

VALIDATION OF VOLUNTEERED GEOGRAPHIC INFORMATION QUALITY
COMPONENTS
FOR INCIDENTS OF LAW ENFORCEMENT USE OF FORCE

by

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A Thesis Presented to the
FACULTY OF THE USC GRADUATE SCHOOL
UNIVERSITY OF SOUTHERN CALIFORNIA
In Partial Fulfillment of the
Requirements for the Degree
MASTER OF SCIENCE
(GEOGRAPHIC INFORMATION SCIENCE AND TECHNOLOGY)

December 2015

DEDICATION

I dedicate this study to anybody who has been impacted by violence. May you be at peace.

Moreover, this study is for all of society, especially those who truly work toward justice.

ACKNOWLEDGMENTS

I couldn't have done this project without the aid of many individuals. To Caiti, my better half, who stood by me through it all (it's your turn next). To Dr. Vos, my committee chair, who was always willing to help. Your insight kept me focused and grounded. Thank you, Dr. Kemp, for your sage advice on all that is spatial, and Dr. Finch, for your willingness to work with me on this project. Thanks go to my cousin, Jen, who used her editing expertise to weed out all those pesky typos. Special thanks to Mr. Brian Burghart who made all of this possible by initiating the Fatal Encounters project. I appreciate your openness and willingness to talk about your dataset. Walt Lockley must be acknowledged for verifying my own work. Credit goes to the Gun Violence Archive who put together a custom dataset for me. Lastly, thank you to all the public servants I interacted with during the sampling process. Your efforts were all an integral component of this study.

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LIST OF ABBREVIATIONS

AGI	Ambient Geographic Information
ARD	Arrest Related Deaths Program
BOJ	Bureau of Justice
BOJS	Bureau of Justice Statistics
CDG	Crowdsourced Geospatial Data
CRS	Creative Research Systems
DOJ	Department of Justice
FBI	Federal Bureau of Investigation
FE	Fatal Encounters
FGDC	Federal Geographic Data Committee
GIScience	Geographic Information Science
GIS	Geographic Information Systems
ICT	Information and Communications Technology
KDE	Kernel Density Estimation
NFIC	National Freedom of Information Coalition
QA	Quality Assessment
UGC	User Generated Content
VGI	Volunteered Geographic Information

ABSTRACT

Progress in information and communications technology (ICT) has enabled members of the general public to contribute to data collection that has traditionally been reserved for trained professionals. Volunteered Geographic Information (VGI), user-generated content with a geographic component, is becoming more widely available with an ever increasing range of data types (Fast 2014). This study extends previous analyses of VGI by investigating a first-of-its-kind dataset, known as Fatal Encounters (FE), which seeks to collect information on incidents involving police use of deadly force on citizens within the United States. Geographers recognize the potential for VGI to enrich existing forms of authoritative data or produce new data, but the consensus is that VGI can be highly variable in quality. Relevant quality components are used to build a framework for validating the FE dataset. The main components include completeness, spatial accuracy and precision, and attribute accuracy. Once these components are assessed, the overall fitness of the FE dataset is determined with an evaluation of its strengths and weaknesses. The resulting analysis showed that the dataset was sufficiently complete for initial spatial analysis, but lacked fitness for specific attributes. Based on fitness of the data, the study also conducts a preliminary hotspot analysis for these incidents in New York City, including an overlay of hot spots on population density and a race-based dot density maps. Before further analysis can be done, recommendations for improving the weak portions of the data are discussed.

CHAPTER 1: INTRODUCTION

Geographic Information Science (GIScience), as a discipline, is driven largely by the acquisition and analysis of data. The fundamental relationship between Geographic Information Systems (GIS) and data means that attention directed toward a dataset's suitability is one of the principal factors that produce reliable analyses. For this reason, detailed data quality standards, including various checks and balances, have been produced so that users can effectively create or assess data. However, advancements in digital technology have widened the range of participants who create, collect, analyze, and communicate geospatial data (Haydn 2014) thereby swelling the ranks of those who choose to participate and interact with data creation. Known as user generated-content (UGC) or volunteered geographic information (VGI), this emergent subdivision of data creation has been increasingly recognized by academics as having qualities with the potential to produce previously unavailable data or enhance existing data, yet its quality can be highly variable (Goodchild 2007; Meek 2014). The juxtaposition between potential value and quality concerns has prompted research that focuses on developing methods that address the various challenges associated with VGI before it can be harnessed as a data source.

The emerging trend in crowd-sourced data has been referred to by many terms that essentially reference the same or very similar processes. Terms include crowd-sourced geospatial data (CGD), VGI (as identified above), ambient geographic information (AGI), neogeography, participatory sensing, and others (Rice et al. 2012). The data in this study is a sort of mixed breed of these terms. However, two ever-present factors place each term under the overall canopy of this type of data. The participation of untrained individuals and the existence of a geographic footprint (i.e. an address or geotag) are all that is needed for a dataset to qualify as this data

subtype. The remainder of this work uses the terms VGI and crowd-sourced data interchangeably and does not focus on where the data belongs in the accepted terminology.

This thesis project focuses on a first-of-its-kind VGI dataset, referred to as Fatal Encounters (FE), relating to police use of deadly force on citizens in the United States. The determination for creating the dataset was to compile a list of every United States citizen whose encounter with law enforcement resulted in loss of life, and the effort employs a variety of methods for compiling each incident. This study relies upon GIS standards to evaluate the collection processes, completeness, accuracy, and consistency of the FE dataset. To accomplish this task, a hybrid framework is developed based on other VGI quality assessments (QA) so that the FE dataset can be appraised. Construction of a unique framework is necessary because none of the prior VGI QAs have examined a dataset with qualities like FE. It is intended that the basis for evaluating the FE dataset will either confirm or deny its soundness, which will determine its utility for scientific analysis.

1.1 Research Objective

The guiding principle in this thesis is that a better understanding of the frameworks that enhance the quality of VGI data will support an adaptive QA of the FE dataset. An exploration of currently existing VGI projects enables better classification of the FE data and a context for determining which components affect quality. Moreover, academic development of VGI QA frameworks meant to assess quality are typically comprised of individual components that influence the overall integrity of the data. The first objective is to identify which components of other VGI QA frameworks may also affect the FE dataset. After gathering the relevant quality components, this study builds a customized framework as the basis for testing the validity of the FE dataset.

The applicable components of VGI QA frameworks are then compared to the FE dataset. The performance of the FE data, with regard to its collection processes, completeness, and spatial accuracy versus the quality controls serves to identify its strengths and weaknesses. The function of this process is to identify the areas where the dataset is fit for analysis or not. Portions of the dataset deemed inadequate are discussed to suggest where weaknesses could be strengthened through curation, modifying collection protocol, or clarifying definitions. Where possible, direct curation is used to improve the dataset, while other weaknesses, where curation is impossible, are evaluated solely to determine fitness for analysis.

The portion of the data that passed QA and was found to be fit was New York State. Incidents were geocoded into ArcMap for a preliminary hotspot spatial analysis, in New York City, on the raw incident count and the incident count normalized by population. Accompanying the hotspot analysis are a population density map and a dot density map of racial dispersion.

Key considerations for this study include the following questions:

1. Can the different methods for validating VGI be customized to assess a dataset unique to other crowdsourced VGI?
2. Is the FE dataset considered fit for analyses based on the custom framework?
3. What are the sources of uncertainty in the FE data and how can these issues be mitigated?
4. Can spatial analysis provide geographic context for FE?

1.2 Motivation

2014 was a year where amplified attention in the United States was directed toward the use of deadly force by law enforcement officers. Nationally recognized cases – such as the shooting of Michael Brown in Ferguson, Missouri (Lowery 2014) and the asphyxiation of Eric Garner in

New York City (Goodman 2015) – generated waves of scrutiny and fueled debate regarding the frequency, distribution, justification, and possible racial profiling regarding these incidents. Amidst allegations of police brutality, answering society’s concerns with relevant data and scientific analysis has been stymied by the fact that no formal data currently exists that identifies incidents where citizens are killed by law enforcement. The absence of this data is remarkable considering that the Bureau of Justice (BOJ) and the Federal Bureau of Investigation (FBI) collect extensive information on aggravated assault, hate crimes, officers killed in the line of duty, and many other areas (Maimon 2011). The obvious gap in data availability was clearly revealed when FBI director James Comey stated: “It’s ridiculous that I can’t tell you how many people were shot by police last week, last month, last year” (Fossett 2015, 1).

This data void exists, not because government has been apathetic, but rather because it has been unsuccessful in collecting data on these types of incidents. The FBI’s Uniform Crime Report recorded around 400 justifiable homicides per year between 2008 and 2012 (FBI 2012). Meanwhile the Bureau of Justice (BOJ) compiled roughly 488 arrest-related deaths from 2003 to 2009 (BOJ 2015). The official statistics of FE for the years when the most complete information was available (2013 with 1,198 incidents and 2014 with 1,233 incidents (FE 2015)), show counts that more than double both the FBI and BOJ figures (FBI 2012; BOJ 2015). It would seem that the number of incidents has increased dramatically in a short period of time. This is unlikely, however, and is explained by the government’s own admission that its data is insufficient. The Bureau of Justice Statistics published a report in March of 2015 stating that, “At best, the Arrest Related Deaths (ARD) program captured approximately half of the estimated law enforcement homicides in the United States during 2003-09 and 2011” (BOJ 2015, 2). The report sites an array of reasons why data collection has failed.

Hence, the dearth of available data specific to police use of deadly force, coupled with the inability of government to effectively track them, has motivated determined citizens to find alternatives. At present, five crowd sourced datasets have emerged that attempt to capture every incident where police use of deadly force occurs. Each dataset has its own unique features, but one stands out as the most likely to hold up to QA inspection.

Reasons for undertaking this project are numerous. First, testing the FE dataset serves as an indicator for whether this type of data is being adequately collected and whether the data that has been collected thus far is sufficient for analysis. Second, vetting the FE dataset to gain a better understanding of its quality is a necessary step before its value can be realized. Finally, evaluating a dataset from the perspective of GIScience augments the idea of what type of crowd sourced-data has potential for spatial analyses. Ultimately, the hope is that the work conducted in this thesis serves as progress toward making available a dataset in an controversial area with a significant data vacuum.

1.3 Purpose

The anticipation generated from the construction of a dataset that lists each instance of police use of deadly force is substantial and is supported by the fact that FE has already seen attention from multiple popular media outlets. The prospect for finally possessing a means for understanding what the national landscape looks like for law enforcement's use of deadly force is tremendous. Citizens in the United States, for the first time, could possess a window that might help contextualize where, why, when, and with what frequency these incidents occur. However, before any analysis and/or conclusions can be attempted, the validity of the FE dataset must be established and weaknesses identified.

The reason for proposing this study stems from its intrinsic value to both the spatial sciences and society. If the FE data is deemed fit, any future analyses will produce the first academically recognized works looking at police use of deadly force on a national scale through the lens of GIS or other sciences. Furthermore, improvements in collection protocol or curation in areas where FE is not of sufficient quality will pave the way for future, more in-depth, analyses. Lastly, this type of crowd-sourced data has never been vetted and therefore adds to the variety of VGI data being studied from a GIScience perspective. Examples in literature where VGI systems implementation is studied are consistently directed to datasets such as Wikimapia or Open Street Map, so the addition of the differing context the FE data offers should be welcome. Finally, the systems that help analyze the nature of VGI are not yet advanced or refined enough for formal standards to be created. The work done in this thesis is a step toward a more formal blueprint.

Another reason for undertaking this study was to help position FE as being the most robust dataset with regard to completeness, attribute richness, and temporal depth. Additionally, this study seeks to define where FE fits into the domain of VGI in comparison to other projects. Understanding the unique characteristics of FE enables the critique of it to establish where improvements will improve overall quality.

1.4 Organization of Thesis

The remainder of this thesis is arranged as follows. Chapter Two summarizes the background and collection protocols of the FE dataset. Chapter Three consists of an examination of VGI and the literature that focuses on quality assessment. An outline of similar, competing datasets is also presented. Also included is a look at the type of spatial analysis used to understand crime-like data that are appropriate for initial spatial analysis. Chapter Four describes the specific methods

employed to test the FE dataset, followed by a description of the actions taken to build a sample dataset to use for comparison. Included are methods for sampling and geocoding the data along with the preliminary spatial analysis. Chapter Five presents and discusses the results of the validation process, outlining areas of uncertainty and recommendations for improvement. This chapter also includes the results of the spatial analysis for New York City. Chapter Six discusses the significance of the results and whether the FE dataset can be considered fit for analysis. It continues by discussing the potential for analysis FE possesses once its quality is deemed to be sound.

