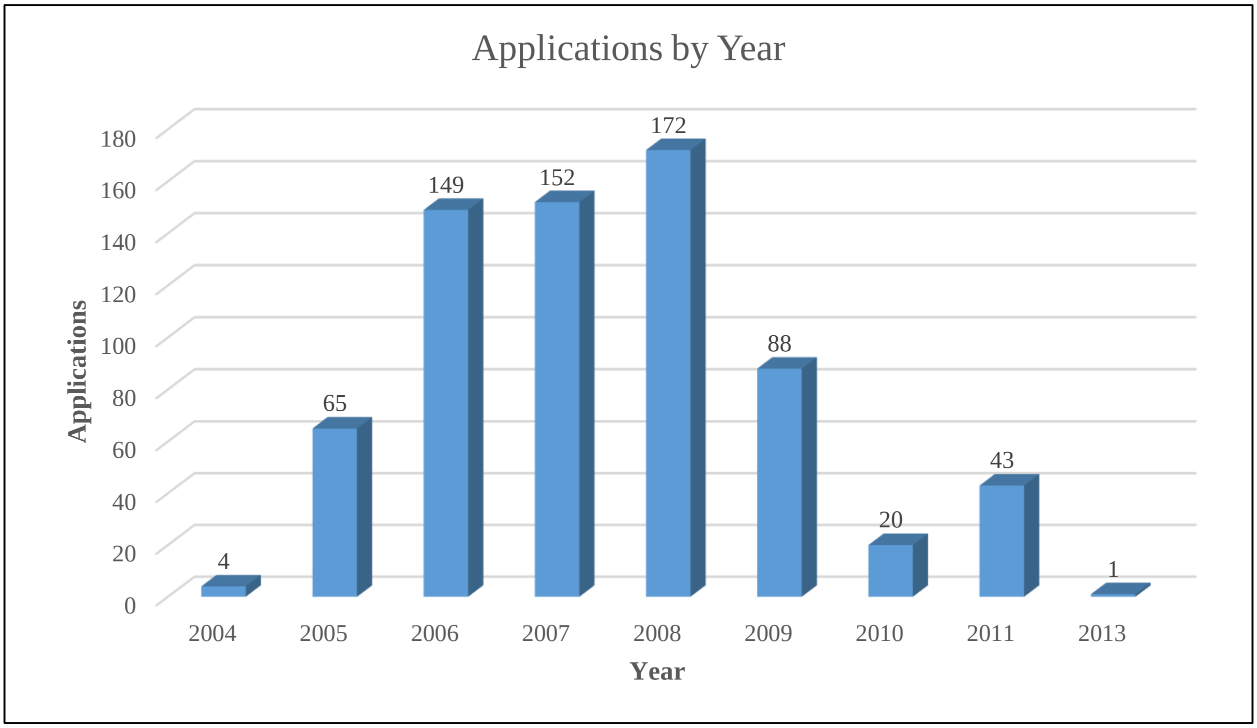


Figure 11. Number of applications received for years covered in the dataset.

Density Calculations

The density of permit applications per census block had a range of 0.00 to ~54.7 and a mean of ~2.00 applications per block. The statistics and frequency distribution show many zero values and a long tail (Figure 12; see also Map 2).

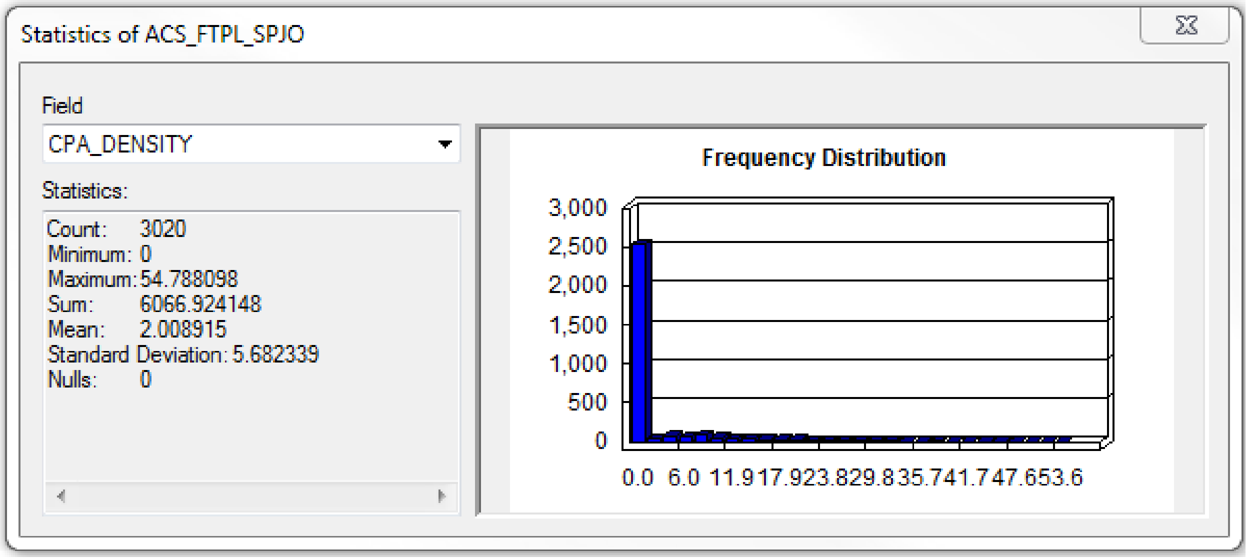
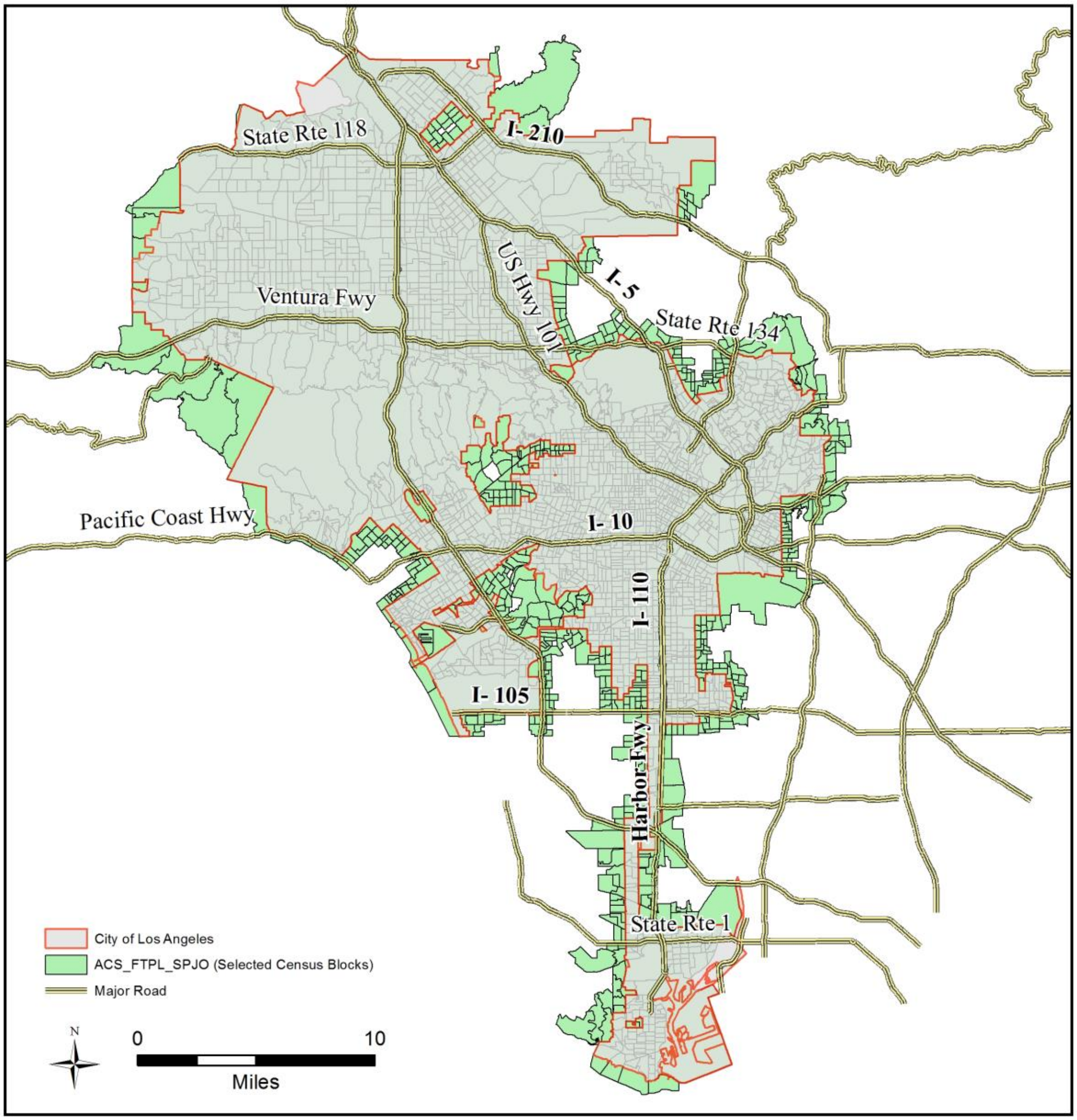


