

GIS-BASED EVALUATION OF THE EFFECTIVENESS OF  
SELECTIVE LAW ENFORCEMENT CAMPAIGNS  
IN REDUCING CRASHES

by

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## ABSTRACT

State Departments of Transportation (DOTs) across the nation fund selective enforcement campaigns to improve traffic safety. The Alabama Department of Transportation (ALDOT) deploys a mobile selective law enforcement campaign targeting the negative driver behaviors that contribute to the most severe crashes, including speeding, driving under the influence, and failing to wear a seatbelt. The focus of this research was to integrate officer patrol routes, citations issued, crashes, and selective enforcement periods into one spatial and temporal map to evaluate the effectiveness of selective enforcement in reducing crashes along state routes in Alabama from August 1, 2010 to July 31, 2011.

Structured Query Language (SQL) and Geographic Information System (GIS) technology were used to organize selective enforcement data into a relational database, geolocate Electronic Citations (eCitations), verify and locate selective enforcement areas, incorporate Electronic Crash (eCrash) data, and evaluate the decreased and/or increases in crash frequencies and the number of citations issued before and during selective enforcement. The approach to locate and verify selective enforcement locations successfully identified 21 locations across the state of Alabama. Statistical analysis was performed using a Paired Difference t-test. When evaluating the locations both by area type of urban or rural and collectively, there were significant increases in the number of citations issued, with an average 254% increase. There were marked decreases in the number of crashes when crashes were separately analyzed by the location type. P-values of 0.148 and 0.122 for urban and rural locations, respectively, confirm the decrease in crash frequency with 85% confidence. There were minimal decreases in the number of crashes when

evaluating the locations collectively; however, there was a slight decrease in crash severity, with an average 2.45% decrease. Therefore, selective law enforcement efforts and the increase of issued citations along state routes in Alabama have started to improve public safety and decrease the number of crashes at select areas. Future work will involve strengthening the crash decreases with a proposed selective enforcement campaign recommendation, developing crash modification factors, and calculating a return of investment.

## DEDICATION

I dedicate this thesis to my family for supporting my dreams, my friends for their constant source of inspiration, my professors for giving me endless opportunities to learn and grow, and my colleagues for assisting in my research.

## LIST OF ABBREVIATIONS

DOT	Department of Transportation
ALDOT	Alabama Department of Transportation
DPS	Department of Public Safety
SQL	Structured Query Language
GIS	Geographic Information Systems
CAPS	Center for Advanced Public Safety
eCitation	Electronic Citation
eCrash	Electronic Crash Report
MOVE	Mobile Officer's Virtual Environment
CARE	Critical Analysis Reporting Environment
DUI	Driving Under the Influence of alcohol or drugs
GPS	Global Position System
UTC	Coordinated Universal Time
OCR	Optical Character Recognition
ORI	Agency identification number
TACT	Ticketing Aggressive Cars and Trucks
SPF	Safety Performance Function

## ACKNOWLEDGMENTS

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Finally, I thank The University of Alabama and the State of Alabama for providing me with the opportunity to continue my education. I hope this work will illustrate to other students and researchers the importance of education and the impact that can be made from research.

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## CHAPTER 1. INTRODUCTION

### 1.1 Introduction

State Departments of Transportation (DOTs) across the nation fund selective enforcement campaigns aimed at intensifying law enforcement at certain locations in the state in order to improve traffic safety and reduce the number of crashes. Traditionally, the most common efforts to combat traffic crash frequencies include engineering and design, outreach and education, and police enforcement. A main goal of police enforcement is to maintain learned, safe driver behaviors by observing, disciplining, and therefore deterring negative driver behaviors (Rothengatter, 1982). Police enforcement of traffic law is a viable and successful way to reduce the number of crashes on the road, as well as the severity of crashes (Walter, et al., 2011). High crash locations are often chosen by Departments of Transportation for additional police enforcement in attempts to deter negative driver behavior in high crash areas.

Driver behavior plays a significant role as a contributing factor in roadway crashes, with the three most prominent negative driver behaviors being speeding, driving under the influence, and failing to wear a seatbelt (Peden, et al., 2004; Erke, et al., 2009). Research shows that speed has a profound effect on roadway crashes (Taylor, et al., 2000). Thirty percent of traffic crash fatalities across the United States in 2012 were due to speeding involvement (National Center for Statistics and Analysis, 2014). Alcohol-impaired driving fatalities accounted for another 31% of all traffic fatalities in the US in the year 2012 (National Center for Statistics and Analysis, 2014). Estimates show that if speeding violations, driving under the influence, and the failure to wear

seatbelts were eliminated, up to 38% of traffic crash fatalities and 17% of other traffic injuries could be avoided (Stanojevic, et al., 2013).