CHAPTER 2: THE FATAL ENCOUNTERS DATABASE

The origin of VGI is consistent and typically begins from a perceived problem, such as a political crisis or natural disaster (Fast 2014). By the same token, out of a deep concern with the frequency of incidents resulting in death between police and citizens in the United States, on May 18, 2012, D. Brian Burghart, editor of the Reno-Review Journal, began compiling instances where citizens were killed by police. Mr. Burghart's goal was to create a comprehensive national database listing every incident from January 1, 2000 through present day. Stimulated by the urge to grant society access to data detailing officer-involved homicides, Mr. Burghart recognized there were multiple methods that could be used to populate such a database. He knew he had to capture all retroactive incidents while also compiling any present day incidents. To accomplish this he developed a multi-tiered system (Burghart 2015). This chapter provides a background of the FE dataset, including its modes for data collection, definitions, scope, administrative hierarchy, and information sources.

2.1 Fatal Encounters Collection Systems

Each of the methods developed by FE calls for varying levels of participation from the administration and volunteers. Depending on the task, the amount of time a volunteer contributes can range from 15 minutes to many hours on consecutive days. The direction of a task fluctuates from querying a search engine and filling out an online form or filing a public records request with law enforcement agencies, to specialized participants who focus on searching one state at a time. The following subsections detail the collection systems used by FE.

2.1.1 Public Records Requests

The first data collection method relies on records obtained from law enforcement agencies through requests made under the Freedom of Information Act (FOIA). Mr. Burghart began by

filing a public records request to the FBI asking for the address of every law enforcement agency that contributes records, such as officers killed in the line of duty, to the FBI's Uniform Crime Report (UCR). A 2008 census conducted by the BOJ found 17,985 state and local law enforcement agencies with at least one full-time officer (BOJ 2008). After studying FOIA exceptions – legally valid reasons for turning down a request – it was determined that 15 data fields could reasonably be requested. They include: subject's name, age, gender, race, date of death, location of death (address, city, state, zip code), agency responsible, cause of death, a brief description of circumstances, and whether the incident was justified or not.

Given the large number of agencies in the UCR database, Mr. Burghart made available on the FE website the name and address for each agency, selectable by state or county. FOIA requests are designated for federal agencies only, but often state and local agencies will honor them. However, each state has separate laws for public records requests meaning that obtaining records from each agency is likely to require special attention. Mr. Burghart had in mind that volunteers from each state would be able to file requests since they were more likely to be familiar with that state's laws. Some agencies require tedious back and forth communications concerning laws or fees before any records are released.

2.1.2 Mining Similar Datasets

The second system includes parsing records from partial, yet related datasets. The objective was to sift through an array of crowd-sourced datasets to accumulate as many incidents as possible, without regard to date or location, so that a preliminary database of names could be built and details researched later. Once these datasets were mined and the names of decedents began accumulating, the incidents could be cross-referenced to a media source.

For this process, volunteers work with two spreadsheets (the official database and the research queue) which are available on the FE website through Google documents. Volunteers are instructed first to pick a name in the research queue that has not been highlighted as completed, and then search the official database by last name to ensure that it has not already been examined. Next, the volunteer is told to enter the victim's name into their desired search engine, comb through the results (at least the first 10 entries), and fill in the submission form on the FE website. Once the record is submitted, Mr. Burghart moves the entry to a third spreadsheet, unavailable to the public, where he personally verifies the record from the links provided by the volunteer. The entry is then moved to the official database and deleted from the research queue.

2.1.3 Specialized Researchers

In this method FE incidents are found through rigorous search engine queries conducted by one specialized researcher, Mr. Walt Lockley. Generally focusing on one state at a time and using a personal methodology he developed to comb media archives, he moves temporally and spatially through the state's media records. From his work alone, FE has seen a dramatic upturn in the number of states they consider to be complete. Once an incident is identified, the information is compiled and sent directly to Mr. Burghart.

2.1.4 Data Capture from Volunteers

The final system is meant to sustain the FE dataset by capturing data that the first two methods do not. Here, volunteers are encouraged to fill in the same submission form mentioned in the previous section with links to their information sources. New entries must also be searched against the official database so as to avoid redundancy. Note that the instructions in this section emphasize finding the most accurate address as possible. The county is found through plugging

the address, city and state into Google maps, then inserting the zip code into the National Association of Counties (NACO) to get the county. The survey form becomes more specific for address entry. It states:

Be as specific as possible with street addresses. For example, 613 North Anna Drive is best; 600 block of North Anna Drive will work; North Anna Drive will work; North Anna Drive and La Palma Avenue will work for an intersection. Most other variations won't work. If you're uncertain, just try what you have in Google Maps. Whatever you do, don't guess. Let the fact-checker look it up (Fatal Encounters 2015).

Written just above the survey form the FE website attempts to enlist volunteers to point out any errors, repeats, or needed clarification through a link to a corrections form. Finally, once all fields are filled in, participants submit directly to Mr. Burghart. Each form is then fact checked for validity before it is moved to the main database.

2.1.5 Verifying Records

Reiterating that Mr. Burghart personally fact-checks every entry submitted is important for recognizing that all data is filtered before becoming accessible. Other VGI studies do not have the benefit of this mechanism. The advantage of one person acting as gate-keeper has a number of positive influences on the data. Mr. Burghart can change inaccurate information, double-check that incidents align with the scope of FE, and expunge redundant entries.

2.2 Administration Hierarchy

Mr. Burghart is the gatekeeper through which all data must pass. Unlike other VGI projects where any user can affect the overall outcome of the data, FE only allows data approved by Mr. Burghart. Mr. Lockley is the second highest level volunteer contributing regularly. Below them are a handful of regular contributors and finally other volunteers allowed to submit information through a registered account or anonymously if they choose.

Other volunteers have helped Mr. Burghart develop tools such as the online submission form, the Google document spreadsheet, and have made video media or preliminary maps supporting the FE website, but they do not directly contribute to data creation (Burghart 2015). Essentially, Mr. Burghart is the sole proprietor and administrator of the data and no entries make it to the master database without his approval.

2.3 Fatal Encounters Summary

FE is a 501(c)(3) non-profit organization that accepts donations. Moneys from donations are not significant enough to pay full-time researchers, but it does help pay FOIA fees and allows small portions of money to be given to regular contributors. At present, funding is being sought through proposals to Federal agencies and an Indiegogo campaign.

Combined, these methods have yielded 7,022 incidents from January 1, 2000 through June 15, 2015. Mr. Burghart estimates the dataset is approximately 40% complete (Burkhart 2015). However, there are twelve states that are listed as complete: Connecticut, Florida, Maine, Massachusetts, Montana, New Hampshire, Nevada, New York, Oregon, Rhode Island, South Dakota, and Vermont. The states declared to be complete have a consistent temporal dispersion which indicates, based on the assumption that incidents are spread mostly even over time, they are indeed nearing completion. Also, the years 2013 and 2014 are closer to complete than other years due to augmentation from competing datasets and increased attention overall from media outlets.

CHAPTER 3: LITERATURE, QUALITY COMPONENTS, AND RELATED DATA

This chapter surveys literature pertaining to quality assurance of VGI data. It also includes a brief summary of popular VGI projects and their relationship to FE. Following this is a discussion of competing datasets to FE that attempt to compile the same information, or are similar enough to capture the data of interest within its scope. This chapter concludes with a discussion of the common types of analyses used for crime data and how they can direct potential analyses on FE.

3.1 Volunteered Geographic Information and the Need for Data Quality Assurance

The rapid advancement of digital technology and information availability has dramatically changed how information is produced, disseminated, and used, often leveraging community (or crowd) participation to contribute data that had previously been reserved for trained personnel (Fan 2014). The term VGI, coined by Goodchild (2007), is defined as the use of tools to create, assemble, and disseminate geographic data voluntarily provided by individuals (Brown 2012). The definition is necessarily broad, and is meant to encompass various projects that relate to this new data category. Discussed briefly in Chapter One, the dynamic nature of this data type has seen the creation of many terms meant to describe the variety of projects with the process of collective authorship by a community of end-users (Howe 2008). Some projects consist of crowd wisdom, crowd creation, crowd voting, or crowd funding. The FE dataset pertains most closely to crowd creation and the associated quality pitfalls.

3.1.1 Volunteered Geographic Information Projects

Crowd data is derived from non-authoritative sources and can be primarily geospatial in nature or contain information without any specific geographic purpose, yet still possess a geographic footprint, such as an address or geotweet (Haydn 2014). The vast majority of VGI projects rely

on participants' use of hardware (i.e. GPS-enabled cameras, smartphones, etc.) to geotag their position along with a photograph or other piece of information (Comber 2013). Examples of these projects include tracking wildlife poaching (Stevens et al. 2013), urban noise pollution (Gura 2013), responses to climate change (Beaubien 2011), and logging or drawing features in OpenStreetMap (Fan 2014).

The diversity of these projects illustrates the dynamism of VGI; however, the signature for this subdivision of data, a geographic footprint, is ever-present. In his journal article, See et al. (2013) points out that the direct manner by which volunteers provide location, such as in the VGI projects mentioned above, the crowd can also produce sources of spatially relevant data in a less direct manner. Referred to as "incidental data" (Criscuolo 2013), these projects rely on mining data from blogs, forums, twitter, media, government and other web-based media. The FE dataset falls into the latter category of VGI, where the geographic footprint manifests from addresses, cross streets, or other place-based nomenclatures harvested from retroactive information, such as media accounts or government records.

What separates VGI from Professional Geographic Information (PGI) is the influence of developed data standards. For example, the National Spatial Data Infrastructure (NSDI) hosted by the Federal Geographic Data Committee (FGDC) provides for the coordinated development, use, sharing, and dissemination of geographic data on a national level (FGDC 2015). Infrastructures like these promote quality data practices which in turn give authority to users of such data. Further, professionals who develop data using refined standards are putting into use practices that help alleviate concerns over quality.

Despite the lack of influence from standardized protocols, as increased attention is directed toward VGI, members of the academic community are attempting to understand if the

perceived value of the data is supported by its quality, noting that the characteristics that mold the information may not be as rigorous as traditional scientific data reporting (Jackson et al. 2013). Jackson et al. continue by asserting that quantifying the key quality characteristics of VGI data would be a step toward realizing the standards that can reasonably be expected to be included in contributed datasets. The implication here is that once these characteristics are identified, the contributed data can then be compared to other, similar professional datasets, termed reference datasets. The first studies of VGI that compare the data to authoritative data were conducted by Haklay (2010), Mooney et al., (2010), and Zielstra (2010). However, in a dataset like FE, no reference source is available for comparison. Since authoritative data comparison is impossible, this study relies upon extracting relevant QA components from academic literature that address VGI quality.

3.1.2 Volunteered Geographic Information Literature

Despite its relative youth, literature concerning VGI data has become quite robust, with one common theme resounding throughout. Consensus among academics is that QA's are essential, no matter the project. With QA concerns ever-present, the emphasis of literature can range from VGI project case studies, (Jackson et al. 2010, Fan 2014, Heipke 2010), to developing validation frameworks (Meek 2014; Fast 2014; Haydn 2014). Some focus on understanding the motivation for participation or creation (Zook and Graham 2010), while others discuss the social implications for the emergence of VGI, like the potential erosion of privacy (Obermeyer 2007), erecting new platforms of activism (Turner 2006), or influencing new forms of exclusion (Zook et al. 2007). The overall diversity of the literature reflects the wide assortment of VGI data. Yet, it is apparent that the same core literature is cited among the works that consider VGI, including

in particular Haklay (2010) and Goodchild (2007). Thus, the best way to characterize and extract QA factors relevant to the FE dataset is to use a conglomeration of the available literature.

3.1.3 Active versus Passive

According to Meek (2014), VGI can be divided into two main types, active (i.e. geotagging and describing a location, digitizing a road, or collecting coordinates) and passive (i.e. information mined from Twitter or media accounts). Dovetailing VGI into one these two categories suffices for most projects but FE cannot be categorized as one or the other because it is both active and passive. FE is active in the sense that participants fill out forms for recent incidents, and passive through the mining of incidents from media accounts or government records. It stands to reason that the ambient nature of the FE dataset requires both active and passive methods in order to collect both retroactive and present data. Ambient, as it were, is data that references location and description to momentary social hotspots (Stefanidis et al. 2013). Because attention is given to instances when law enforcement uses force, there are often archived accounts of the incident. FE relies upon these accounts to gather data both actively and passively.