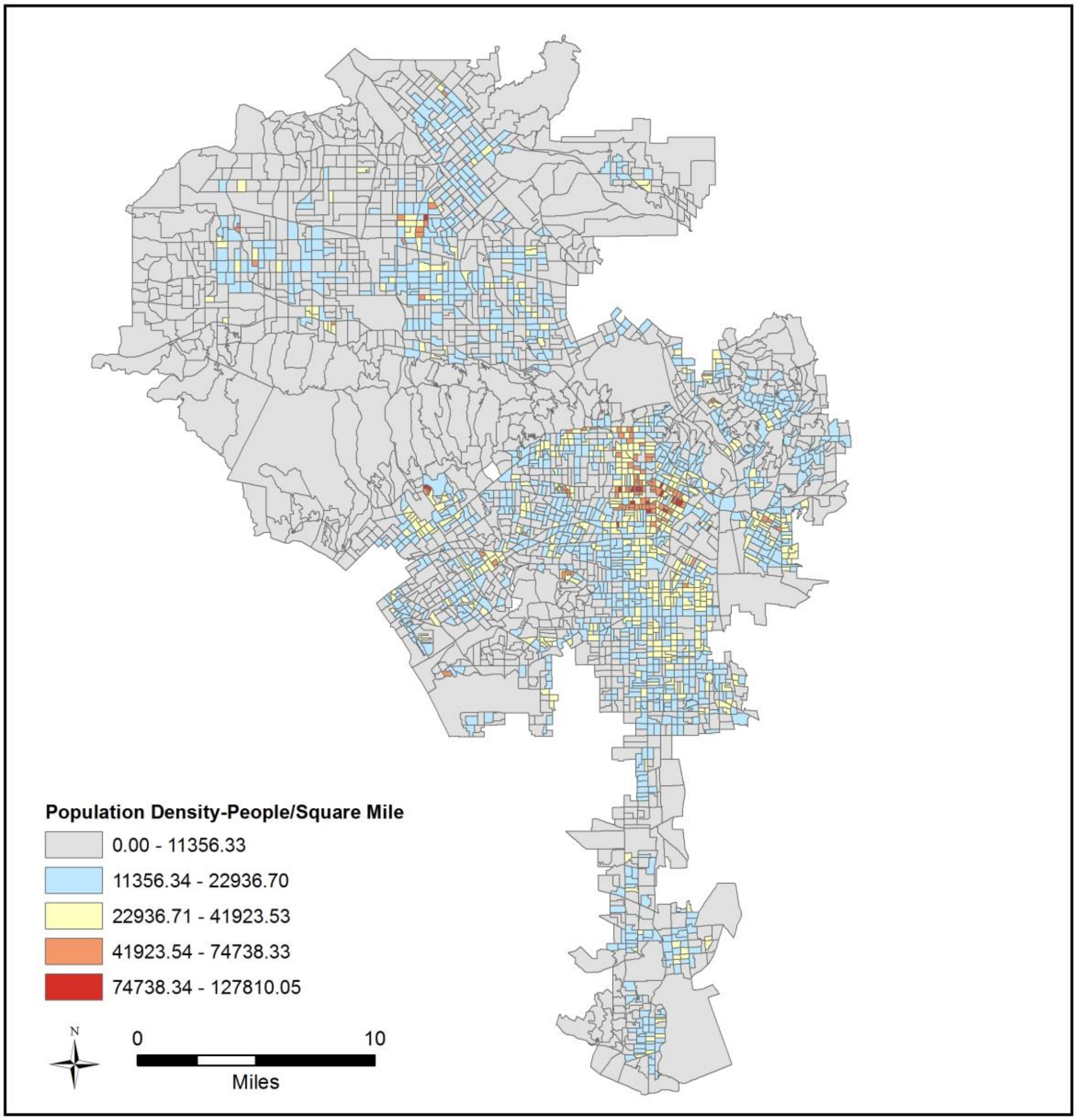
Figure 12. Statistics from CPA Density calculation of Census Blocks layer.

Demographic Layers

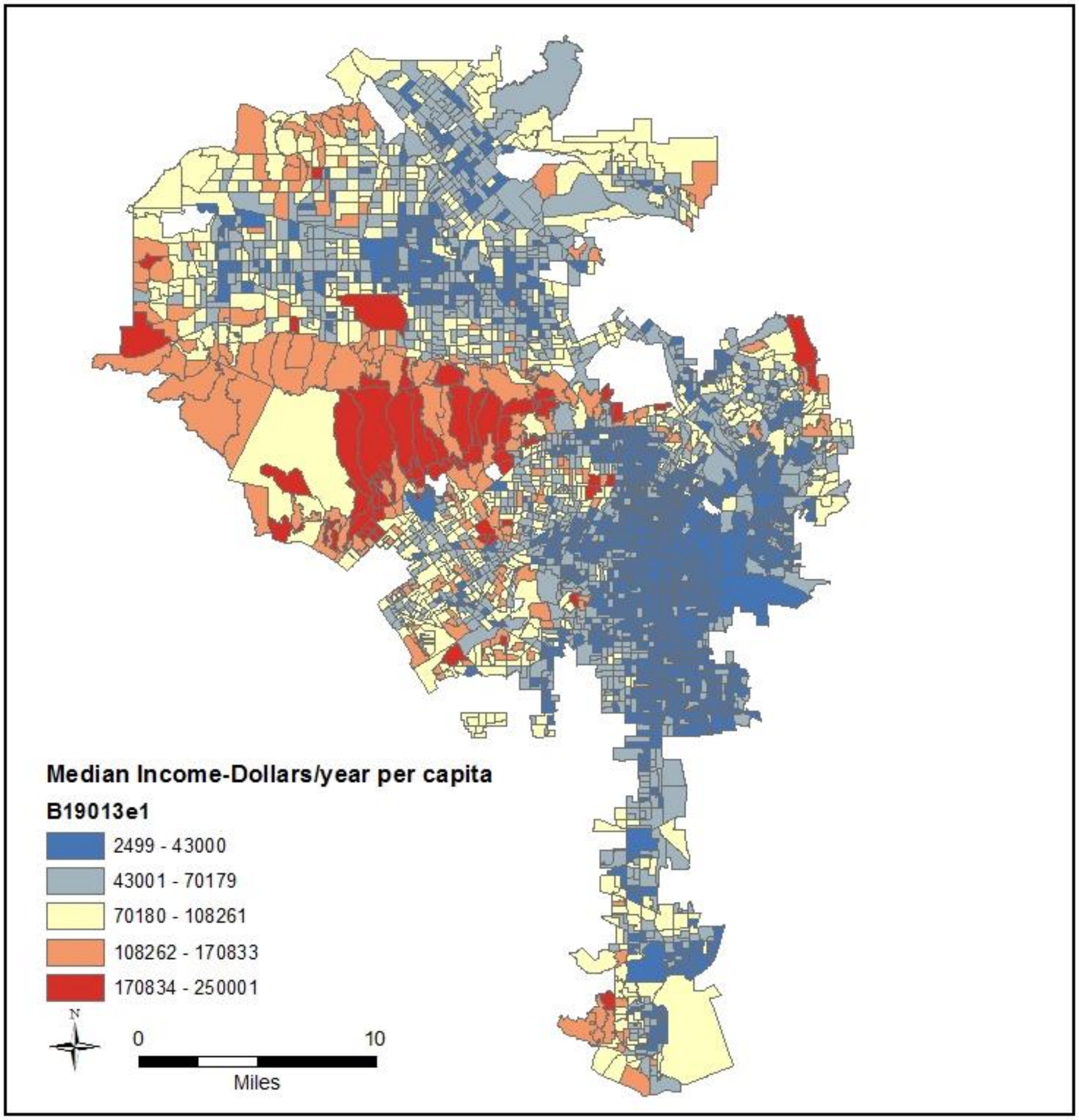
The edited census block layer **(**Map 5) was used to investigate density of applications, human population and income. Population density in Los Angeles is concentrated in a few areas, with the highest concentration around downtown and the Wilshire corridor (Map 6). The highest income census blocks, however, are concentrated in the western Santa Monica Mountains (Map 7). Visual inspection of the density of cat trap permits per block suggests influence of these two parameters, but is clearly not determined by these factors alone (Map 8).



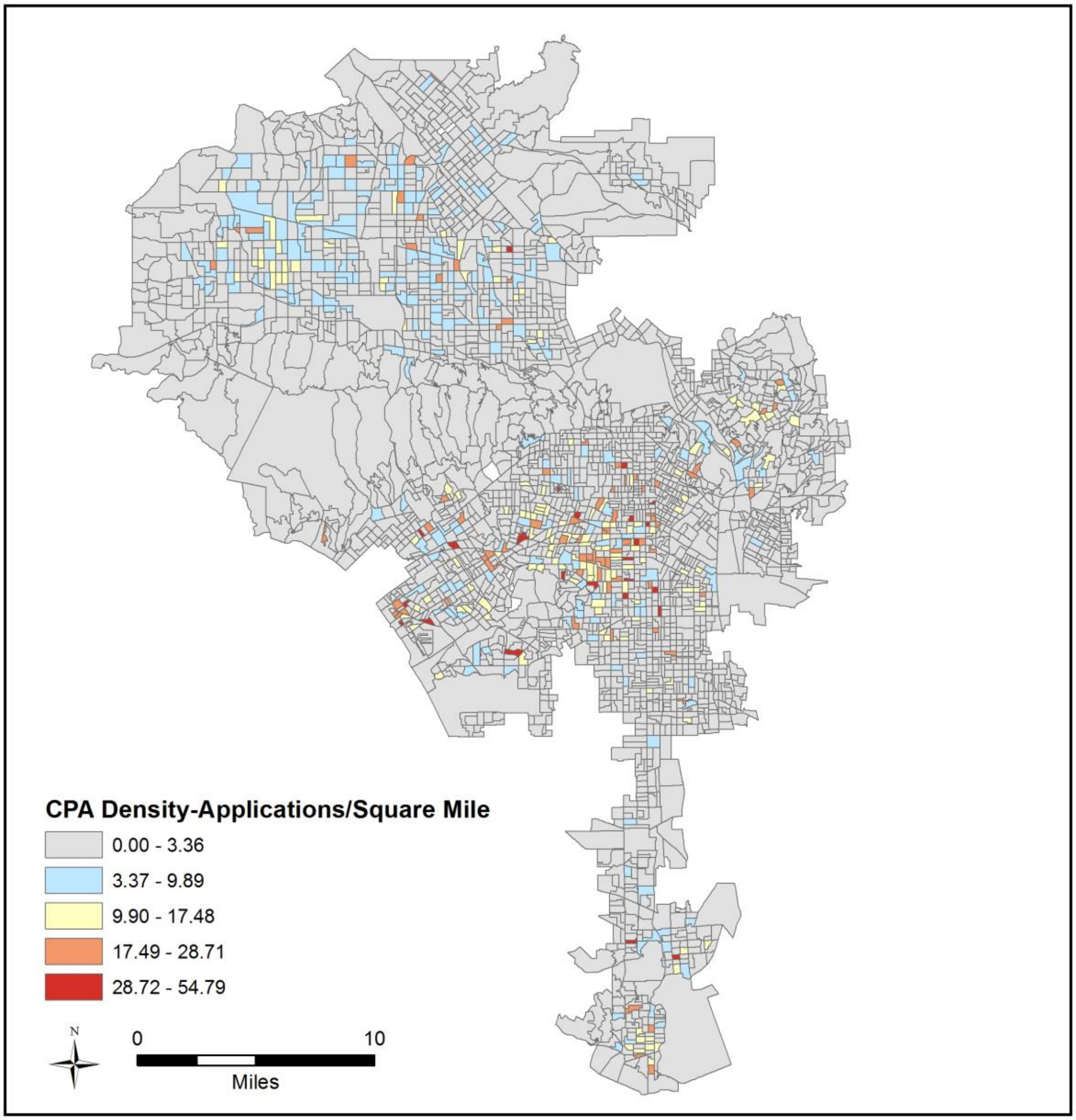
Map 5. ACS_5YR layer in relation to the AOI.



Map 6. Population density in Los Angeles calculated from raw data by area



Map 7. Median Income per person in Los Angeles, annual dollars per year per capita



Map 8. Total density of CPAs in the Los Angeles AOI for the years 2005-2013

Land Use Evaluation

Most (85%) permit applications originated from residential neighborhoods (Figure 13). Given the preponderance of values showing up in the Residential category of the graph further analysis of land use was deemed to be unnecessary unless changes were made in how to model this factor.