3.1.4 Describing Location

Sui (2014) explains that the perception and description of space and place for geographers differs from that of the general public. GIScientists emphasize as precise a description of a feature as possible (i.e. X, Y coordinates), expending great effort to ensure boundaries and locations are accurate and easily discernable. As such, GIS functionality is best when these descriptors are most accurate. In contrast, VGI, because it emanates from the crowd, reflects more closely the popular interpretations of place. People tend to refer to locations by place-names, addresses, or a point of interest, with little relation to precisely bounded features (Sui 2014). This presents a problem when attempting to apply VGI to GIS. How can informal human discourse for places be

translated to precise locations on the earth's surface? The imprecision in human discourse is a significant factor for the FE dataset. For example, a media report may describe an incident's location as being in "Southeast Portland" rather than referring to a street address. Any instance where informal rhetoric is used directly affects the ability to precisely locate an incident.

Here it is important to distinguish between accuracy, precision, and the possible error for both. Accuracy is the degree to which the information in a database matches the true or accepted values (Rambaldi 2006). Conveyance of accurate information is a risk for FE because it relies on accounts from media and government along with, at times, further interpretation from volunteers or administration. Vague or misguided descriptions of place can have large effects on how well an incident can be located on a map. Precision refers to the spatial resolution or the exactness of the description (Rambaldi 2006). For FE, an example of optimal precision and accuracy would be a truthfully reported numbered street address. The FE dataset is at risk for increased locational error whenever reports are erroneous or lack specific description.

The address field presents the best possibility for precise locating but is most susceptible to ambiguities, and therefore inaccuracies, because the information is derived from accounts with varying degrees of description. These sources can vary widely in their portrayal of place, sometimes providing a full address, while in other instances, only cross-streets or single roads are given. Furthermore, there is no system for determining which address best fits an incident. There is also no descriptor indicating whether the event happened inside a building or outside, thereby decreasing the certainty of the exact location of the event. For this reason, the source from which the data is derived comes into question just as much as the participant researching the incident. There is no way to evaluate media or government sources accounts of address, or how they chose to describe a particular location. The FE dataset relies on well reported records

for each incident, meaning any imprecision in reporting is expressed in the data. However, a marginal level of positional uncertainty for the FE data may be permissible for some analyses as is discussed in the methodology.

3.1.5 Hierarchical Structure

The systems that produce VGI can be regarded as the environment where information is derived (Fast 2014). This environment consists of building blocks for the systems that rely on interdependent relationships between the project's initiators, participants, and the technical infrastructure (Fast 2014). Within the technical infrastructure lie the functions that allow for the input, management, and dissemination of the data. Chrisman's (1999) nested rings, used to understand how GIS operates, provides context for the hierarchy of the FE dataset (see Figure 1). This straightforward structure relates effectively to the FE dataset and is important for understanding the interdependency of these components.

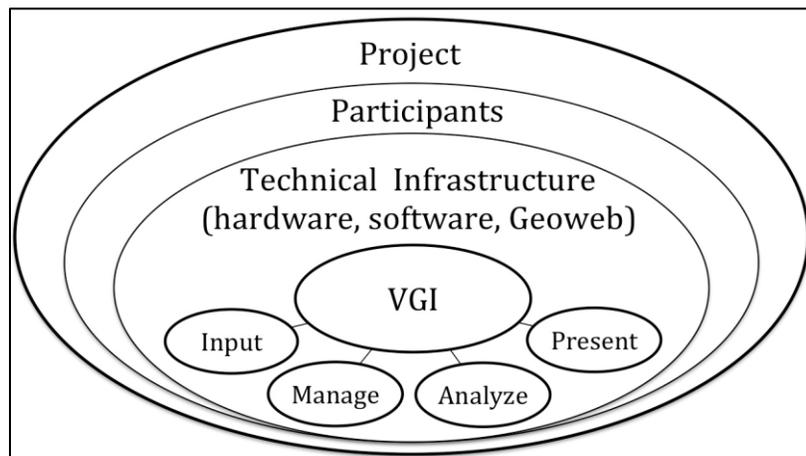


Figure 1: Components of VGI Systems (Source: Adapted for VGI from Chrisman (1999))

3.1.6 Authoritative versus Anarchic Control

One framework compares and contrasts the elements typically associated between extreme authoritative control for data collection versus the idea of anarchic systems that encourage full volunteer participation with no guidelines or standards (Rice et al. 2012). Table 1 shows the two variants, from extreme data control to anarchic systems. At times VGI is possibly perceived as anarchic, which fundamentally reduces data quality, but many VGI projects display multiple elements of authoritative data collection control (Rice et al. 2012). Categorizing FE for each factor provides context into whether FE has more or less controls. The comparison shows that FE has many practices that reflect authoritative control of the data.

Table 1: A Spectrum of Control between Extreme Anarchy and Extreme Control

Extreme Anarchy	Extreme Control	FE dataset
No contributor expertise required	Certified technical expertise required	Anarchic
No user registration	Verified user registration	Both
No training required	Certification required	Anarchic
No production practices	Established production practices	Controlled
Any geospatial inputs	Approved geospatial input	Both
No specified positional accuracy/precision	Specified positional accuracy/precision	Controlled
No attribute specification	Full attribute specification	Controlled
Users decide which feature collected	All feature meeting specification collected	Controlled
No validation of data	Point of entry validation	Controlled
No review	Professional review	Controlled
Multiple user edits	Single user edits	Controlled
No user edit tracking	Feature level user edit tracking	Anarchic
No edit temporal tracking	Edit temporal tracking	Controlled
No database rollback	Database rollback	Controlled
No Metadata	Standards compliant metadata	Somewhat controlled
Data immediately available	Data available after review	Controlled
Unrestricted data availability	Proprietary data	Anarchic
Unrestricted usage rights	Restricted rights	Anarchic

Source: Table adapted from (Rice et al. 2012, 4)

3.2 Quality Assurance Components

Quality issues associated with VGI have been widely deliberated by academics and geospatial practitioners. Many of the traditional concepts for quality assurance arose from the practice of paper mapping but have been subsequently adapted to accommodate the transition to electronic GIS (Rice et al. 2012). Considering that the FE dataset has no authoritative data for comparison, the strategy for analyzing its quality is guided by multiple sources that outline common fitness indicators. This section introduces the components that might cause FE's fitness to suffer.

3.2.1 Lineage

In the Federal Geographic Data Committee's (FGDC) Content Standard for Digital Geospatial Metadata, they define lineage this way: "Information about events, parameters, and source data which constructed the data set, and information about the responsible parties" (FGDC 2012, 1). Lineage is especially important for the FE dataset because information is derived from a number of different sources. Ideally, lineage has a stored component for each feature in a dataset. However, lineage can be quantified by enumerating the primary source(s) for each entry.

The quality of the source is also important, as discussed earlier, where media or government accounts inevitably vary in the accuracy and /or precision of their reporting. Because of the heavy reliance on these sources, this is an inherent deficiency for this type of data.

3.2.2 Attribute Accuracy, Completeness, and Consistency

Attributes, in a geospatial sense, are the non-spatial data that are connected to location (Haklay 2014a). For the FE dataset, attribute accuracy is inextricably linked to lineage. The accuracy of attributes is directly reliant on the quality of the sources. Knowing how effectively these sources populate the database is one aspect that needs to be measured. The number of null values in a field versus the number of entries populated by data is a function of completeness.

Attributes assigned to a field are only as good as the definitions and rules that govern them (Morris 2008). For example, the cause of death should have specific rules stating information that can be entered for each incident. If there are multiple causes of death, there should be clear rules for dealing with outliers. Another example would be the difference in the interpretation of a journalist versus what the justice department might consider as to whether an officer's use of force was justified. One might be an opinion, while the other is the result of due process. Errors due to misclassification or incorrect attribute values can be common in VGI (Rice et al. 2012).

Once fields are established, the information contained within them must be consistent. Number fields should contain only numbers and text fields should have only text. Features, like cities should be entered the same every time. New York City cannot also be listed as NYC. Exploring the database for these potential problems will give an idea how well the data would perform in analyses.

3.2.3 Positional Accuracy

Positional accuracy refers to the deviation of feature positions from their real world position in the vertical and horizontal domains (Rice et al. 2012). The positional accuracy for the FE dataset is not as reliant on exact location as other VGI projects. However, it is important to establish what is meant by the location of an incident and how well the address field defines an incident's location. Further, helping alleviate positional accuracy concerns, vertical data is not relevant to the FE dataset. Yet, it is important to understand how well the database can describe the location of an incident.

The address field in FE identifies location through place name. For example, a numbered address is given in most instances, which provides an acceptable positional accuracy. However,

other instances simply list cross roads or a street name, which degrades the ability to precisely locate incidents. Low-level description is a concern for the FE dataset. Instances where locational description is vague must be inspected and curated before they can be properly imported into GIS.

3.2.4 Completeness

Completeness is the number of objects expected to be found in the database but are missing or are present but should be excluded (Haklay 2010). It is vital to ensure that the definitions of criteria for information that should be included in a dataset are as precise as possible. Without the ability to discern which incidents qualify as fatal encounters, the risk for entering non-applicable cases escalates. Also, comprehensively capturing incidents is of paramount importance. An incident not being captured by FE is likely to be the greatest source of criticism from critics and analysts of VGI. However, the assessment of each of these components yielded the first academic understanding of the data's fitness.

3.3 Competing Datasets

Before describing the FE data set in detail, it is important to understand how other similar datasets relate. Police use of deadly force has always been a topic that has generated debate, but in the last two years, increased attention has been directed toward gun violence, including mass shootings and cases where law enforcement's use of deadly force is perceived to be excessive. Given the fact that data is useful for providing context to violence in the United States, several datasets now exist where gun violence or law enforcement's use of force is being compiled, whether it be by an individual, the collective public, or government entities.

3.3.1 Datasets Collecting Related Data

The scope of a project is important for determining exactly what information should be collected.

Two entities collect data that overlaps with the scope of the FE dataset.

3.3.1.1 Homicide Watch D.C.

Homicide Watch D.C. tracks the details of every homicide, from crime to conviction, within the bounds of the District of Columbia (Homicide Watch D.C. 2015). Using media reporting, court documents, social media, and the help of involved families or neighbors to compile information, this group of local citizens has built an open-access database (Homicide Watch D.C. 2015). The advantage this dataset has over the FE dataset is that the study area is small enough that members can personally follow each case. Furthermore, the crowd, in this example, consists of a few contributors, which eliminate the variability of relying on possibly hundreds of volunteers to compile the data. Because of the scale Homicide Watch D.C. can focus solely on local information sources, which results in greater confidence in completeness.

3.3.1.2 Gun Violence Archive

Another group began compiling every gun related incident in the United States since the Newton, Connecticut shooting on December 14, 2012. After one year of sourcing only media accounts, the project was picked up by the Gun Violence Archive (GVA), a non-profit organization who now detail near real-time data concerning every incident involving firearms (GVA 2015). Comprised of 10 paid researchers, the GVA perpetually scans 1,200 media, government, and commercial sources (GVA 2015). Utilizing full-time employees enables the GVA to effectively gather and publish information in a real-time, user-friendly interface. Gun violence is categorized into one of a possible 100 associated causes. Among them are hate crimes, domestic violence, gang involvement, and police action. Data also includes whether

victims were injured or killed. The spatial precision is high and provides both the address of the incident and X, Y coordinates. How the high degree of precision is achieved is unclear, but the project's high level of organization and polish exhibits authoritative qualities. Despite the GVA's authoritative surface, clean website design, and near instantaneous updates, the GVA lacks temporal depth, which limits retroactive analysis. However, the ability to sort by law enforcement-related incidents makes the GVA a prime candidate for comparison to the FE dataset.

3.3.2 Datasets Collecting Same Data

Other datasets compete directly with the FE dataset. They attempt to compile the same information but have variations that, for one reason or another, make them less attractive for validation and subsequent analysis.

3.3.2.1 Killed By Police

There are three datasets that focus solely on police use of force on citizens. The first, Killed by Police (KBP), was initiated on May 1, 2013, and is compiled solely by an individual who prefers to remain anonymous. This individual utilizes media-sourced searches to hunt for incidents daily. KBP defines incidents in its database as: "Corporate news reports of people killed by nonmilitary law enforcement officers, whether in the line of duty or not, and regardless of reason or method with inclusion implying neither wrongdoing nor justification on the part of the victim or the officer involved" (KBP 2013). Averaging approximately four incidents per day for nearly two years, the data appears complete but not broad, enlisting only seven fields (date of death, state, gender, race, name, age, and a link(s) to the media source). While likely capturing the bulk of incidents, KBP lacks a precise geospatial footprint (i.e. address field). Given that KBP is operated by one individual, the variation introduced by crowdsourced data is not a factor,

meaning that the collection protocol is likely consistent. Given that KBP has just over 2 years of data, its main weaknesses are a lack of explicit protocol, attribute broadness and temporal depth. Because of its similarity to the FE dataset, KBP is an excellent candidate for comparison.