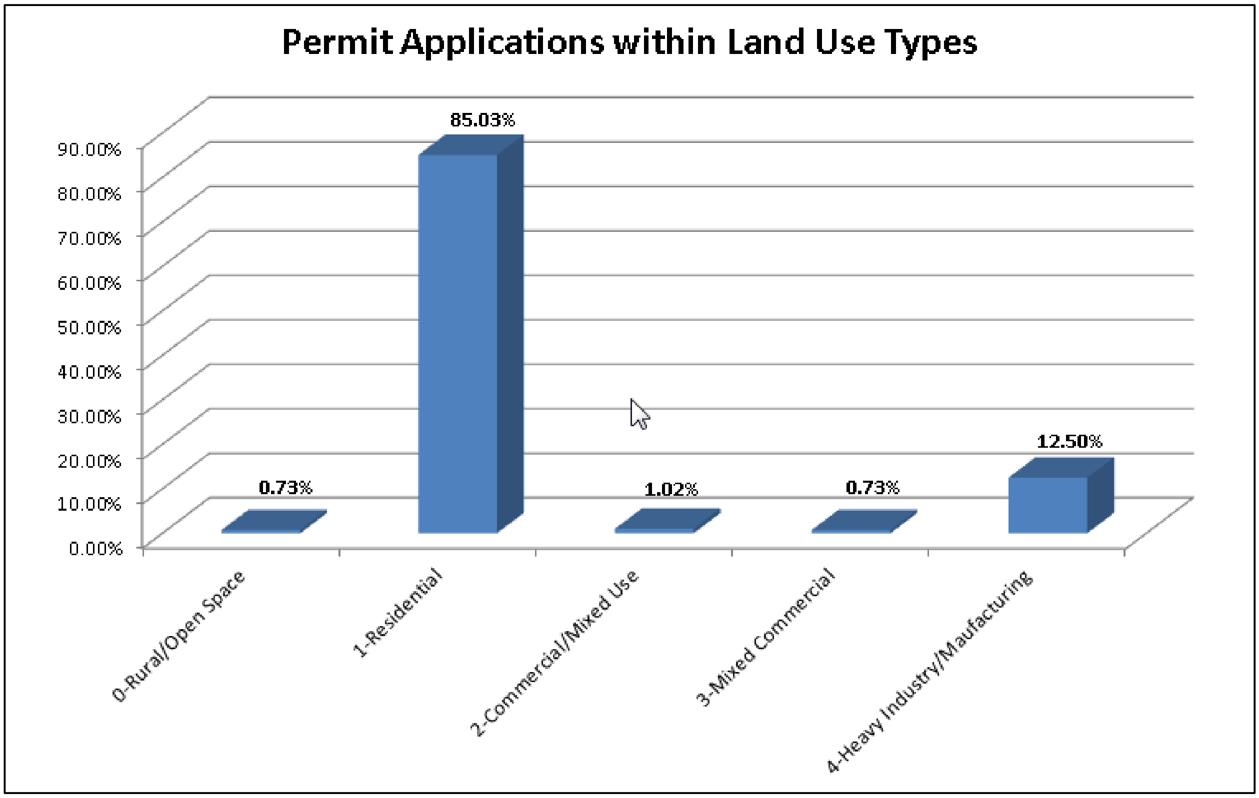
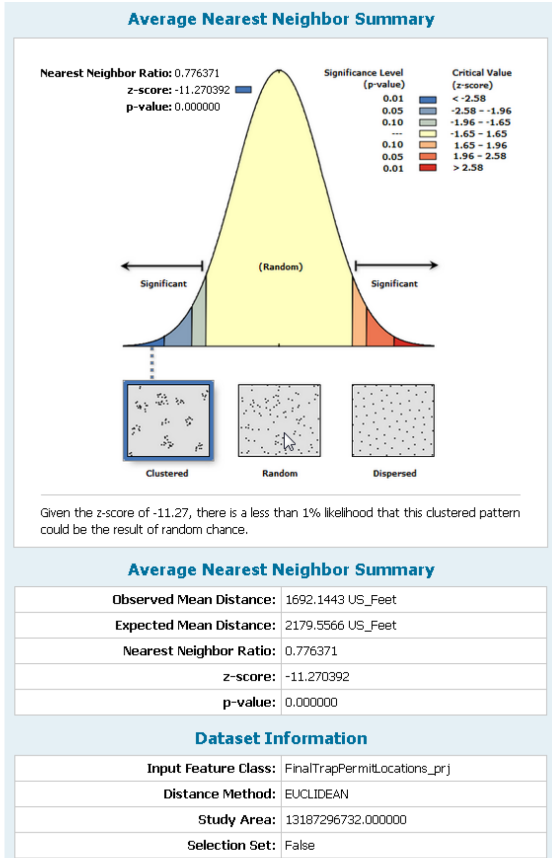


Figure 13. Percent of cat trapping permit applications originating by land use

Average Nearest Neighbor

The results of the Average Nearest Neighbor analysis showed that the CPA layer was clustered. The z-score obtained was -11.270392, well below the critical cutoff of -2.58 standard deviations from the normal. With a Nearest Neighbor Ratio of ~0.77 (the ratio of Expected mean distance to Observed mean distance) below 1, clustering is also indicated (Figure 14).



Average Nearest Neighbor Summary

Observed Mean Distance:	1692.1443 US_Feet
Expected Mean Distance:	2179.5566 US_Feet
Nearest Neighbor Ratio:	0.776371
z-score:	-11.270392
p-value:	0.000000

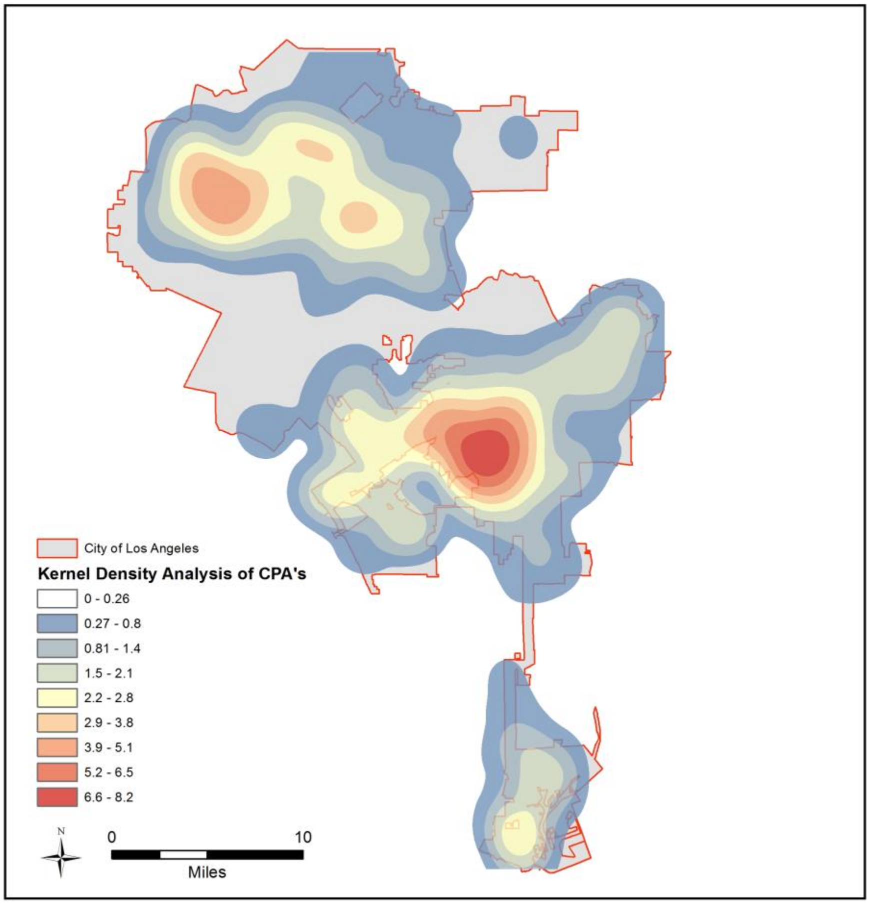
Dataset Information

Input Feature Class:	FinalTrapPermitLocations_prj
Distance Method:	EUCLIDEAN
Study Area:	13187296732.000000
Selection Set:	False

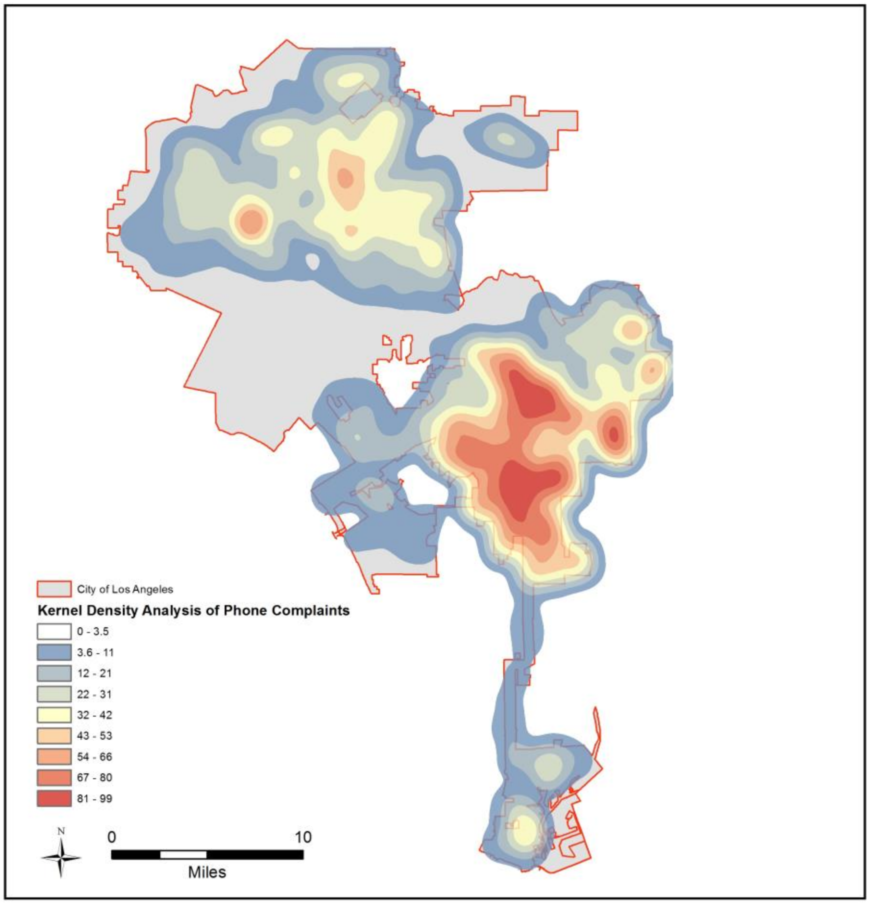
Figure 14. Average Nearest Neighbor analysis output report

Kernel Density Estimation (KDE)

Maps 8 and 9 below Kernel Density Estimation provides a visualization of the density of trap permits (Map 8) and phone call complaints about stray cats (Map 9). Initial visual inspections show that CPAs roughly mirror the phone call data, with some outlying areas. This is positive support for the use of the permit application data as an indicator of concentrations of feral cats. This is one of the caveats of using this method in that it is visually enticing, but it must be remembered that the input parameters can create different maps with the same data, and that this method can suffer with “small” data sets (Chainey, Tompson and Uhlig 2008).