3.3.2.2 U.S. Police Shooting Data

The final relevant dataset was started by a journalist, Kyle Wagner, from Deadspin who is attempting to compile every officer-involved shooting – including non-fatal incidents – since January 1, 2011 (Wagner 2014). This project is purely crowdsourced. There are explicit instructions for volunteers to upload data through a form for days that have yet to be researched. Volunteers query search engines, filter by day and research, and then enter all incidents for that date. As of April 2015, they claim to have incidents for 60% of the days since January 1, 2011 (U.S. Police Shootings Data 2015). The database is similar to the FE dataset but is again missing a field with a specific geographic footprint, like an address. Also, this dataset does not have an administrative fact-checking team, which has left a large number of entries with missing field values, thereby lowering attribute consistency. The strength of this dataset is that participants can access an interactive spreadsheet to see which days are complete and do their research for specific dates. Early participant momentum has declined significantly since the project's inception. However, this data is directly relevant to the FE dataset, thus justifying a comparison.

3.3.2.3 Arrest Related Deaths Program

The Arrest Related Deaths Program (ARD) is a spinoff from a program initiated in 2003 by the BOJ, under legislation for the Deaths in Custody Reporting Program (DCRP). This program utilizes state-reporting coordinators (SRCs) to track deaths that occur while an offender or suspect is in the custody of a local jail or state prison facility as well as deaths that occur anytime a person's freedom to leave is restricted by law enforcement (BOJ 2015). The goal of the ARD

program is to have a comprehensive data-collection process that compiles information from every state and law enforcement agency in the United States.

The ARD program has data from 2003-2009 and 2011. It possesses a much clearer collection protocol and very detailed definitions for describing which incidents to include, and also has a broad range of attributes. However, the program does not mandate that each state participate making contribution to the program voluntary. Nevertheless, participation has been high with as many as 46 states contributing in a given year.

Despite these strengths the Bureau of Justice Statistics (BOJS) published a technical report in March 2015 analyzing the program's data quality. The deficiencies found in the data and collection process were extensive. The ARD is explicit for describing what type of incident qualifies and how the data can be submitted by SRCs, but allows collection methodologies to be determined by the SRC in that state. This variability has resulted in a lack of standardization at the state level. The report states: "The manner in which incidents are identified and subsequent information collected varies between and within states and over time, leading to nonsampling errors from differences in use and interpretation of definition, scope, and data collection modes" (BOJ 2015, 11). Concerns about the coverage, bias, reliability, and completeness of the ARD data are extended by the fact that their technical report estimates that only approximately 50% of all incidents were captured during 2003-2009 and 2011 (BOJ 2015). Furthermore, even though SRCs have a less restrictive access to law enforcement records, the report indicates that the primary source for gathering information come from media related searches. Admittedly, the ARD data is unfit for analysis, but because it emanates from government and dates farther back than the other projects mentioned above, it remains as a good candidate for comparing to the FE dataset.

3.4 Analysis Possibilities

FE is similar in nature to crime data which is frequently analyzed to inform policy makers. Crime analysis and mapping, realized through GIS, plays a major role in the reduction of crime and improving police strategies (Kumar 2011). Publications by Chainey (2013) and Levine (2004) have emerged as popular guidelines for crime analysts. These works are lengthy and provide many examples for analyzing crime. One such method is the Getis-Ord G_i^* statistic, which is a complement to Kernel Density Estimation (KDE), and are both available in ArcMap. The tool works by looking at each feature within the context of neighboring features to identify statistically significant hot and cold spots (Esri 2015).

The idea for using hotspot analysis with the FE data is similar to law enforcement's use of the strategy to mitigate crime. Understanding where hotspots exist allows analysts to focus greater attention on these areas so that they can uncover underlying reasons for the causes of the hotspots. Of course, the fitness of the FE data is contingent upon producing analyses that are useful for understanding police use of force.

CHAPTER 4: METHODOLOGY

This study endeavored to develop a customized framework for validating a unique VGI dataset that is attempting to compile a list of every citizen who has died through interaction with law enforcement. As such, this study individually examines a number of various components, discussed in Chapter Two that affect the overall quality of VGI data. Through an array of evaluation strategies of the FE dataset, the fitness of the data, including the identification of its main strengths and weaknesses was determined. A better understanding of the quality will increase the confidence of users who wish to use the data, as well as provide advice to the administrators of the dataset regarding where and how their methods might be improved.

This chapter discusses the methodology for evaluating each of the quantifiable quality assurance components. The strategy for designing a hybrid framework is based on components outlined in other VGI QA studies (Haklay 2010, 2014; Meek 2014; Fast 2014). These are combined to customize an approach that addresses the specific features that make up the FE dataset. Next, methods used for geocoding incidents into ArcMap and the process for conducting the subsequent preliminary hotspot analysis are outlined at the end of the chapter. Also, the reasons for selecting the study area where the analysis was undertaken are explained.

4.1 Dimensions of Quality Assurance

The factors that affect data quality vary. It is for this reason that each of these factors is seen as a separate dimension that should be evaluated individually, building strategies customized to address specific characteristics. That is to say that the general criteria for quality need to be defined and based upon the planned use of a given dataset (Sui 2014). This approach is necessary because some quality elements might seem independent of a specific application, but in reality they can only be evaluated within a specific context of use (Haklay 2014). For example, the

question of completeness can only be measured within the bounds of the area of interest within the scope of what qualifies as the type of incident in question.

Often, reviewing metadata is the fundamental method to evaluate data quality (Rice et al. 2012). However, the FE dataset does not have formal metadata and therefore requires an *ad hoc* evaluation of the main quality components that affect quality. Because the FE dataset is not yet 100% complete, the evaluation of each quality component focuses on different portions of the dataset both spatially and temporally depending on the quality component being assessed. Since the FE database is continually updated, the data underwent analysis from a download on June 15, 2015. Any errors, such as repeat entries, within the data were documented and sent to administration for curation. These errors were also corrected in the version used for analysis.

4.1.1 Completeness

Arguably the most important data quality component for FE is completeness. It is defined by the number of objects expected to be found in the database but are missing, as well as the existence of excess entries that should not be included (Haklay 2014). Assessing this requires a multi-faceted approach. If it is found that several incidents are not being captured by FE collection methods, the integrity of the data suffers. One of the main worries from media, is that crowd-sourced projects compiling police use of force are missing large portions of data (Fossett 2015). The strategies for quantifying completeness are outlined in the proceeding sections.

4.1.1.1 Public Records Requests

The FE dataset claims there are 12 states (CT, FL, MA, ME, MT, NH, NV, NY, OR, RI, SD, VT) where every incident has been collected from January 1, 2000 through June 20, 2015 (Burkhart 2014). To test if FE is capturing incidents in these states, FOIA requests were sent to a stratified random sample of law enforcement agencies. Maine was exempted from this process

because they are one of two states who require that the State Attorney General investigate incidents where police use deadly force so data was acquired directly from this source (Maine Attorney General 2015).

For all states except Maine, a database of the law enforcement agencies, obtained from a 2008 FBI census, was used to determine how many and which agencies to sample. The sample size was determined by compiling the total number of agencies within 11 of the states, then inputting that number into an online sample size calculator, developed by Creative Research Systems (CRS 2015), The CRS calculator returns a sample size based on a desired confidence level and confidence interval. These values were set at 95% and +/- 5% respectively. After calculating the sample size for agencies to be sampled, the sample size was increased by 25% (oversample) to provide extra samples in case of delayed or non-responses to the FOIA requests. The total number of samples required was 410.

The sample was also stratified by state and agency type (local Police, Sheriff, State Patrol and other, i.e. University, Airport, Game and Fish, etc.). The proportion of agencies was calculated against the total sample size to determine how many agencies, by type, to be sampled. Since there is only one State Patrol department in each state, a records request was automatically sent to this agency. Table 2 lists the total sample for each state along with the total for each agency type, calculated as a proportion. The calculations and the number of agencies, by type can also be viewed in Table 2.

Table 2: Number of Agencies (by Type and State) Sampled

State	Total Agencies (% of total) [# Sampled]	Police Departments	State Departments	Sheriff's Department	Other
CT	143 (6.5%) [27]	120 (84%) [21]	1 (0.7%) [1]	1* (0.7%) [1]	22 (14%) [4]
FL	387 (17.2%) [71]	270 (70%) [49]	1 (0.02%) [1]	65 (17%) [12]	51 (13%) [9]
MA	357 (15.9%) [65]	314 (88%) [57]	1 (0.02%) [1]	11 (3%) [2]	31 (9%) [5]
MT	119 (5.3%) [22]	54 (45%) [9]	1 (0.08%) [1]	55 (46%) [10]	9 (8%) [2]
NH	208 (9.3%) [38]	187 (90%) [33]	1 (0.05%) [1]	10 (5%) [2]	10 (5%) [2]
NV	76 (3.5%) [14]	38 (50%) [7]	1 (1%) [1]	16 (21%) [3]	21 (28%) [3]
NY	514 (22.8%) [93]	391 (76%) [71]	1 (0.02%) [1]	57 (11%) [10]	65 (13%) [11]
OR	174 (7.3%) [30]	129 (74%) [21]	1 (0.06%) [1]	36 (21%) [6]	8 (5%) [2]
RI	48 (2.1%) [9]	39 (81%) [5]	1 (2%) [1]	1* (2%) [1]	8 (15%) [2]
SD	155 (6.9%) [28]	80 (52%) [14]	1 (.064%) [1]	66 (42%) [11]	8 (5%) [2]
VT	69 (3.2%) [13]]	50 (72%) [9]	1 (1.4%) [1]	14 (20%) [2]	4 (6%) [1]
Totals	2250 (328 x (1.25% = 410)	1672 (296)	11 (11)	330 (60)	237 (43)

(*) Denotes that the state has one overarching division representing all Sheriff's departments that is sampled.

Requests were written using templates from the National Freedom of Information Coalition (NFIC 2015). The FOIA letters define the incident type and ask for complete records for all incidents fitting the criteria. Each state has different laws governing the response

timeframe limit, which was cited within the body of the letter. Also, a waiver of fees was requested for academic purposes that would benefit society without commercial application.

During the response period, a database was constructed using the received records. It was expected that not all requests would be filled due to the provisions of various laws, extensive fees, or extended time to complete the request. The database was designed to include the same 15 fields as FE. However, when agencies could not provide the entire record, a reduced request was made asking for basic information (name of decedent, age, date of injury causing death, and address). Monetary fees less than or equal to \$20 were paid in order to receive records. In cases where fees were extensive and could not be waived a request was rescinded. The new FOIA database was then used to compare to the FE dataset, noting which records were in the new FOIA database versus the FE dataset.

4.1.1.2 Comparison to competing datasets

The years 2013 and 2014 are considered complete by the FE administration. In order to test completeness for these years, the FE dataset was also compared against two competing datasets: KPD and GVA. The ARD program and the Deadspin dataset were not evaluated against FE. Data for the ARD program could not be obtained in time, despite concerted effort by Michael Planty from the BOJ. The Deadspin data was deemed impossible to compare due to extensive missing attribute values and copious redundant entries. All of the relevant datasets had differences in the attributes they reported but the name, state, and age fields were common, enabling comparison. Association between datasets occurred manually by printing each dataset and highlighting the entries that matched and counting those that did not. Completeness for the years 2013 and 2014 was determined by reporting the percent of entries represented in each competing dataset versus the FE dataset. Any records in KBP or GVA and not in FE were

researched to determine if they fell outside the scope of FE. Any missing incidents not in scope were not counted against FE.

4.1.2 Attribute Accuracy, Completeness, and Consistency

Understanding the overall quality of sources used to populate the FE dataset is difficult. Linked to each entry in the FE dataset is the main source from which information is mined. Because the FE data does not have stored information detailing the source for each of the 15 fields, an evaluation of the source linked to each entry was conducted. In order to assess the credibility of media accounts, a sample of the FE dataset was used to verify the information contained in the media account versus attribute content in the FE database. Using the CRS sample calculator, with 95% confidence level and +/- 5% confidence interval, 364 entries needed to be verified based on the 7,022 incidents in the FE database. After randomizing, the incidents were removed from the FE dataset and each media link was examined to verify that the correct data had been extracted and entered correctly. Any differences were tracked and reported. Unfortunately, it was not possible to assess the quality of the information in media accounts because they were written relative to what each journalist deemed was important to report. This also made it impossible to validate the accuracy of reporting.

The completeness of the attributes within the FE database was assessed. The occurrence of incomplete fields, or null values, was counted for each field. To check this, each field was sorted and the number of null values was calculated as a percent against the number of populated entries. Throughout the process, a logical check for the classification of each field was done. For example, were the categories for cause of death clear-cut and without ambiguities? A field's ability to report information with a high degree of completeness, along with sound logic for the content being reported, is a crucial component to understand before analysis can be undertaken.