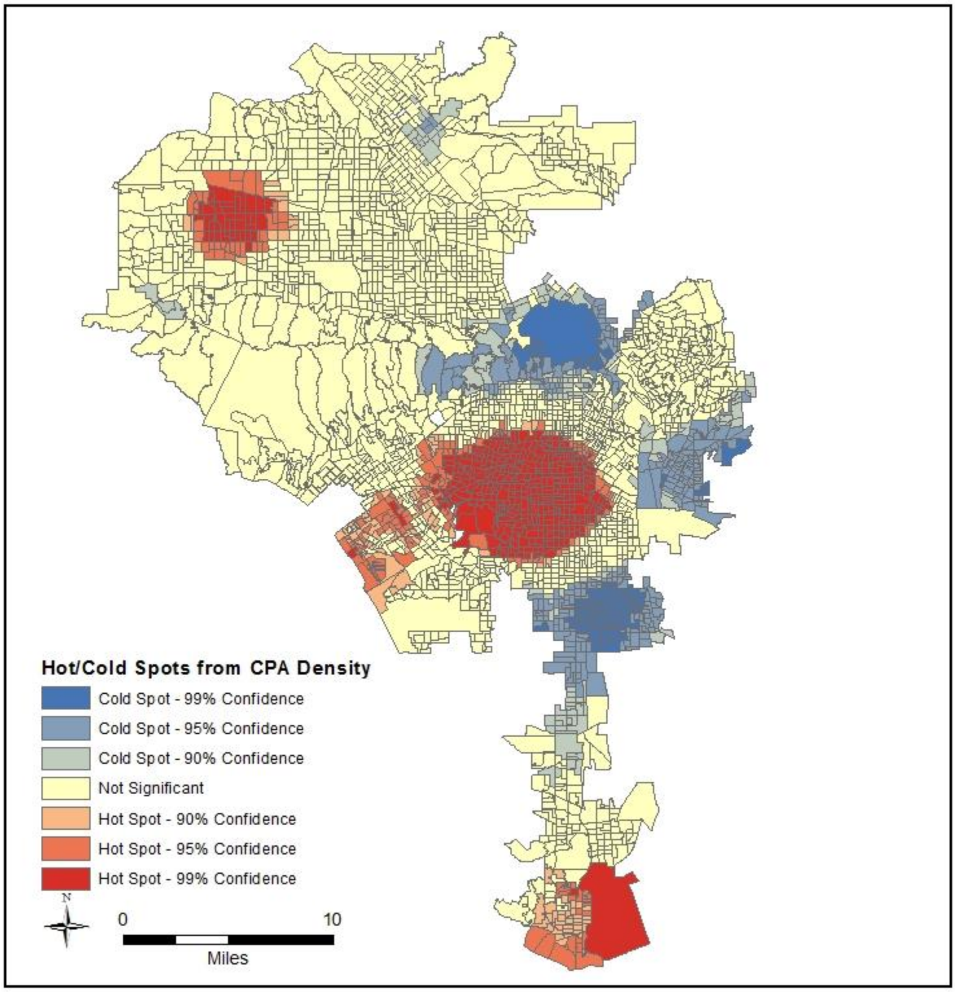
Map 9. Density (# of applications) of CPAs in the City of Los Angeles from 2004 to 2011



Map 10. Density (# of applications) of unowned cat reports by phone from 2004 to 2011

Optimized Hotspot Analysis (Getis-Ord Gi* statistic)

The layers created from the Hotspot analysis for the entire dataset showed groupings according to densities of CPAs. Running the tool reported that there were 59 outliers not included in the distance band calculation, and the optimal distance band was ~15,043 feet. Z-scores indicate census blocks where densities were significantly higher or lower than the means for the densities and p-values indicate the confidence level (probability) that the z-scores arise from random chance. Areas with high z-scores and low p-values have a high probability that the z-scores do not arise from random chance. Several significant hot and cold spots were identified across the study area (Map 10).



Map 11. Hotspots and coldspots for CPAs by confidence level

Z-scores for the joined census and CPA layer had a range of -4.09 to 12.42 (Figure 15) and provide an indication of how "hot" or "cold" the significant hotspots and coldspots are (Map 12).

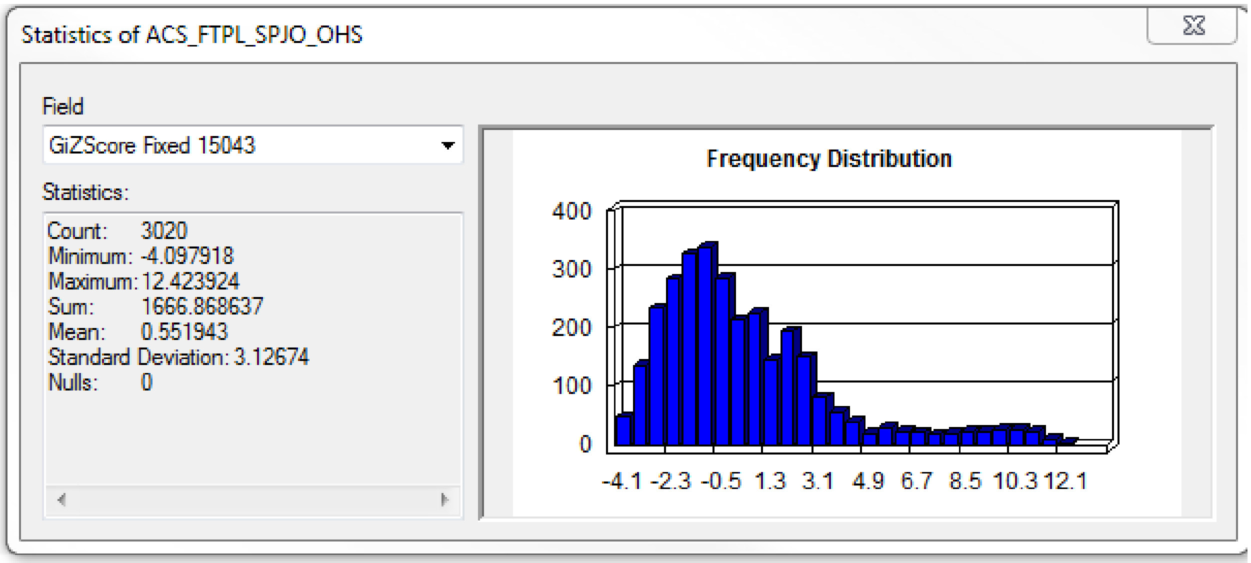
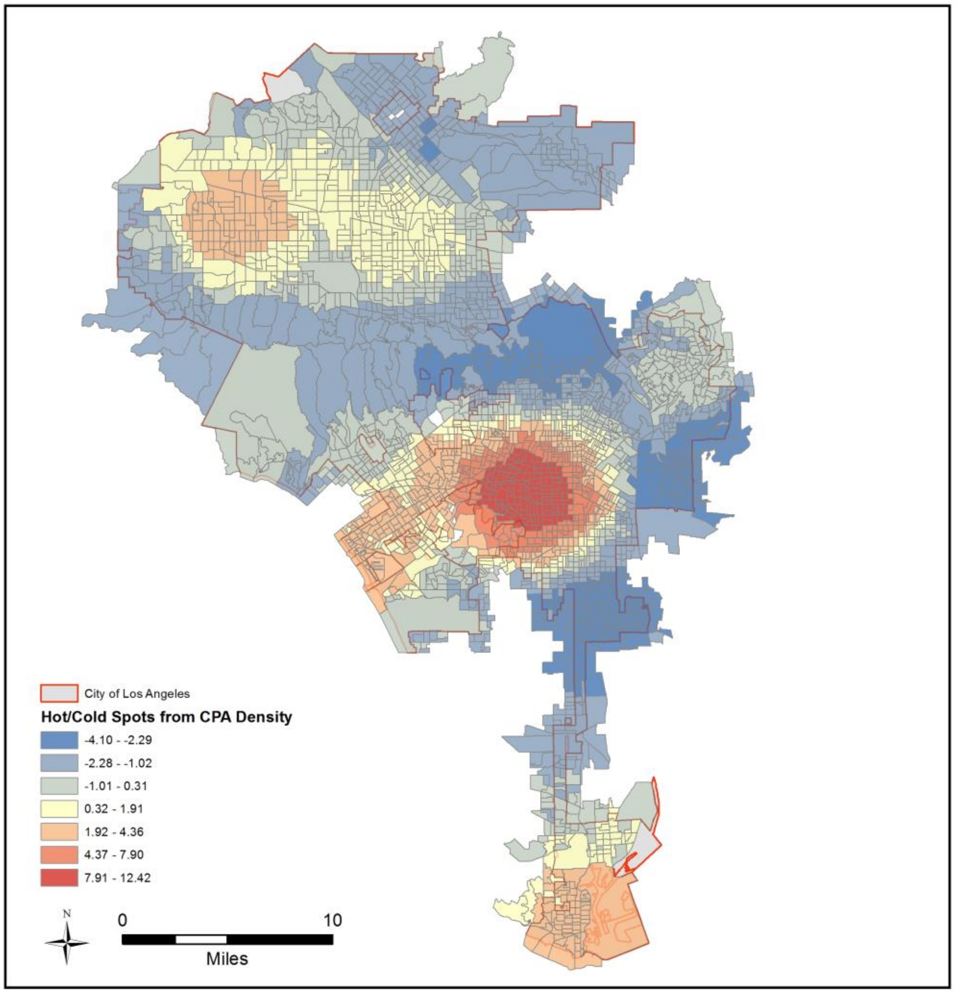
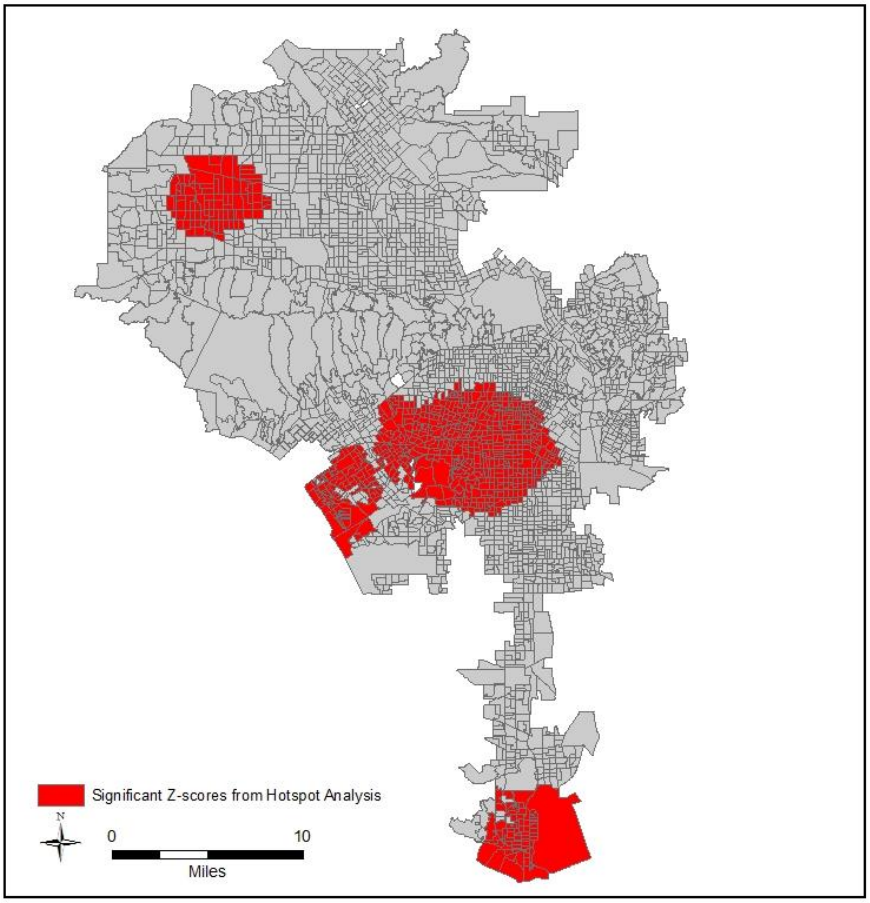


Figure 15. Z-score statistics from hotspot analysis of CPAs



Map 12. Strength of hot and cold spots (Z-score) of CPAs

By selecting the areas from the tool output where $p < 0.05$ (95% confidence level) and $z > 1.96$ (the cutoff for z-scores at the 95% confidence level), the large, significant hotspots for CPAs can be identified (Map 13).

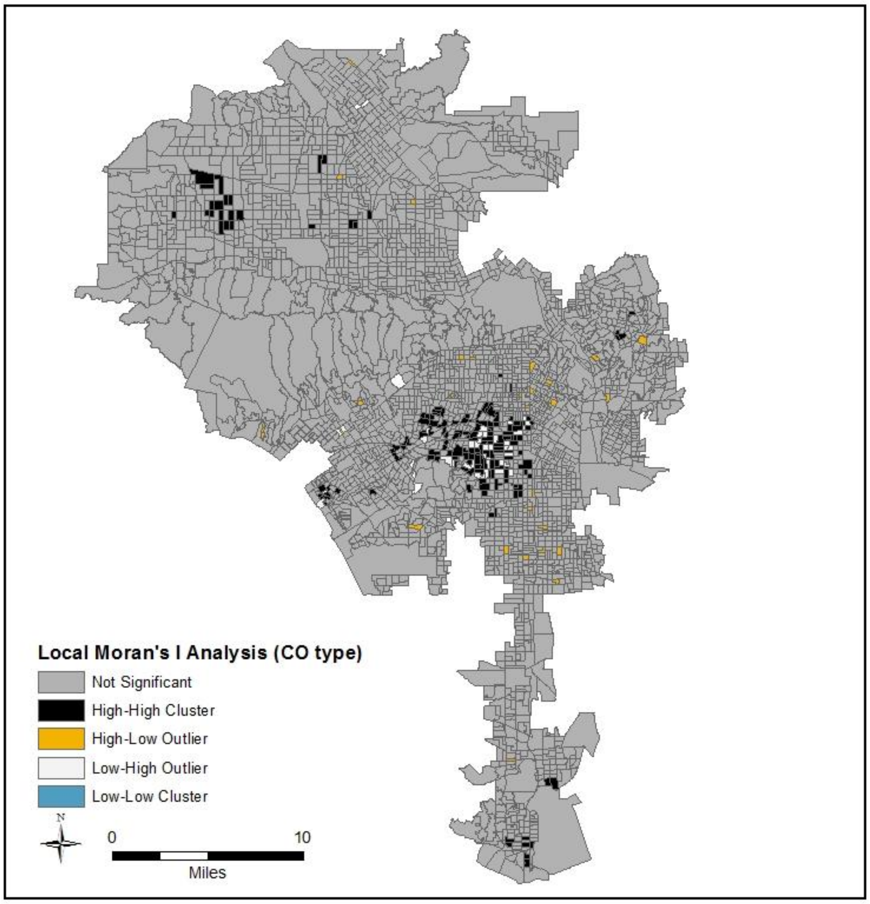


Map 13. Census blocks with the largest, significant hotspots of CPAs (p<0.05 and z>1.96)

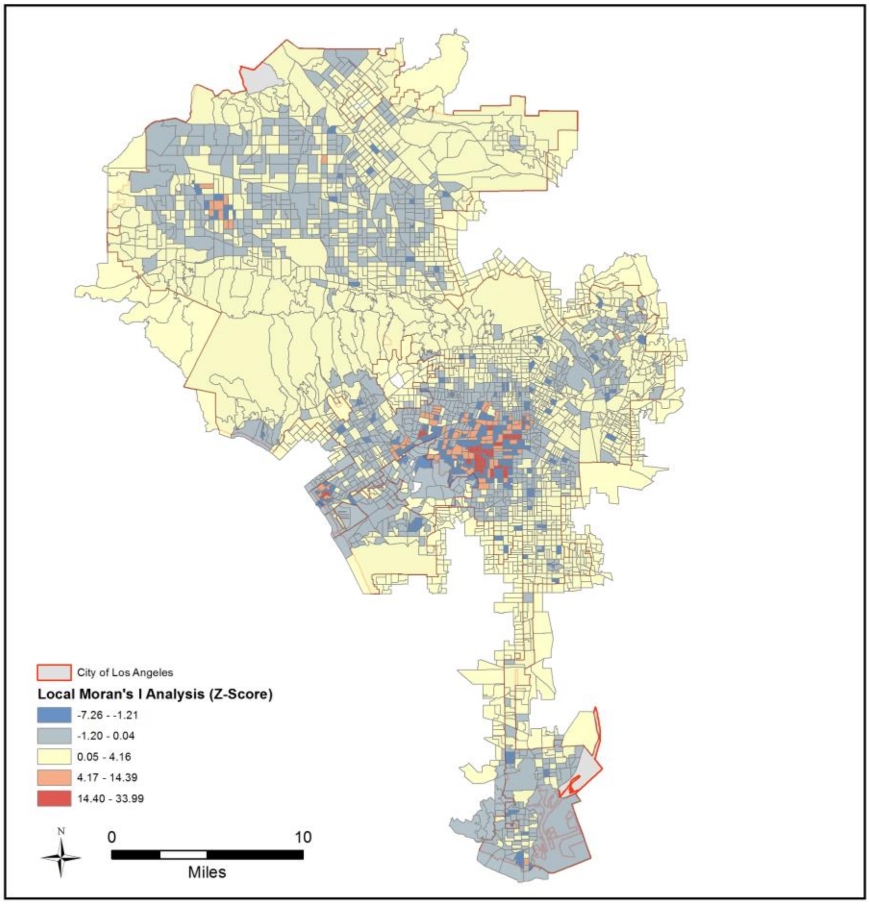
These maps exhibit spatial clustering in many of the census blocks in Los Angeles. Areas where z-scores are high and p-values low are notably in the Hollywood and Downtown areas of the city. While this is a step towards identifying “problem” areas in the city, it is not necessarily a complete picture of feral cat density. To determine if these areas are isolated instances of high rates or are part of a more regional trend, the Local (Anselin) Moran’s I analysis results are useful.

Local Anselin Moran's I

Local (Anselin) Moran's I classifies census blocks into HH, HL ,LH, or LL categories that indicate whether a high value parcel is surrounded by other high values, surrounded by low values, or the converse (Map 14). Many of these categories are significant (Map 15).



Map 14. Local Moran's I Cluster/Outlier type of CPAs



Map 15. Local Moran's I Z-score of CPAs

Statistics from the LMI Z-scores of the census blocks are shown below in Figure 16.

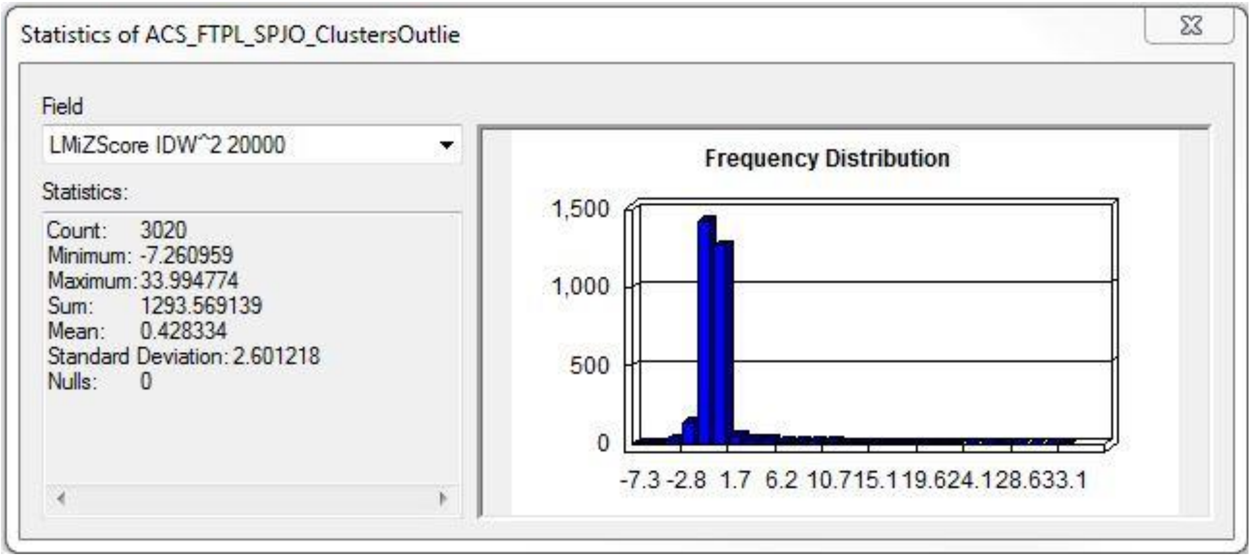


Figure 16. Statistics and distribution of z-scores from Local Moran's I

Scatterplot Matrices

Both median annual income (Figure 17) and population density (Figure 18) were correlated with the number of cat trap permit applications.