Lastly, assessment of the consistency for the way the field is populated by information was conducted. For example, is the official disposition consistently reported? Do all of the categories make sense? Consistency was not quantified in this study because it was clear that there existed a large number of inconsistencies in the database. Therefore, the overall impression of consistency was reported in the results.

4.1.3 Positional Accuracy

Positional accuracy of incidents, as it pertains to the FE dataset, is not as crucial for precision as other VGI projects. Yet, a certain degree of precision is necessary, especially for large scale analyses. Further, the accuracy/the description of place must be correct before an incident is located spatially. Therefore, the address field needed to be assessed to ensure that accuracy in place description was present as well as to determine how precisely locations could be geocoded into GIS.

To get an idea of the level of precision the FE data exhibits, the address field was evaluated for the 12 complete states and classed into five tiers with decreasing levels of expected precision. Table 3 shows how the tiers were broken down. The twelve complete states were copied into separate spreadsheets with an additional field that was used to assign the tier class to each address entry. Then, the count for each tier was tallied and calculated to predict the overall level of precision associated with the data. The idea is, that the more accurate the description of place, the greater the chance GIS software will have locating that incident precisely in space. Lower tiers of accuracy exponentially increase the locational error in turn escalating the possibility of negatively affecting analysis.

Table 3: Precision Classifications

Tier 1	Numbered Street or Cross Streets	452 Aberdeen Rd Aberdeen Rd and Crowley St
Tier 2	Hundreds Block	300 Block Aberdeen Rd
Tier 3	Road Name	I-94 or Platte St
Tier 4	Place Name	New York City Hall
Tier 5	Unknown	N/A

Once it was known how precisely the address could be geocoded into ArcMap, it was determined that New York state had a high number of incidents plus a high percentage of tier one and tier two address entries. Because of these traits it was selected for curation and subsequent analysis. Curating insufficient addresses required a number of creative strategies.

The strategies employed used an array of resources in an attempt to improve descriptive precision for the 32 incidents not falling under tier one or tier two. First, in depth research through search engines was done to explore alternative sources other than the source provided from FE. For 14 of the cases the address was found within the body of a media account. This information was then written as the new address and the record was upgraded to tier one. In eight instances a place descriptor was given such as the name of a business, apartment complex, or an on-ramp for a highway. For these cases, Google maps was used to ascertain the address. In another case, a photo preceding an article depicted the house number where the incident occurred. In three cases, the address was found within the records received from the FOIA sample. Three more cases occurred on roads that were less than 300m in length or occurred in a cul-de-sac. For these instances the address was ascertained by clicking a spot in the middle of the road in Google Maps. Three remaining cases could not be curated and were omitted before analysis.

As a result of the curation process, the overall precision of the address field for the state of New York was improved spatially to an approximate error of 300m. This error could potentially be large enough to affect some large scale analyses but was deemed acceptable for the analysis in this thesis.

4.2 Hotspot Analysis

Preliminary hotspot analysis for this study was conducted in the New York City area which included all five boroughs (Queens, Manhattan, Staten Island, Bronx, and Brooklyn). This area was chosen because it had a high density and high number of incidents. Hotspot analysis is sounder when there is a larger incident count (Esri 2015).

To ensure that distance was preserved during spatial calculations, each layer used in the analysis was projected using the NAD 1983 StatePlane NY FIPS Meters. Next the FE data was geocoded using the U.S. Geocoding service, requiring a match score of at least 80%. If any entries were not matched with the requisite score, the entry was re-matched to the next closest street address as long as it was within 50 points above or below the actual address being geocoded. This decreased precision but stayed within the accepted 300m error band for an incident.

Hotspot analysis cannot be calculated using point data. Instead it requires weighted or count data. To accomplish this, a hexagonal polygon grid was built with a width of 1,200m, and then clipped to the study area. The width was determined by two factors. First 1,200m is a effective width for achieving a variable count of incidents within each polygon in the grid. Greater count variation within the polygons increases the statistical robustness of the hotspot analysis. Secondly, a study from the department of planning from the city of New York created a boundaries shapefile, known as neighborhood tabulation areas (NTAs), was created by the city's

GIS department to project demographics in small areas. They state that their new geographic areas offer a good compromise between the overly detailed data for census tracts and the broad strokes provided by community districts (NYC Planning 2014). These units have value because they enable the city to look at data at the neighborhood level. The logic used above also made sense for this study because the average area of these units was approximately equivalent to the width of polygons in the grid created in order to achieve an acceptable variance count of incidents per unit.

Often hotspot analysis is conducted using a square polygons grid. In contrast, there seem to be strong qualitative advantages from using hexagonal polygons. Birch (2007) points out that hexagonal grids have a simpler and more symmetric nearest neighbor, are better for measuring connectivity between neighbors, outperform for dispersal modelling, adhere more naturally to the shape of the earth, and provide greater clarity for visualization. For these reasons the hexagonal grid was chosen as the geometry unit to be used for the hotspot analysis.

The hexagonal grid was created by downloading a script that would create the hexes, obtained from a link on the Esri (2013) blog. Once the grid was created and clipped to the New York City area, the geocoded FE incident points were spatially joined to the hexagons to create a field with the count for the number of incidents within each hexagon.

It was determined that two hotspot analyses would be conducted. The first would be with the raw incident count and the other would be normalized by total population. Using a weighted overlay technique in ArcMap, T.I.G.E.R. census tract demographic data polygons were used as input data to reaggregate race counts into the newly created hexagons. The tabulate intersection tool calculated the ratio of the census block polygon within each hexagon, then assigned a percentage of the population based on the containment ratio. The output was a table that was

then joined to the the hexagon layer with the incident count. Lastly, a field was created for the normalization calculation which was a division of total population and incident count per hexagon.

The hotspot analysis calculation requires the specification of the distance band. This specifies a cutoff distance for what is considered a neighbor. Anything outside the distance neighborhood has no influence on the calculation. The distance was decided from the peak z-score taken from the incremental spatial autocorrelation tool. This tool calculates the level of influence features have upon one another and plots the results on a graph. The peak z-score indicates the distance with the most interaction between neighbors. Using this strategy, this study decided on the fixed distance of 6,500m.

After the hotspot analysis was run, two additional maps were produced for comparison. The first map was simply a population density map of New York City. The second map was a dot density map of the four predominant races in the study area. They were White, Black, Asian, and Hispanic. These maps were preliminarily examined without asserting any conclusion except that these types of analyses can be done with FE data when and where it is sound.

CHAPTER 5: RESULTS

This chapter reports the results from testing the various quality assurance components against the FE dataset. Of the various data quality tests, for hotspot analysis, the most important components are spatial accuracy and completeness. Numerous other aspects of the dataset were evaluated with some found to be lacking for analysis. Another number of attributes were short on consistency and quality. The problems with these attributes limit other analyses that might be contemplated but does not affect the hotspot analysis in this study.

The findings of these tests are the focus of this chapter which is divided into four sections. Section 5.1 concerns FE's lineage and attribute accuracy. Section 5.2 addresses completeness. Section 5.3 details the spatial accuracy. Lastly, section 5.4 illustrates the result of the hotspot analysis.

5.1 Lineage and Attribute Accuracy

Each of the 15 fields in the FE database was examined in two ways. First, how many entries per field have null values? Second, how well does the FE database adhere to specified class parameters? The address field is excluded here because it was evaluated in the previous section. It was found that there were some fields that were very complete and consistent while others were deemed inadequate.

5.1.1 Name

The name field consists of at least the first and last name of the decedent. In some cases the middle name is provided or the nickname is given in quotations between the first and last name. Of the 7,022 incidents contained within the FE database there occur 87 instances where the name is not complete. In these cases, the entry lists that the "name is withheld by police." Thus, the FE

database provides the name of the decedent 98.8% of the time. This indicates that one of the most reported facts in sources is the name.

5.1.2. Age

The age field simply lists the number of years the decedent had lived until death. The field is not as precise as using the actual date of birth despite the actual date of birth being reported regularly. Table 4 depicts the evaluation of the field. Only the exact age was considered complete in the calculation with any variation considered incomplete. The age field should be considered fit for analysis.

Table 4: Age Coverage

Exact age	6,916
Age range < 10 years	8
Age range < 5 years	4
Unknown	94
% where age is known	98.5%

5.1.3 Gender

The gender field can be entered as male or female. Table 5 shows the number of entries for both along with the number of incidents where gender was unknown. This field is very accurate and could be used for gender-based analysis.

Table 5: Gender Distribution and Coverage

Male	6,481
Female	537
Unknown	4
% where gender is known	99.9%

5.1.4 Race

The race field can be entered as one of nine classes. Table 6 indicates how many of each race is contained in the FE database. The unknown race category is problematic because it makes up 36% of the FE database. Because over one-third of the incidents do not have a reported race, any analysis based on this field would not be credible. This could be due to the fact that racial identities can be fluid and difficult to distinguish, especially from media accounts. This field could be improved through the use of name specific FOIA requests. Experience from the FOIA process in this study indicated that the race of the decedent was reported for every response.

Table 6: Race Distribution and Coverage

European-American/White	1,986
African-American/Black	1,451
Hispanic/Latino	905
Asian	88
Middle Eastern	8
Native American/Alaskan	39
Pacific Islander	15
Mixed	25
Unknown Race	2,505
% where Race is known	64%

5.1.5 Date of Injury

Every incident in the FE database contains a date (day, month, and year) associated with when the fatal injury transpired and is therefore 100% populated. The range of dates in the database spans from January 5, 2000 through June 2, 2015. The high degree of completeness and consistency for this field means it could validly be used for temporal analysis. Further improvement of the field would be include time of incident which would provide greater depth for temporal studies.

5.1.6 Image URL

The image URL provides a link to a photo of the decedent. Of the 7,022 entries in the FE database, 3,043 have hyperlinked image URL's. This is 43.3% of the total entries.

5.1.7 City, State, Zip Code, County

The city, state, zip code, and county are recorded in the FE database and are reported in nearly every record. City and state are straightforwardly populated from media accounts. The county and zip code fields are more difficult. Mr. Burghart (2015) admits that county and zip code are the most difficult to verify and are components that people frequently get wrong. He states that there is almost always enough context in a story to deduce the zip code. Mr. Burghart double-checks each incident before inclusion into the database using mapping tools to identify locations. Overall, FE exhibits excellent completeness and consistency for these fields (see Table 7).

Table 7: Location Coverage

Field	# Missing of 7,022	% Populated
City	1	99.9%
State	0	100%
Zip Code	20	99.8%
County	0	100%

5.1.8 Agency Responsible for Death

The agency responsible for death can be a difficult field to fill accurately. Often, incidents involve officers from multiple agencies who discharge their firearm simultaneously, which can make it challenging for law enforcement to determine the agency responsible. The FE database, where applicable, attempts to list all agencies involved for each incident. In other cases, the agency responsible is not disclosed by the source. Despite the inherent difficulty of populating

this field, the FE database manages to list involved agencies for a majority of the incidents. 233 of the 7,022 entries do not list an involved agency which calculates as 96.7% coverage. This field should be considered fit for analysis.

5.1.9 Cause of Death

The FE database allows 12 different categorizations for cause of death (gunshot, vehicle, taser, bludgeon with instrument, beaten, medical emergency, asphyxiation, domestic violence, stabbed, drug overdose, beanbag rounds, and other). The “other” category is necessary because often interpreting the cause of death can be ambiguous. This problem is apparent in the database where numerous entries list multiple causes of death. Further examination of individual incident descriptions showed that even when only one cause of death was listed, there could have been others selected as well.

Only 15 incidents have an undetermined cause of death which calculates as a 99.8% population rate. The database lists gunshot as the cause of death for 5,818 of the 7,022 incidents which is 82.9% of the total. However, this field should not be considered sound because of the difficulty of determining cause of death. This field needs exact definition for cause of death, better categorization of incidents, and curation of the incidents already in the database before any analysis.

5.1.10 Symptoms of Mental Illness

The mental illness field is populated and determined by whether the officer(s) should have known at the time of contact if the decedent was mentally ill or altered by drugs or alcohol. Table 8 shows how many of the incidents fall into each category.

Mental illness is another field that requires interpretation from the submitter. There are cases where a healthy or mentally ill person could be on drugs or alcohol which makes it difficult

to discern how to categorize the incident. Further, as seen in Table 8, there were two entries that listed the official disposition of death rather than symptoms of mental illness. This is another field that requires more precise definitions and curation before being useful for analysis.

Table 8: Mental Illness Distribution and Coverage

Drugs or Alcohol	399
No mental illness	4,453
Yes mental illness	1,166
Unknown	952
Null	50
Justified	2
% where symptoms of mental illness is known	99.6%

5.1.11 Official Disposition of Death

The disposition of death can be categorized as justified, unreported, criminal, excusable, pending investigation, or other. The field seeks to state the legal determination of the incident. It is difficult to ascertain the disposition of death from media sources because they can be unclear or even biased in the reporting. Another problem is that incidents “pending investigation” eventually conclude with an official disposition. These entries must be researched at a later date so that the official disposition can be changed. Likewise, the “unreported” category requires further investigation to yield official disposition. Yet, in the FE database, there are still a large number of incidents that show the incident is pending investigation (see Table 9). Further, the “other” category in many cases offers a brief explanation rather than adherence to one of the categories. This field is not fit for analysis until the category definitions become more coherent and extensive curation occurs.

Table 9: Official Disposition Distribution and Coverage

Justified	2,164
Excusable	89
Criminal	145
Unreported	3,417
Pending Investigation	517
Other	690
% where official disposition is known	34.1%

Note: Only justified, excusable and criminal were considered “known” official disposition

5.1.12 Source

The source field is a link to a news article from which most of the information was sourced. Every incident in the FE database has one and only one link. Some links are to news articles while others link to official government reports. For most incidents one article does not contain enough information to populate each of the 15 fields, which means more research is required before an incident can be included in the database. However, a link is a good starting point but there is no way of knowing if other sources were used. A system that could provide every source used to fill in the incident would be more practical. Nevertheless, having at least one link offers evidence to the occurrence of an incident. This begs the question that there may be incidents not captured by the FE protocol if an incident was never reported.

5.1.13 Submitter

Having a field that gives credit to the submitter of an incident should add accountability. However, this is not the case for FE since it allows the crowd to submit information anonymously. The field is difficult to evaluate because of the variability in how the submitter is reported, thereby reducing consistency. Interestingly, despite being considered a crowdsourced dataset, 3,987 of the 7,022 incidents were submitted by either Mr. Burghart or Mr. Lockley (57%). The next major portion of the dataset was contributed by what Mr. Burghart (2015)

described as regular contributors with at least 50 entries each. A total of 12 users have contributed an additional 2,725 (39%) of the entries. The remainder of entries has been added by approximately 234 different members of the crowd, sometimes working jointly. Therefore, the majority of the FE dataset has been built by individuals who supplement the dataset on a regular basis.

Overall, the submitter field is inconsistent making it difficult to track who the contributor was. Over half of the entries cite more than one submitter further confusing things. This field needs more precise definitions in how the submitter is documented. It could be argued that this field is somewhat arbitrary since every incident is cross-checked by Burghart meaning that any errors in the database emanate directly from administration.

5.1.14 Source Validation

A random sample of 364 entries from the FE dataset was generated to test for source validation, giving a 95%, +/- 5% (n=364) confidence. For each of these entries the source link was followed and the information contained in the link was compared to the attributes for each entry. The source link for each incident contains varying degrees of information. However, after comparing the information in FE to the source for the incidents in the sample, the results were that the information was input successfully in 100% of the incidents evaluated. Thus, it can be deduced that the processes for mining sources is effective.

5.1.15 Redundant Entries

The result of combing the FE database for redundant entries yielded 44 instances where the same incident was recorded. These entries were recorded and sent to the FE administration where they were confirmed and edited. One potential reason for these redundant entries is that the lack of consistency in the database as a whole makes it more difficult to pick out redundant entries. For

example, the decedent's name was often misspelled in one entry. However, as a result of this task the FE database no longer has any redundant entries.

5.2 Completeness

As described in Chapter 4, comparisons with several alternative datasets were carried out to analyze how completely the FE dataset captures incidents where interaction with law enforcement results in death. The result for each of these comparisons is reported separately and then combined to summarize overall completeness. Overall, the FE dataset exhibited a high level of completeness. It outperformed comparisons to competing datasets and was found to have only about 1-2% of missing observations from the FOIA process. As detailed below, the coverage for a few particular states may be somewhat less complete and was also difficult to verify.

Every incident found to be missing from FE was forwarded to FE administration to verify that the records do in fact belong in the dataset. Once missing incidents were confirmed they were added to the database.

5.2.1 Freedom of Information Requests

The FOIA sampling process was challenging to execute, especially in a 3-month study period. However, of the 410 agencies sampled, enough responses were obtained to achieve the number necessary for the desired confidence interval 95%, +/- 5% (n=328). Yet, the original plan to obtain all records within the scope of FE was not achievable. Obstacles preventing this were numerous. Some agencies asked for fees in the thousands of dollars, others did not have databases that allowed a search for the type of encounters being requested. Other than Montana, New Hampshire, and South Dakota, there did not seem to be a discernible pattern showing why a request was filled or not. The three states mentioned above often cited specific state laws explaining why a request could not be filled. In other instances, agencies were willing to fulfill

the request but could not fill them within the study period. Table 10 is a summary of the reasons, with the associated count, for a request not being filled.

Table 10: FOIA Reasons for not Being Fulfilled

Denial citing law	20
Extended fulfillment time frame	15
No response	37
Extensive research fees	10

Often an alternative strategy had to be employed when agencies sought fees to print records or to conduct research. In these cases, a reduced request asking for only the name and age of the decedent, location, and date of injury usually produced results. This strategy was successful enough to confirm the existence of an incident while achieving the target number of sample agencies. It would have been better to receive entire records for each incident, but it was not possible because of financial and time constraints. This would have enabled the verification the other attributes in FE. Table 11 outlines the success rate for each of the sampled states. It should be noted that agencies with zero incidents to report were very responsive to requests, while large agencies required greater communication and persuasion.

Table 11: FOIA Response Coverage

State	# Sampled	# Fulfilled	% Fulfilled
CT	27	23	85
FL	71	61	86
MA	65	58	89
MT	22	7	32
NH	38	19	50
NV	14	13	93
NY	94	85	90
OR	30	29	97
RI	8	8	100
SD	28	13	46
VT	13	12	92
Total	410	328	80

Overall, the FOIA process was successful for building a database of incidents with at least the name and age of the decedent, location, and date. In some cases, responses included incidents not within the scope of FE, such as a death that occurred while the decedent was incarcerated. Expunging non-relevant incidents required verifying the incident by reviewing the record provided, or when a record was unavailable, utilizing media accounts. Once the database was built from responsive agencies with records, each incident was compared to the FE database. Table 12 shows the number of records obtained for each state along with any incidents missing from FE.

The FOIA process, despite its flaws, shows that the FE database is largely complete. The database missed more incidents in Florida than other states, but this could be a function of the fact that the sampling turned up more incidents in Florida than any of the other states (see Table 12). However, the results show that even in Florida the completion rate was 95% and the overall completion rate was found to be 98% for all states.

Table 12: Missing Incidents from FE by State

State	# of Incidents	# of Missing Incidents	% Complete
CT	12	1	92
FL	161	8	95
MA	9	0	100
ME	44	0	100
MT	3	0	100
NH	12	0	100
NV	135	0	100
NY	26	0	100
OR	46	0	100
RI	3	0	100
SD	0	0	100
VT	11	0	100
Total	462	9	98

5.2.2 Killed by Police

Table 13 shows the result of comparing the KBP data to FE. Initially, comparing the two datasets appeared straightforward. However, two major differences increased the complexity of the operation. Firstly, the date field in KBP lists the date the incident was entered into the database, not the date the incident occurred. This meant that matching records required a wider range of examination (i.e. matching state, age, and name rather than date). Secondly, there were 39 incidents originally thought to be missing from FE, but after closer examination, these incidents transpired while the decedent was incarcerated. Deaths in custody, based on definitions, fall outside of the scope for both datasets. After these incidents were withdrawn, raw totals could be gathered and comparative completeness calculated.

Results show that FE outperforms KBP for completeness. It should also be noted that FE is much clearer in other areas such as attribute accuracy and consistency. It is also capturing more total incidents indicating that the collection systems used by FE are superior to KBP.

Table 13: Completeness: Fatal Encounters versus Killed By Police

Dates	Fatal Encounters	Killed By Police
May 1, 2013 – December 31, 2013	Incident Count: 805 Missing Count: 9	Incident Count: 807 Missing Count: 67
January 1, 2014 – December 31, 2014	Incident Count: 1183 Missing Count: 9	Incident Count: 1150 Missing Count: 118
Totals	Incident Count: 1988 Missing Count: 18	Incident Count: 1957 Missing Count: 185
Completeness	99.1%	91.4%

5.2.3 Gun Violence Archive

Officer involved shooting data obtained from the GVA was compared to FE for the year 2014. The GVA data’s scope pertains to all gun related shootings but the data compared was filtered to their officer involved shootings only. The data logs incidents where the incident is fatal, non-fatal, or when an individual is unharmed whether they are citizens or law enforcement. So long as a firearm is discharged and the incident involves a law enforcement officer, the GVA categorizes the incident as an officer involved shooting. The overlapping scope of the two datasets provided an opportunity to test FE for completeness.

The GVA data contained a number of weaknesses that made comparison difficult. The primary matching field, decedent’s name, was only 38% complete eliminating the possibility to compare name directly. On way around this problem is fuzzy matching of incidents, where multiple attributes are compared simultaneously for matching credentials, but this was impossible because there were only two fields, city and state, that were similar in both FE and

GVA. Further reducing the count of comparative incidents was the fact that the 821 incidents with a name, 112 were redundant. Once attribute inconsistencies, and out of scope incidents were removed, 709 entries were checked against FE. Of those, four incidents were not in FE and can be counted as missing from the database. The completeness calculation showed that FE was 99.4% complete when compared to GVA.

5.2.4 Arrest Related Deaths Program and Deadspin Dataset

The arrest ARD program data had not yet been obtained at the time of writing despite consistent, helpful, and informative assistance from Mr. Michael Planty of the Bureau of Justice Statistics (BOJS). According to the BOJS they are in the process of redacting the names of decedents in adherence to the law. Future comparison and reporting of the ARD data is recommended once the data is released.

The Deadspin dataset was not compared to FE because of the gross number of errors in the data. Errors spanned from redundant entries to high levels of attribute accuracy and completion. In short, the Deadspin data was not fit for comparison.

5.3 Spatial Accuracy and Precision

The classification of incidents for the complete states into their respective tiers showed that 88% of the incidents were tier one or two (see Table 14). These two tiers could be geocoded into a GIS with a relatively high degree of precision or within 100m of the description of that location (Goldberg 2008). The other three tiers made up 12% of the incidents where geocoding precision is questionable. These incidents could possibly have an associated error of many kilometers or may not be able to be geocoded at all. For these incidents geocoding the zip code or curation would be the only alternatives that could improve the precision of lower tiers. Thus, the reduction of 12% of the incidents, due to unacceptable spatial imprecision, is significant.

Table 14: Tier Distribution and Coverage by State

State	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Total
CT	59	1	7	4	0	71
FL	731	145	67	13	9	965
MA	83	0	15	1	1	100
ME	31	0	22	0	1	54
MT	29	2	1	5	3	40
NH	16	0	5	2	0	23
NV	213	8	11	3	0	235
NY	347	5	29	3	0	384
OR	123	28	23	5	10	189
RI	15	1	2	0	0	18
SD	15	0	4	0	2	21
VT	9	0	7	0	1	17
Total	1,671	190	192	37	27	2,117
Percent	79%	9%	9%	1.7%	1.3%	

As discussed in Chapter Four, multiple curation strategies in the state of New York were used to improve the accuracy of tier three through tier five incidents, in turn increasing the geocoded precision for those incidents to within the acceptable 300m error. If this could be done in New York it stands to reason that it could be done for other states. However, without curating first, ensuing spatial analyses would lose credibility. Therefore, the accuracy in FE must improve before spatial precision becomes good enough for serious analysis, especially at large scales.

5.4 Hotspot Analysis

This section contains the results from the preliminary hotspot analysis conducted in the New York City region. Four maps were generated in ArcMap. Figure 2 shows the hot and cold spots of the raw count of incidents generated from the Getis-Ord G_i^* statistic. It displays that hotspots are located in all of Manhattan, Northern Brooklyn, and in the West Bronx. Staten Island is composed of nearly all cold spots and the majority of Queens has cold spots.

The distribution of the hot and cold spots can be explained by the fact that Getis-Ord G_i^* is an inferential statistic, meaning that the result of its calculation is interpreted within the context of the null hypothesis. The null hypothesis supposes that incidents are distributed randomly across the study area. So, if the statistic rejects the null hypothesis then the output denotes where the spatial clustering of incidents occurs. The calculation yields a z-score, measured by the standard deviation from the mean, where high values indicate stronger clustering intensity, low values indicate negative clustering intensity, and near zero values indicate no apparent spatial clustering.