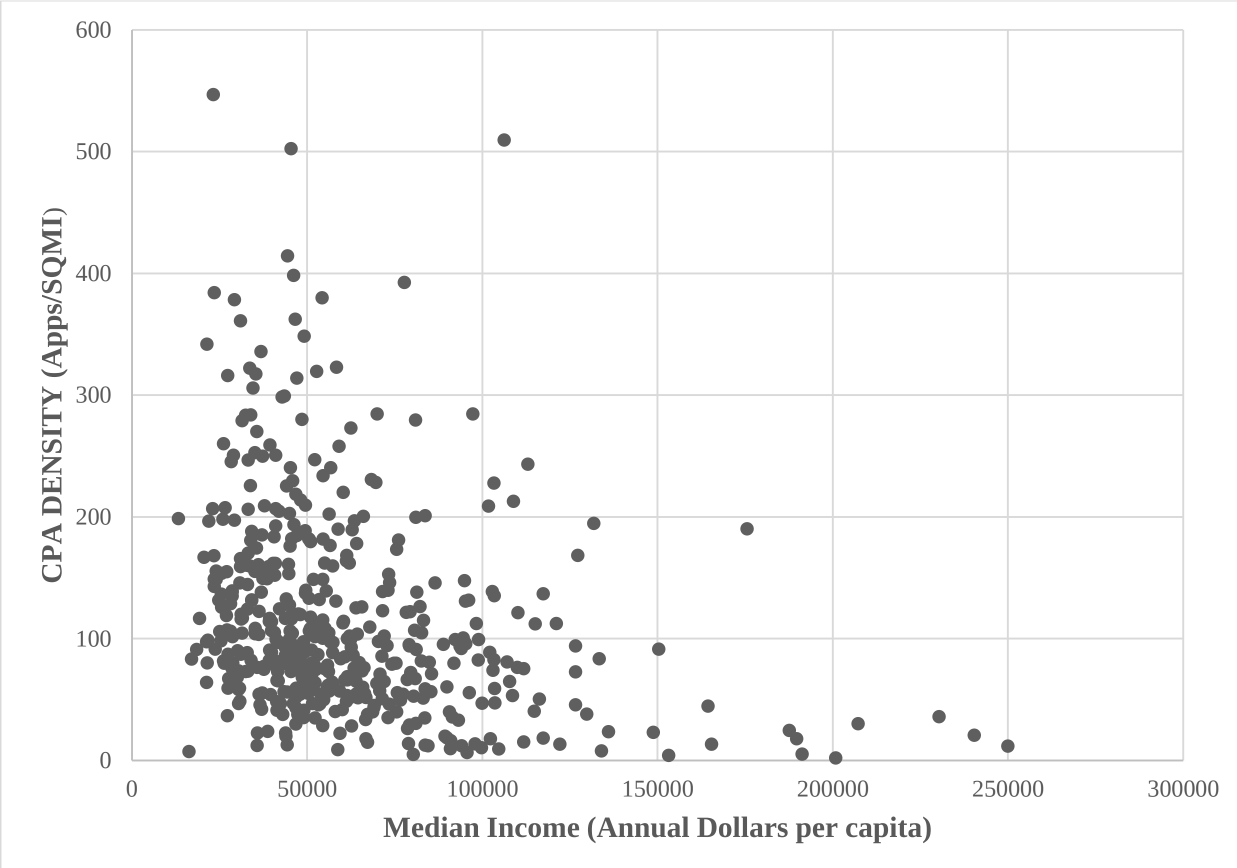


Figure 17. Median income plotted against CPA density

A trend line fitted to this graph shows a negative relationship between income and CPA density, which is what was expected, however this does not explain the complete story. The points are clustered around the lower ends of both axes, indicating that there may be a non-linear relationship between income and the desire to trap cats. This indicates that income is a correlate in trapping, but the relationship is complex.

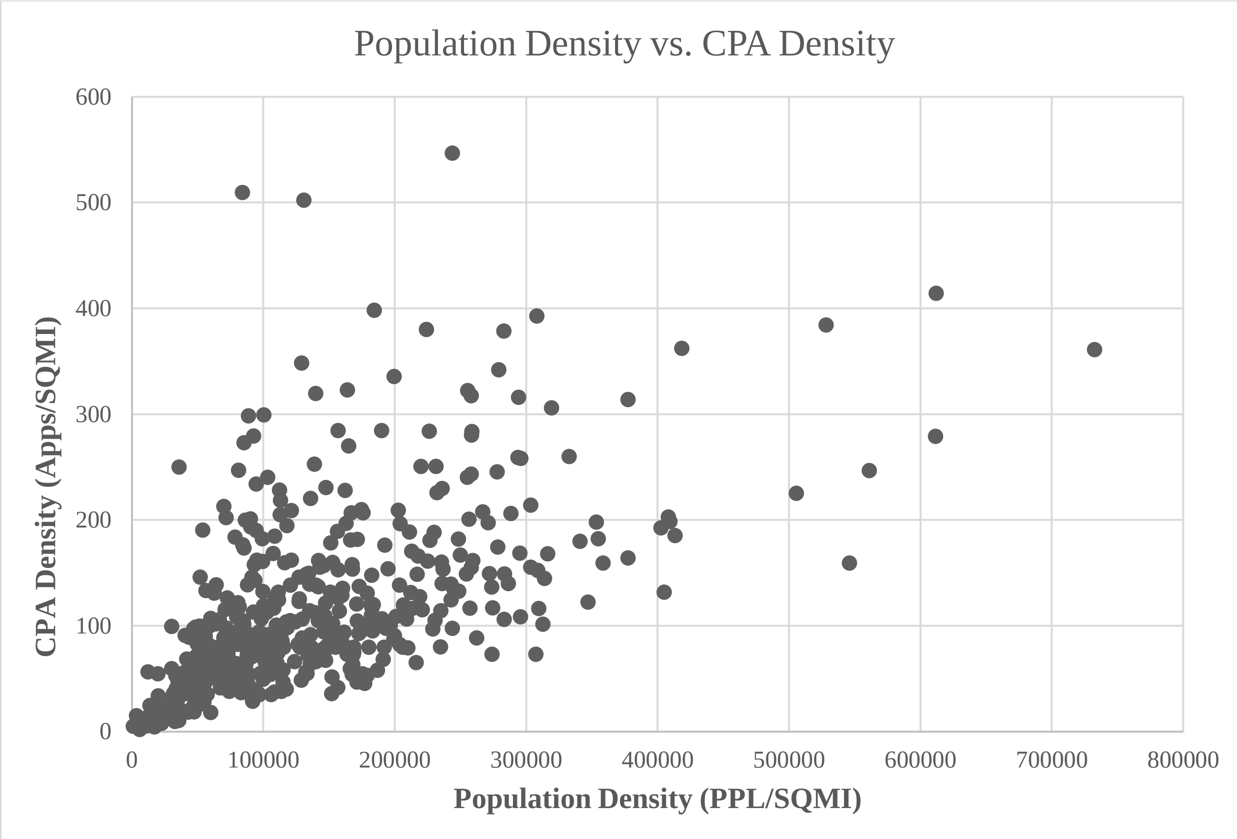


Figure 18. Population density plotted against CPA density

A positive relationship between population and the number of cat trap permit applications was found. At low population densities, few cat trap applications per square mile are found, but the spread in applications increases as the density increases. This indicates that additional factors are affecting the combination of number of stray cats and desire to trap those cats.

Ordinary Least Squares Regression

Ordinary Least Squares regression using both population density and median income as explanatory variables accounts for about 33% of the variability in cat trap permit applications. The output was as follows:

Number of Observations: 489
Akaike's Information Criterion (AICc): 5539.197764

Multiple R-Squared: 0.336876
Adjusted R-Squared: 0.334147
Joint F-Statistic: 123.447205 Prob(>F), (2,486) degrees of freedom: 0.000000*
Joint Wald Statistic: 227.651705 Prob(>chi-squared), (2) degrees of freedom: 0.000000*
Koenker (BP) Statistic: 5.092833 Prob(>chi-squared), (2) degrees of freedom: 0.078362
Jarque-Bera Statistic: 1324.509758 Prob(>chi-squared), (2) degrees of freedom: 0.000000*

A Multiple R-Squared value of ~0.33 indicates that income and population are accounting for approximately 33% of the variation in the model. The Joint F- statistic (which can be used to assess model significance since the Koenker test is not significant) probability is 0, showing that the explanatory variables are not insignificant. While the Koenker test is not significant, indicating stationarity, the probability value (0.07) is on the borderline of $p < 0.05$ significance. The Jarque-Bera Statistic shows significance, indicating a non-normal distribution of residuals.

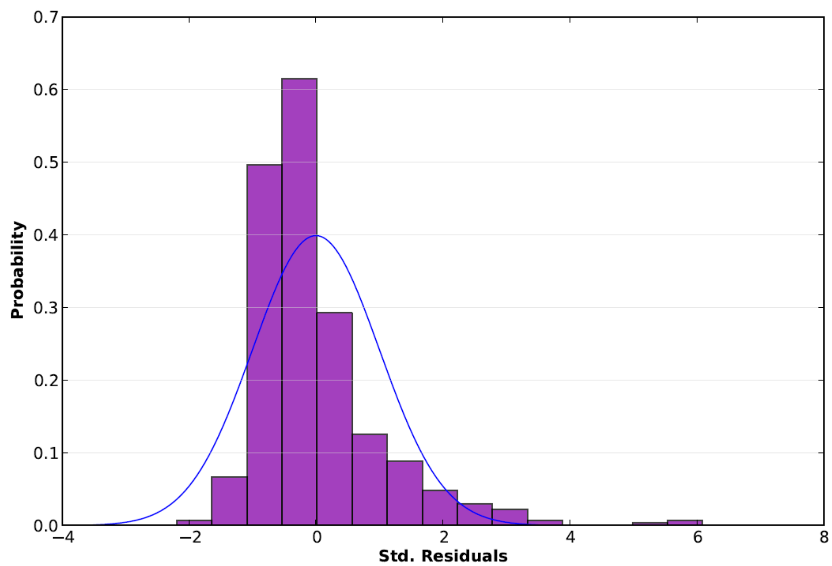
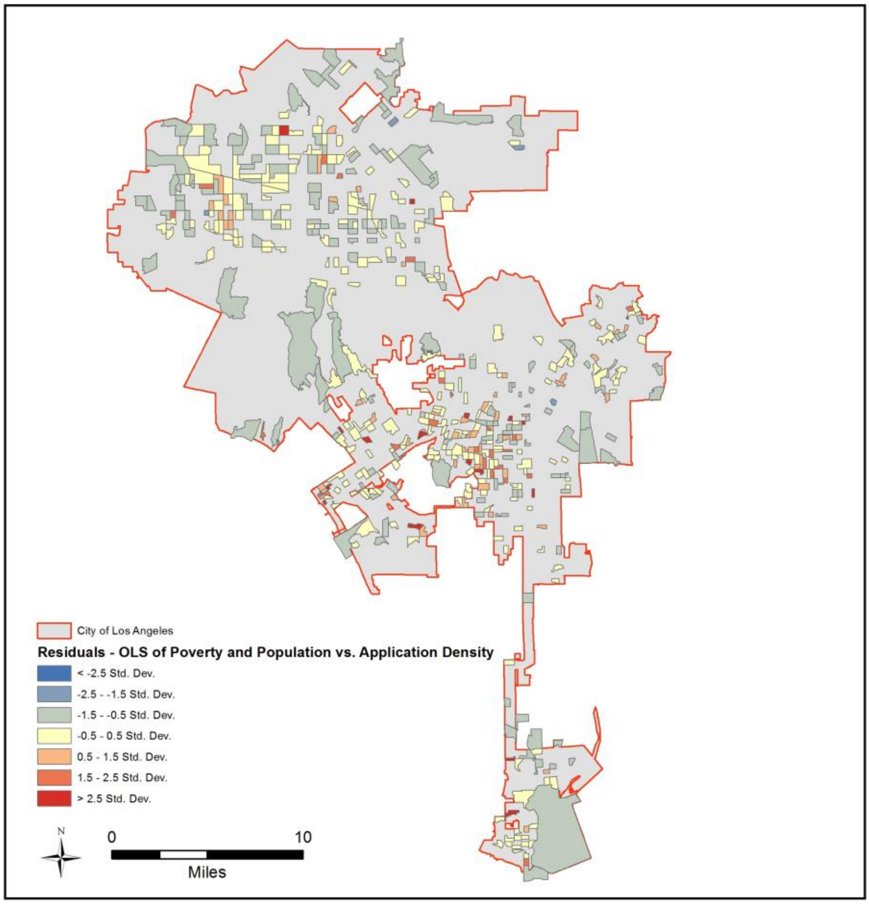


Figure 19. Distribution of residuals from OLS

Visualization of the residuals (Figure 19) provides insights on locations where observed density of cat trap permit applications was higher or lower than explained by income and population density (Map 16). Hotter colors in this map indicate areas where observed values were higher than the estimated values while cooler colors are lower than expected.