The final z-score computed for each hexagon in the study area is the result of taking into account the incident count for every hexagon within the specified distance. These hexagons are considered neighbors while every other hexagon farther than the specified distance is omitted from the calculation. Thus, hexagons without any incidents can still receive a high z-score because their neighbors contain a significant number of incidents. This is also the case for cold spots where a hexagon and its neighbors have a significant absence of incidents so as to produce a negative z-score.

Getis-Ord G_i^* is a local statistic useful for finding variance across a study area. Global statistics measure the pattern of the entire study area and does not indicate where specific patterns occur, whereas local statistics identify variation across the study area, focusing on individual features and their relationships to nearby features (Chainey 2014). Figure 2 is the representation of incidents that are unusual in a statistical sense and are not the result of complete spatial randomness. The legend's thematic descriptions were derived from the resulting z-score where the hot and cold spots have the highest and lowest values and are depicted by the relative intensity of clustering. The not significant category show areas where the z-score was near zero.

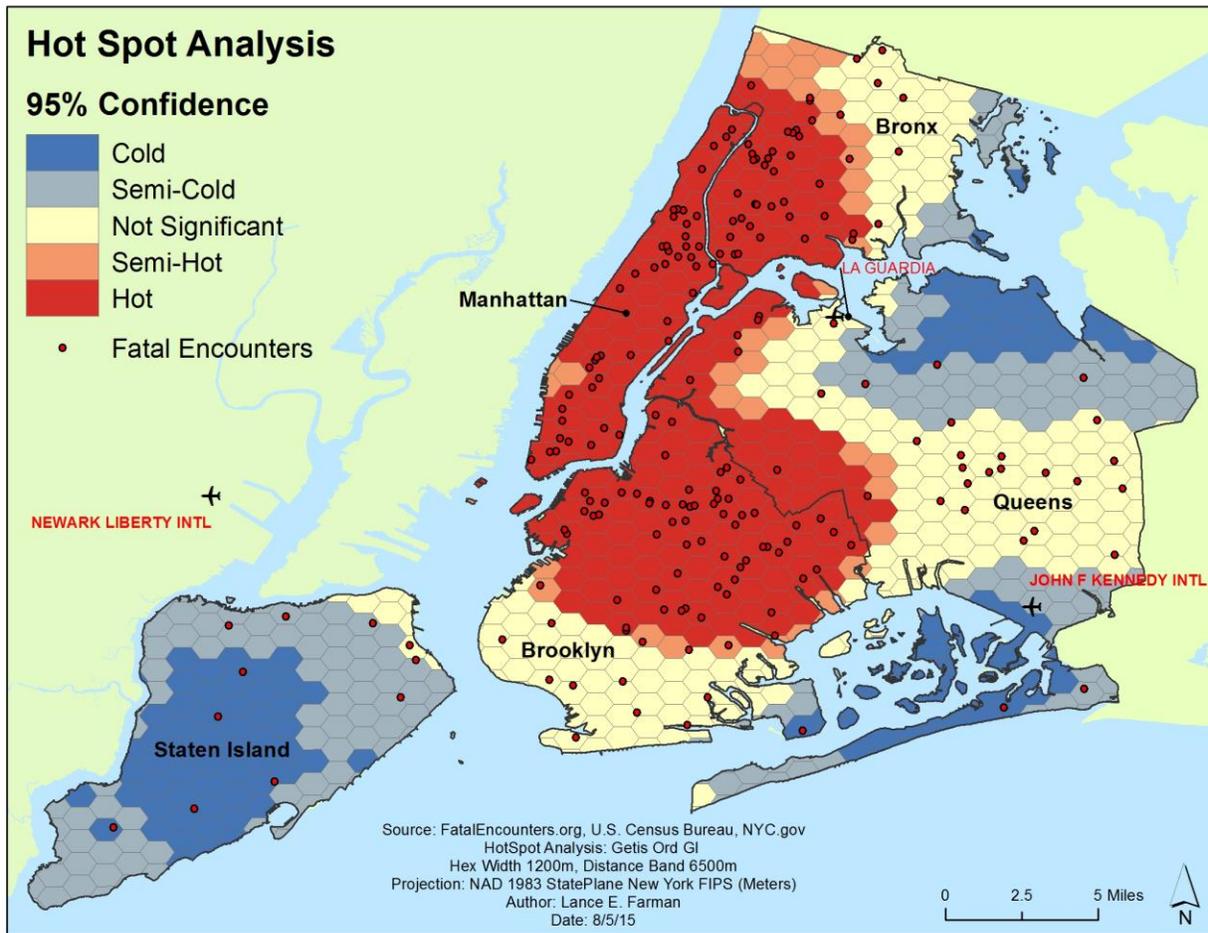


Figure 2: Raw Incident Count

The next logical question to ask is whether the clustering seen in Figure 2 is a function of population. In Figure 3 the incident count is normalized by population. The conclusion to be made here is that population does influence where clustering occurs. When comparing the raw count map to the normalized map it can be seen that in general there is some significant overlap of population density and fatal encounters, but not so much overlap as to completely flatten out the intensity of the clustering profile. Some areas still stand out as hot or cold spots beyond population. This would imply that there is a variable at work affecting why these regions have

clustering. The next step would be to begin exploring some of these variables to see if they are possible indicators.

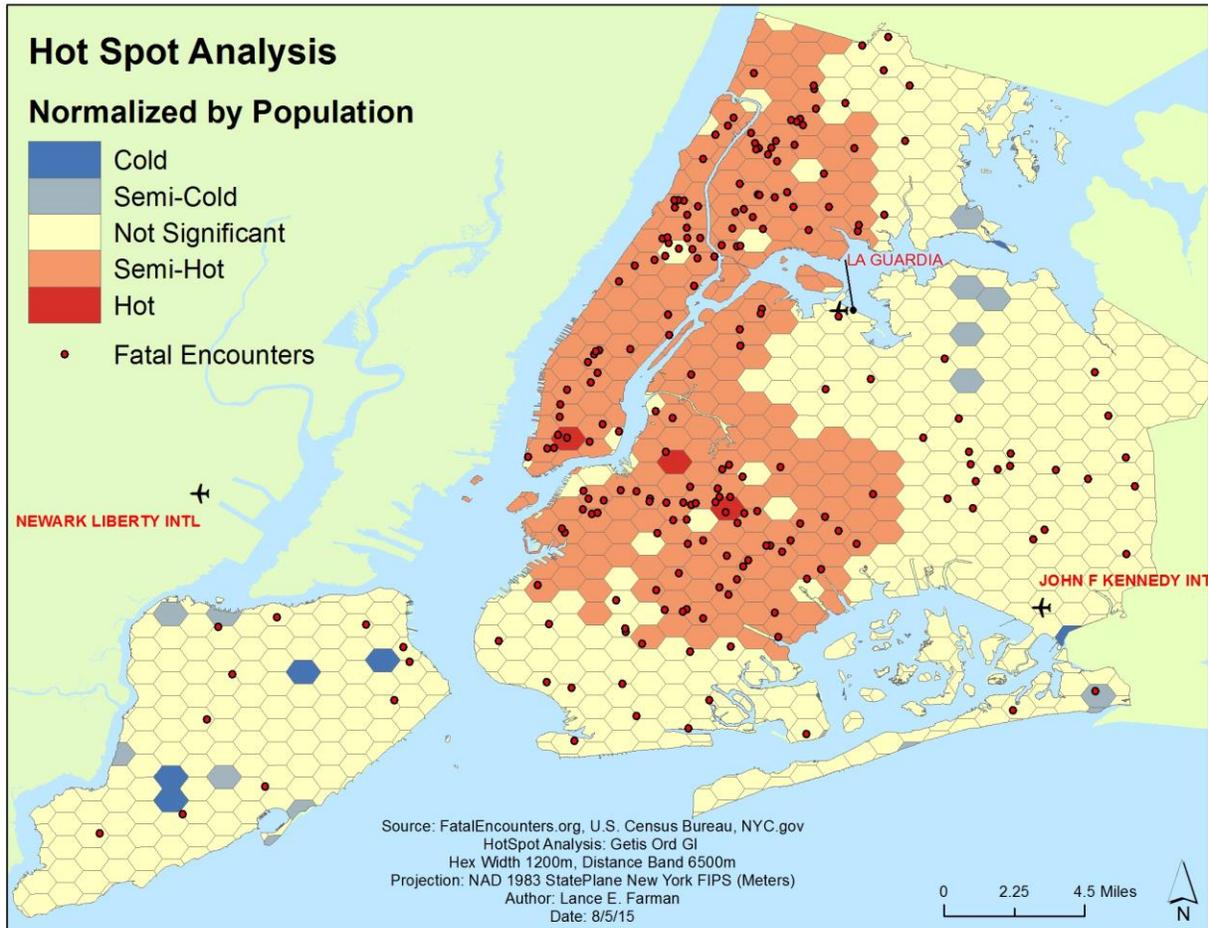


Figure 3: Normalized by Population

To test the raw count and normalized hotspot maps visually, a map of population density was created (see Figure 4). The areas with high population density do seem to correlate with the hotspots and low population densities with cold spots. It could be preliminarily argued that

population density does play a role where hot and cold spots of fatal encounters occur.

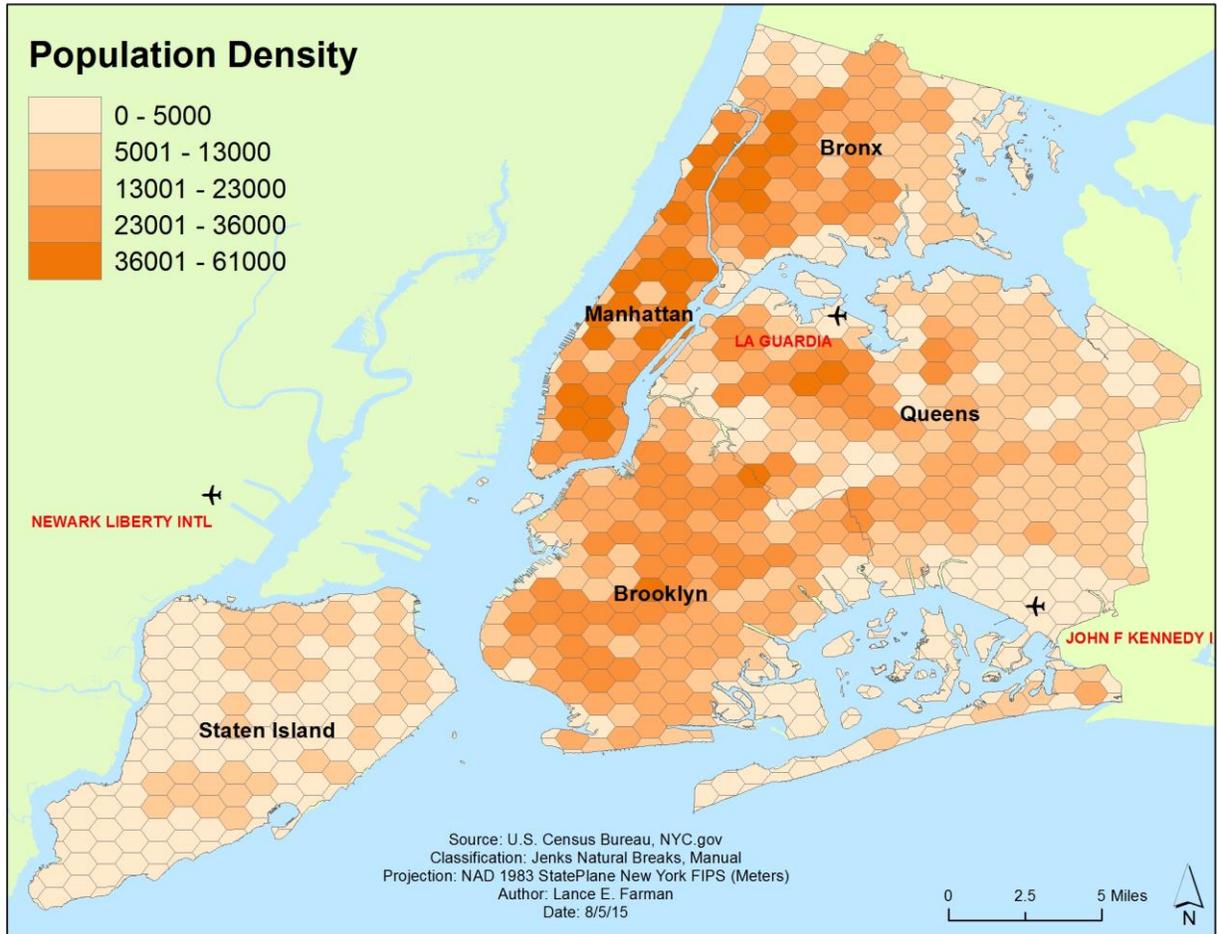


Figure 4: Population Density in NYC

The last map that was created was a dot density representation of the four predominant races in New York City (Figure 5). The map shows there are areas where one race makes up the majority of the population. However, there does not seem to be one race that dominates the hotspot areas. Yet, one hotspot in lower Manhattan is mostly white. The Western area of the Bronx consists mostly of Hispanic population. The North Brooklyn hotspot is comprised of mostly Black population. It appears that there are hotspots for every race except the Asian population. Interestingly, the Eastern portion of Queens is mostly made up of Black population,

but it was found to be statistically insignificant. Note that these are just preliminary maps and make no claims regarding spatial association of race or ethnicity and these incidents.

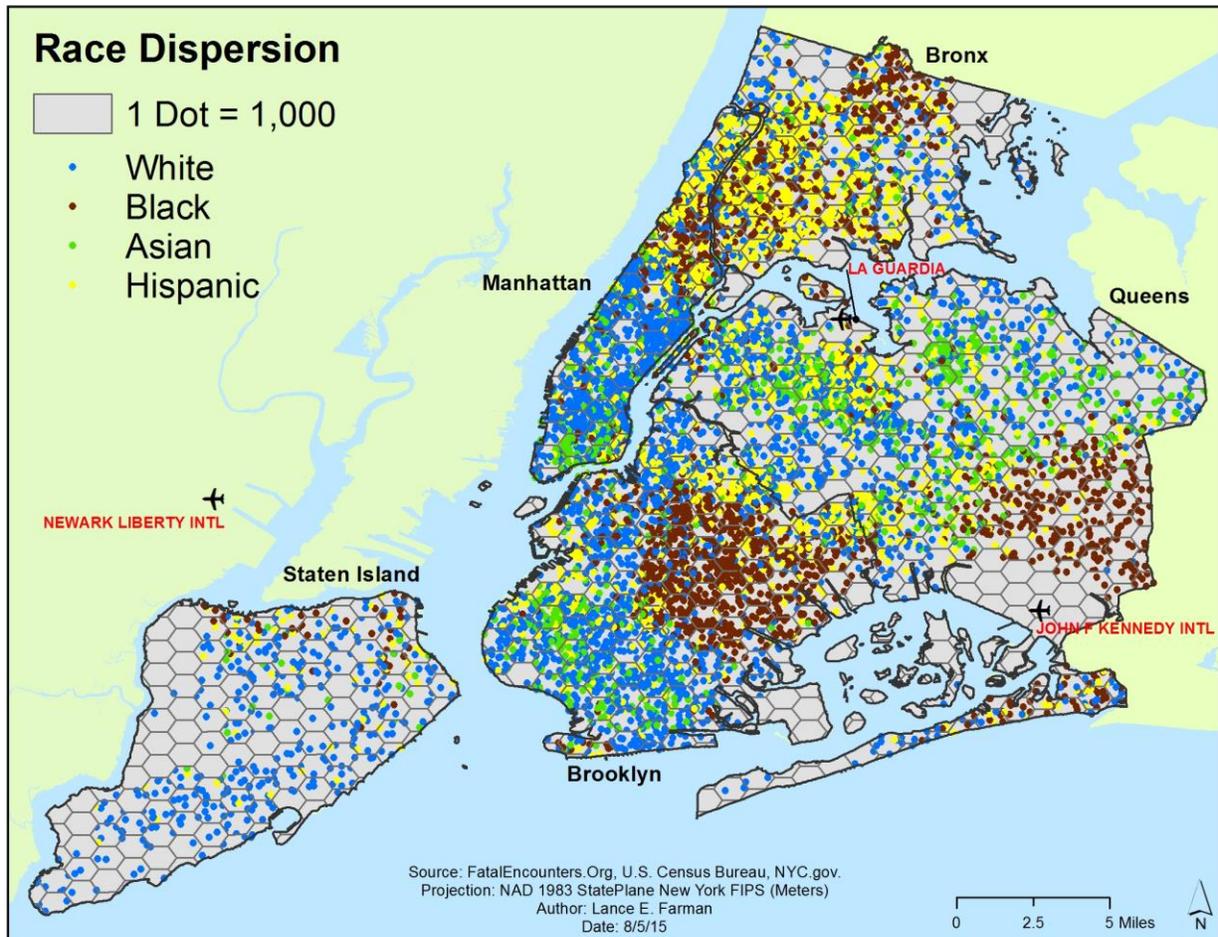


Figure 5: Race Distribution in NYC

If the race field had been found fit for analysis, it would have been interesting to categorize incidents based on the decedent's race. This would answer questions like, are these incidents happening to a specific race where another race is predominant? If so, which races and where? Understanding if there are patterns for race in certain areas, for example, a hotpot in a white neighborhood, where another race is dying more often would add some context to these incidents.

CHAPTER 6: DISCUSSION

This study endeavored to build a customized framework for validating the FE dataset. The custom framework relied on parsing QA components from other studies that could directly affect the overall quality of the FE dataset. These components were evaluated in order to check that the collection protocols are rigorous, reliable, and verifiable. The results of the validation checks showed where the FE data's strengths and weaknesses existed. FE was found to possess a high level of completeness in the complete states and for the years 2013 and 2014. The spatial accuracy and precision were on the cusp of being acceptable for analysis but need further curation. Attribute accuracy, consistency, and lineage were determined to be of insufficient quality for any credible analysis and need both curation and concise definitions. To this end, one purpose of this thesis, determining the overall fitness of the dataset, was achieved.

Moreover, this study looked at FE from a VGI perspective. This was done in order to produce insight into how FE fits into the VGI domain. Doing so provided valuable insight into the reliance of crowd data upon QA controls no matter what the project focus is. This study reinforced the idea that FE, though it is not like traditional VGI projects, does qualify as being in the same domain because it contains a geographic footprint that can geocoded into a GIS.

The final part of this study was devoted to conducting a preliminary hotspot analysis in a location and at a scale where there were enough incidents for a more robust statistical calculation as well as where the data could be made fit for spatial analysis. As such, the hotspot analysis was successful for identifying where incidents cluster in New York City.

The remainder of Chapter 6 discusses these findings further and is composed of three sections. In section 6.1 the relation of FE to other VGI projects is discussed. Section 6.2 discusses the strengths and weaknesses of the FE dataset and includes recommendations for

future improvements. Section 6.3 discusses the future of FE and potential analyses that might be done once the data is ready.

6.1 Fatal Encounters as Volunteered Geographic Information

There is no doubt that FE is within the domain of VGI because of its ability to describe location through its geographic footprint. In addition, FE is certainly an emanation from the crowd. If the crowd is composed of people who are untrained in professional data management then FE qualifies in many ways. Mr. Burghart, very much a member of the crowd, started FE with little training in the management or creation of data. Further, every contributor to the dataset, whether a journalist writing a story, a law enforcement agency creating a record, or a volunteer who mines information, is a member of the crowd. The influence of professional data managers is absent at all levels.

FE is completely reliant on what are essentially secondhand accounts of incidents. It was not possible for this study to confirm that the information contained within records or media accounts were actually accurate. One underlying assumption by the FE dataset is that its sources are reported correctly. This is an inherent weakness in the data because the sources are very difficult to verify themselves. This problem makes FE different than other VGI projects because source information can usually always be verified via ground truthing or from another authoritative source.

FE is a unique dataset from typical VGI in many other ways. First it has a defined hierarchical structure. Mr. Burghart is the gatekeeper double-checking every piece of work from the volunteering crowd before uploading to the main database. Secondly, FE imposes parameters on volunteers, via a submission form, ultimately limiting the criteria that can be contributed. This reduces the breadth of errors that the crowd can commit versus a project like

Wikimapia, where a volunteer can digitize anything they choose in any place. Lastly, because FE can limit contribution criteria, small tweaks to collection protocol, definitions, and database design/curation would significantly boost overall quality. Other projects may not be as flexible in this regard. This fact gives FE an advantage over other VGI because of its potential to adapt.

6.2 Strengths and Weaknesses

The evaluation framework and strategies employed in this study exposed the dataset's strengths and weaknesses. It turned out that FE is a good dataset but is in need of improvements.

Fortunately, it will be possible in the future to improve the areas deemed to be unfit. The relative youth of the dataset, along with the fact that it is not yet complete, means that a slight overhaul at this stage would have a direct and immediate positive effect.

It would have been a heavy blow to FE if it had been found that it was not counting incidents in places it believed to be complete. Moreover, completeness is arguably the greatest hurdle and the most susceptible to criticism, meaning this was a crucial component to verify. However, the data was found to exhibit a high level of completeness, missing only 1-2% of incidents from the checks in this study. Compare these results to the ARD program's self-analysis of completeness for their data as being only 49% complete. The results of this study should reduce the concern that FE is letting a large number of incidents slip through the cracks. Nevertheless, the FOIA sampling process should be extended to all agencies in the future. This would ensure that as many incidents are being collected as are possible.

Spatial accuracy and precision were found to be mostly suitable. The top two tiers for accuracy comprised of 88% of the incidents in the complete states, meaning there is only approximately a 300m error for precision for the majority of incidents in those states. It was shown that the lower accuracy tiers could be curated for improvement. In addition, it was found

that the records obtained from law enforcement consistently contained an accurate description of place. FE could benefit from sending a decedent specific FOIA to the responsible agencies to further improve the accuracy of the geographic footprint. These records could also be compared each of the other attributes which would improve the accuracy of the database as a whole.

Consistency in the FE database was found to be lacking for two main reasons. Firstly, the data entered into the database needs to be curated so that every field, along with the corresponding categories, is uniform. A knowledgeable data manager could easily redesign the database by implementing it into data management software. This would improve the cleanliness and cohesion of the FE database. Secondly, the definitions that describe each field need to be concisely expressed so that there is no ambiguity as to what is being meant. Additionally, FE would benefit from the development of metadata so there is no question as to what is being meant. Doing so would be a big step toward solidifying credibility. In conclusion, FE is excellent at nominating incidents but needs to be better at confirming and verifying the associated attributes.

6.3 The Future of Fatal Encounters

As expressed earlier, FE is a young dataset that was created on the fly from a reaction to the social status quo. With every new entry, the dearth of data on police use of deadly force is in the progress of being reversed. However, FE may undergo some growing pains if it wants to maintain the early attention it has received from the media. It will be subject to even higher levels of inquiry than in this study. The recommendations suggested above are meant to enable FE to strengthen its qualities so that it can withstand intensified scrutiny.

Furthermore, fitness would open the door to an array of subsequent analyses. Not just in the spatial realm but many others. The type of analysis done in this study could be redone with

greater depth and in other areas, potentially unearthing any underlying patterns. An example of one approach might be combine spatial analysis of the predominant race in a given area with the race of the individual decedents in that area. Disparity between the two might indicate that policing in that area is motivated by racial bias.

Another potential analysis would be to use law enforcement jurisdictions to identify agencies with unbalanced numbers of decedents or who are targeting a particular race, gender, or age group more often. In response to the unrest in Ferguson, MO over the death of Michael Brown, the DOJ conducted an investigation on the Ferguson Police Department (FPD). The results were staggering. The investigation found that the city's law enforcement practices focus on revenue rather than public safety. This results in unconstitutional policing, injustices during due process, the sowing of citizen distrust toward police, and extreme discriminatory bias toward African Americans (DOJ 2015). The study shows that an agency's approach to law enforcement can profoundly affect the outcomes of their interactions with citizens. Information regarding FPD's enforcement tactics were only unearthed after residents expressed discontent, receiving substantial national attention. It begs the question: Where else might Ferguson like police culture be taking place?

FE offers the opportunity to detect possible problem areas. Early identification of these areas, unlike in Ferguson, would enable the DOJ to evaluate policing and to implement reform for the agency in question before tumultuous situations arise. A comparison to agencies in non-problem areas might also yield examples of effective policing protocols that could then be used to inform others. This might shift the paradigm of government response from being reactive to proactive.

But, before any of this can occur, FE needs to continue recording incidents in areas where coverage is not complete and upgrade the quality of the information it reports. If FE improves its quality, it will undoubtedly be the most comprehensive dataset regarding police use of force. This would in turn grant society, for the first time, access to a dataset that could begin to explain the context behind these incidents. Ford (2015, 1) writes: “Statistics are more than just numbers: they focus the attention of the politicians, drive allocation of resources, and define the public debate.” The truth resounding in this statement amplifies the effect a sound and valid FE could have upon society.

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