Map 16. Residual map of OLS

OLS output shows that median income and lower population density are associated with lower densities of cat trap permit applications (Table 2). Probabilities and robust probabilities for the variables indicate chances of the coefficients being zero. In this case, the chances of the population coefficient being zero are nil, but there is a greater chance that the income variable is having no effect on the model. The Variance Inflation Factor (VIF) is well under 7, so the two variables are not likely "double counting" information. Population density is the far more important variable when compared with income in the model.

Variable	Coefficient	StdError	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	56.218891	9.871609	5.695008	0.000000*	8.532636	6.58869	0.000000*	--------
MEDINC	-0.000085	0.000103	-0.828706	0.407665	0.000086	-0.995301	0.320074	1.233263
PPL_SQMI	0.000472	0.000034	13.768964	0.000000*	0.000035	13.51844	0.000000*	1.233263

Table 2. Summary of OLS regression coefficients and probabilities

CHAPTER FIVE: DISCUSSION

Use of a Legacy Dataset

Overall the efficacy of this data as a proxy for the spatial distribution of feral cats in Los Angeles is positive. In particular, the comparison of the KDE rasters produced indicates that this type of data is a viable source of information regarding cats, their locations, and where efforts could be focused to deal with overpopulation and nuisance issues. This type of data is an inexpensive alternative to a resource intensive field survey of cats, cat populations, and locations.

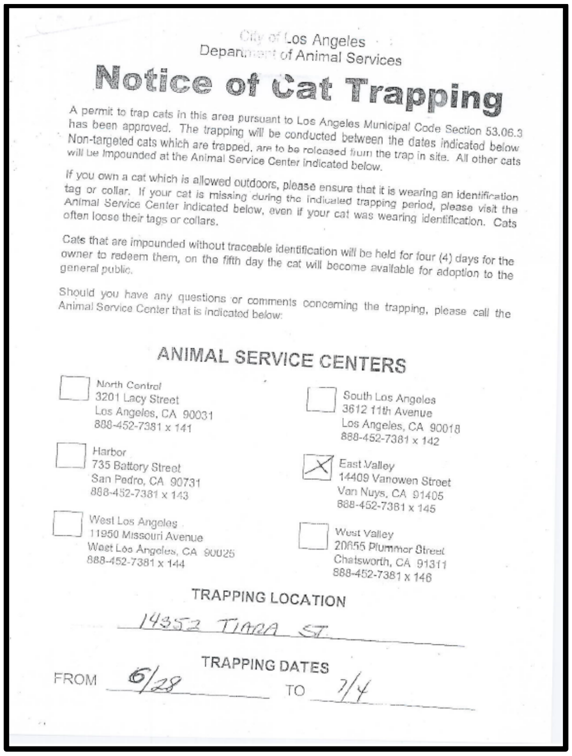
The time involved in preparing this data for GIS analysis must be considered. Manual entry of forms is also time consuming, and presents many problems with the decisions made to include or not include certain data. The data may be incomplete (e.g. no records for certain years), lacking, or incorrect, and these reduce the ease of use and potential accuracy of these data for use for this type of analysis. Given the choice between the error-prone process of entering the forms by hand and using a pre-populated spreadsheet (i.e. the phone call records provided by the Animal Service centers), the phone records are likely a better choice for future research.

Data Acquisition

By far the most intensive part of this work was acquiring and formatting the data necessary to visualize and analyze the spatial distribution of CPAs within the city. Entering data from scanned documents into a spreadsheet consumed a large amount of time preparing the data and entailed numerous decisions about what was pertinent and what was not necessary. This factor brings the complication that this study is not necessarily reproducible from scratch, since a different investigator may have come up with different reasons for keeping or discarding various records. While there was a rubric for this in place, how closely it is followed and the vagaries of the human mind at different periods in time could produce higher or lower record counts and/or reasons for wanting to trap cats.

Another complication of the data entry was the fact that the data in question was delivered asynchronously, one set of records at a time. This meant that later deliveries of data may have had information not covered in earlier iterations of spreadsheets or databases, and in one instance, an entire set of records had to be revisited to add information to a field. While this piecemeal data entry is not optimal, it allowed for refinements to the spreadsheet/database that was ultimately created.

Problems were encountered when entering data from hand-written forms. Some forms were not completed, hand-writing could be illegible, or the form poorly scanned. In a few cases, explanations were not written in English, but Spanish. In these cases and others, the decision was made to not use the form. The bulk of the forms entered had at least a minimum of information to allow their entry into the spreadsheet. Even an application with just an address and no ancillary information could be entered since this indicated that there was some type of cat activity present at that location. As mentioned, the scanned sheets did not only contain the initial application, but sometimes a scan of the permit itself (if one was issued), a driver's license, a trap rental agreement, or the notice to be posted declaring the trapping (see Figure 20). Addresses were sometimes legible on these accompanying documents and sometimes only a bit of information could be used to complete an address. By example, if a few letters of a street or avenue could be discerned, by entering some possibilities into Google Maps©, the search function would often turn up likely spellings of streets in the Los Angeles area. The same technique was used for street numbers and for determining whether an address was a street, boulevard, avenue, place etc. when that information was omitted.



City of Los Angeles
Department of Animal Services

Notice of Cat Trapping

A permit to trap cats in this area pursuant to Los Angeles Municipal Code Section 53.06.3 has been approved. The trapping will be conducted between the dates indicated below Non-targeted cats which are trapped, are to be released from the trap in site. All other cats will be impounded at the Animal Service Center indicated below.

If you own a cat which is allowed outdoors, please ensure that it is wearing an identification tag or collar. If your cat is missing during the indicated trapping period, please visit the Animal Service Center indicated below, even if your cat was wearing identification. Cats often loose their tags or collars.

Cats that are impounded without traceable identification will be held for four (4) days for the owner to redeem them, on the fifth day the cat will become available for adoption to the general public.

Should you have any questions or comments concerning the trapping, please call the Animal Service Center that is indicated below:

ANIMAL SERVICE CENTERS

North Central
3201 Lacy Street
Los Angeles, CA 90031
888-452-7381 x 141

South Los Angeles
3612 11th Avenue
Los Angeles, CA 90018
888-452-7381 x 142

Harbor
735 Battery Street
San Pedro, CA 90731
888-452-7381 x 143

East Valley
14409 Vanowen Street
Van Nuys, CA 91405
888-452-7381 x 145

West Los Angeles
11950 Missouri Avenue
West Los Angeles, CA 90025
888-452-7381 x 144

West Valley
20655 Plummer Street
Chatsworth, CA 91311
888-452-7381 x 146

TRAPPING LOCATION

14352 TIARA ST.

TRAPPING DATES

FROM 6/28 TO 7/4

Figure 20. Example of a possible secondary source of address information.

Some of the applications were scanned in such a fashion that the accompanying documents (e.g. trap rental agreement, driver’s license) were covering possible information. Because the applications were scanned, some illegibility was caused by the scanning process making the writing too light to read. Sometimes zooming in or adjusting the contrast was helpful in these instances.

It was important to note whether the trapping application was in fact for trapping cats. One set of applications contained many requests to trap squirrels, opossums, raccoons or other wildlife. If there was a permit associated with the application this would indicate what the person was intending to trap, but the bulk of the applications were for trapping cats.

A final issue with data entry concerned the address used. Two spaces were provided for the address (a home and business address) and a person’s home address may not have been the location where the cats were causing a problem, as in the case where a property manager desired to trap cats at an apartment complex rather than their own neighborhood. Care had to be taken to make sure that the address used for the "Trapping location" field was where the intended trapping was to take place.

Once data entry and parsing was accomplished, the data were not final and had to be geocoded and cleaned to encompass the study area while maximizing the amount of records that could be analyzed. These processes entailed a learning curve; for example, a field or column in an Excel© spreadsheet had to be formatted correctly to translate into a data type that ArcMap© would accept and be able to use as a valid value. Various pitfalls were encountered in dealing with the interface between these two programs.

Geocoding presented its own fallibility. While this process is widely used for extracting geographic data, accuracy is always in question no matter the integrity of the inputs. In addition, this study used a mash-up approach to the process combining the out-of-the-box capabilities of ArcMap© with a freely available online geocoder. The intention was to avoid the tedious process of manually geocoding missed results; however the time spent on reconciling and merging the two resulting data sets may have resulted in little time saved. The process had not been tested and although the results seemed to approximate one another, it would be advisable to quantify the error in locations between the two processes. Were the study to be repeated, the author would pick one of the systems and rely solely on that result.

In terms of acquiring demographic data, while census data are often used for this type of analysis, it is well known that this data has its own inaccuracies, is only an estimate of values at one point in time, and has already been aggregated into arbitrary blocks. The advantage is that it is freely available and translates well into a GIS.

Initial Analysis, Visualization, and Data Summary

A constraint of the study is that in terms of statistical summary, there is not very much to summarize by year and district because the records provided by the City were apparently not complete. Binning the data by date and district produced intervals where instances of applications were high or low for certain periods and areas, but no specific pattern can be determined.

A further question to be investigated is the areas where data is not reported. Some of these areas, particularly areas of higher elevations or high instances of predators that may prey on cats are readily explainable. However, certain areas where one would expect to find reports of cats or cat colonies are not reported. Notable on this point is the strip in Los Angeles that connects San Pedro with Downtown. This strip is an area of higher population density and medium to low income housing, so one would expect stray cats to be more prevalent.

The results of the study set up a set of hypotheses that would benefit from field investigation. Census blocks in the high-high or high-low categories may have within “problem houses” that are either abandoned and thus provide shelter for feral cat colonies or that are inhabited by people who are actively feeding local stray cats. Local knowledge of individuals or groups that participate in feeding cats would certainly improve understanding of the patterns observed in the trapping permit applications.

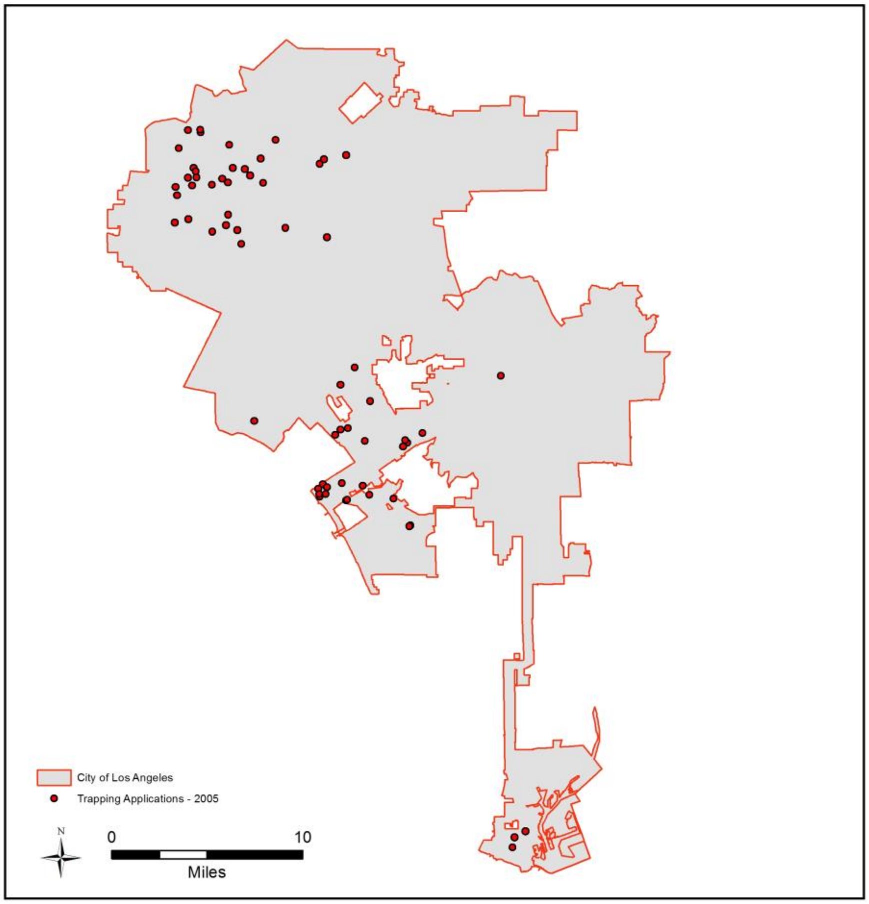
Land Use

The result in this study mirrored that of Aguilar and Farnworth (2013), and is not surprising due to the nature of the data (i.e. most people seeking to trap cats and going through the process of applying for a permit would be living in a residential area). A finer scale of analysis (binning the residential applications into sub-types of residence) would be of value if the question of what types of residence were related to cat trapping should be pursued.

Average Nearest Neighbor

While the ANN analysis did confirm that CPAs are clustered for the whole of the AOI, a better analysis could be performed by modifying the parameters used in the tool. Since the analysis used the total area of the City of Los Angeles layer, a more robust estimate of clustering in the AOI could be determined by elimination of areas that likely do not have an effect on the probe. Areas of higher elevation and areas frequented by predators that hunt cats (e.g. coyotes) could be eliminated from the test, thereby reducing the area used in the calculation. We would expect a lower z-score, a higher NNR, and a lower mean distance between CPAs from this audit. The decision on what areas to eliminate from the analysis remains on the table for future analysis of this type of dataset. Metrics derived from this analysis may be useful as input values for other tools and examinations. A reasonable starting point for this determination could be derived from the hotspot analysis of the dataset.

A next step would be to bin the data by time or area to see if clustering is apparent during certain times of the years for which data is available or for certain areas of the city. For example, by selecting data for just the year 2005, the ANN tool returns a z-score of ~-6.72, which still exhibits clustering, but is different from the score for all years. This selection also exhibits significant geographical variation, since the binned permit locations show a trend in the western part of the city, shown with CPAs isolated for the year 2005 (Map 17). This pattern may be the result of incomplete data delivery by the City of Los Angeles or differences in practices for issuing cat trap permits in the different Animal Service Centers (e.g., denying applications to reduce the number of cats returned to shelters).



Map 17. Cat trapping applications for the year 2005

Kernel Density Estimation (KDE)

Visual analysis of the KDE layers produced show differences between the permit applications and the phone call data, but these difference appear to be minor i.e. a slight eastward shift in density values. Since the data are relative and not based on absolute values, it is evident that permit applications are a good indication of problem cat areas in Los Angeles, though not complete. Were the application dataset to have a comparable number of records to the phone data, one would not expect a radical departure of where the highest densities would fall.

Optimized Hotspot Analysis and Local Moran's I

Statistics from the Getis-Ord Gi* test show that ~94% of the blocks exhibit z-scores below 1.96, or one standard deviation (at the 95% confidence level.) From visual analysis, blocks with the highest scores coincide with areas of high residential concentrations including Downtown, Reseda, San Pedro, and Highland Park. Local Moran's I showed that these areas exhibited significant clustering of high rates of applications surrounded by other areas with high rates. Since these results and methodology are preliminary, contain no longitudinal component, and require further refinements of accuracy, they should not be construed as conclusions as to where the highest rates of feral cat occurrence exist. Rather they are pilot reports on how concentrations of feral cats may be distributed around the city, and further investigation of the common attributes of these areas is recommended for determination of additional variables. Aguilar and Farnworth (2012) advise that data of this range and quality not be used to make judgements about correlates of the distribution of cats, but do suggest that results could be used to target certain areas with increased education about the animals e.g. visits to schools, pamphlet distribution.

Default values for the tools were used in this analysis and it is credible that parameters could be refined to create a better model of data distributions. Establishing a likely distance threshold could eliminate global comparisons of data values, and establishing weights for neighbors by way of a matrix would increase variation of the data. This is where some local knowledge would be helpful in identifying areas that were particularly noted for large concentrations of cats. Finally, increasing the resolution of the study area by breaking the analysis into smaller areas containing notable values would advance the investigation of these patterns.

Scatterplot Matrices

The scatterplots created showed that the only variable showing a distinct trend on the distribution of trapping applications is population, that being the higher the density of people, the more likely it is to have high instances of permit applications. Median income contributed to a significant model but itself was not significant as a variable.

Income does not appear to be a heavy factor in whether or not people endeavor to trap cats when compared with population density. Not surprisingly, plotted points are aggregated towards the low end of the income scale, and the highest application density outliers fall within this area. This trend, while not an exact fitting line, may indicate that wealthier people either do not live in areas where feral cats are a problem or are not themselves involved in dealing with the problem. Conversely, people of lower or middle means may live in these areas and are following legal means to deal with the problem. It is possible that people of the lowest socioeconomic levels may deal with the problem by illegal means (i.e. taking it upon oneself to control nuisance cats), but the data are inconclusive. Either the problem is being ignored, or people are resolving it through means other than obtaining a cat trap permit.

The variables investigated do not paint a full picture of processes at work in the spatial distribution of permits. An underlying assumption in this work is that the data on trapping applications is a proxy for spatial variety in feral cat populations, so the variables investigated should reflect this. Variables like proximity to food sources and refined data on the physical environment that cats enjoy would have to be investigated if work on these data should continue.

The results of the OLS analysis show that at the least there are some variables missing from the prediction model. With an R^2 of 33%, this alone would indicate that there are factors missing, but in addition the residuals were not normally distributed and the stationarity of the data was borderline. Further inquiry into the types of variables that may have effects on the distribution of cat permits would be an objective of future research. Imaginable candidates for these factors are availability of food and the cultural makeup of the city. How to capture and best represent these variables if they were to be included in the equation is a future consideration.

Future Work

A better unit of analysis would augment the accuracy of the study. Since census blocks and tracts are arbitrary units they are not very indicative of the urban morphology or "flavor" of an area. Organizing the unit by using a non-administrative parcel would be a more suitable unit in that areas such as neighborhoods or police beats tend to propagate due to geography and social factors. This layer organizes the city by neighborhoods rather than the municipal boundaries delineated by the city, and may be more representative of the make-up of an area.

Data from the Census Bureau is advantageous in price and in the array of variables contained in the set, but for spatial analysis the arbitrary nature of the polygons (e.g. differences in area and geometry) elicits the problem of the Modifiable Areal Unit Problem (O' Sullivan and Unwin 2010). This presents itself when areas, such as administrative boundaries, are delineated and then the data within them is aggregated. The data that is encompassed by the area can change with the area, and this change can be used to highlight certain facets of a community or region. Analysis of the neighborhoods layer may be more indicative of the cultural identity of areas rather than strict census blocks. In addition, the range in size of the polygons is not as great as in the Census block layers. Gathering demographic data from the neighborhoods layer about cultural identity, incomes, population etc. may be more fruitful for analysis.

Disaggregation of the census blocks is a possible, though arduous, option to obtain a better model. However the effort put into this would outweigh the value of continued analysis of this relatively small (compared to the data analyzed by Aguilar and Farnworth) and likely incomplete dataset.

An obvious further analysis would be to look at the data longitudinally by binning the data by data and looking for patterns over time. This was initially planned for this thesis and some work was done, specifically a Kernel Density Estimate over time. This work is not included here since it was done without a complete dataset.

Pertinent analyses include an overlay of the different methods used to compare their (dis)similarity and performance. Performing the analyses in strictly vector format precludes the use of raster math where one can use arithmetic and algebraic expressions to perform overlays resulting in indicative values for areas. Converting the vectors layers to raster format would expand the array of raster calculations that could be performed. Converting discrete data, such as census blocks, to raster has the effect of pixelating the data and changes in values can be abrupt. Applying a smoothing factor or algorithm to any created rasters would bring data closer to continuous values.

A richer and more variable dataset is what all examiners wish for, and these data already exists in the form of the telephone call log used in the KDE for comparison with the permit data. The file contains over 10,000 records of calls made about feral and stray cat sightings, complaints, and concerns of the citizenry. Addresses and dates are present in most of the records as well as ancillary information on what had transpired. Preliminary cleaning of the file yielded ~8000 records, a number that could be ameliorated with further geocoding. Repeating and refining the steps taken in this study on the telephone log is the logical follow-up to this work. Given the time and resources to repeat this study, this dataset would be more appropriate to expend energy on analysis.

While OLS is a powerful statistical tool, it is based on the assumption that the data will not change over space. Geographically Weighted Regression was developed to account for this assumption and takes into account changes in geography when computing coefficients, essentially creating a local regression line for each area in the dataset based upon a kernel or the number of neighbors in the areas. Using this approach is an option, but a properly specified OLS model is required to follow that path, and key variables are missing from the model, as well as a determination of a proper bandwidth for such an analysis.

Considering the literature and findings herein, it is conceivable that correlations might not surface with such a small dataset. Without doubt is the necessity for more accurate data analyzed in concert with properly specified variables.

Conclusion

This study shows how this type of found dataset can be used to mine more information about geographically specific phenomenon. The continuing spatialization of under-used data will allow researchers to access information previously unavailable in a digital and spatially dependent world. While the analyses performed were able to show clustering of statistically significant areas, the scatterplot matrix shows few parallels with the population and income variables isolated. A better unit of study and more relevant variables would improve further research with this dataset. More and better data are necessary, and these data exists in the form of the telephone call data referred to earlier. The next step would be to refine this study with further inquiry into the variables driving these patterns and then apply the refined model to the telephone call data.

The work done on the permit applications for trapping cats is both incomplete and not properly specified. Continued work on this particular set of data is not likely to produce better results without a concentrated effort on ground truthing and collection of data layers that may have more obvious effects on the distribution of permit applications.

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