In 2011 in Alabama, 814 fatal crashes occurred, killing 899 people. Speeding and driving under the influence were the major contributing circumstance for 54% of fatal crashes, collectively (Center for Advanced Public Safety, 2011). Of the 814 fatal crashes in Alabama in 2011, there was a lack of seatbelt restraint use in 42% of the crashes. Reports show that if a crash occurs, occupants in the front seat without a seatbelt have a 50.5 times higher chance of being killed than someone using a seatbelt (Center for Advanced Public Safety, 2011). The breakdown of specific driver contributing circumstances by percentages of fatal crashes for Alabama in 2011 is shown in Figure 1.

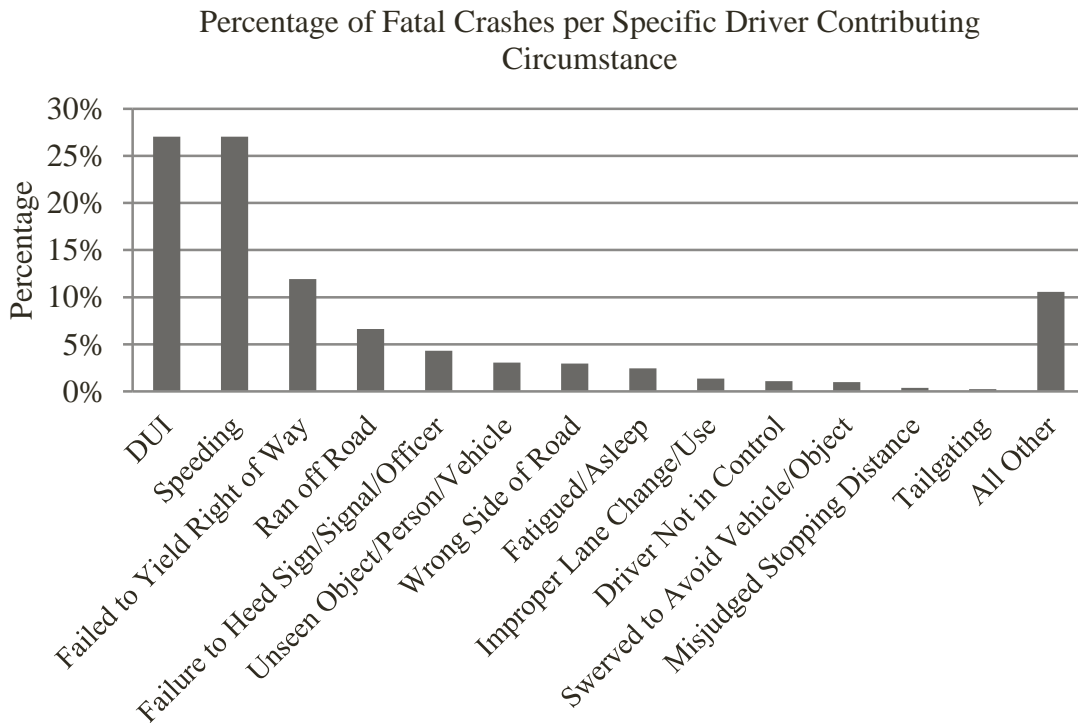


Figure 1. The breakdown of specific driver contributing circumstances influencing crash occurrences by percentage of fatal crashes in Alabama in 2011 (adapted from Center for Advanced Public Safety, 2011).

There may be multiple contributing circumstances for a fatal crash, but the primary cause of the crash determined by the reporting officer is recorded as the main contributing circumstance. For fatal crashes, speeding and driving under the influence are notably more prominent than other contributing circumstances.

The Alabama Mobile Selective Law Enforcement Campaign attempts to change the negative driver behaviors that contribute to fatal and severe crashes, including speeding, driving under the influence, and failing to wear a seatbelt. An agreement between the Alabama Department of Public Safety (DPS) and the Alabama Department of Transportation (ALDOT) was in effect between October 2007 and September 2011 in order to protect the citizens of the State of Alabama by providing increased law enforcement efforts on various state and federal roadways while supporting a goal of the Strategic Highway Safety Plan for Alabama, which is to reduce crashes, injuries, and fatalities in Alabama by 50% over the next twenty years.

Police officers ranging from State Troopers to Sergeant Classifications worked extra-duty shifts after their normal hours or on off-duty days. Officers were allowed two hours of funded travel time to selective enforcement locations, and shifts were not to exceed 12 hours in length. The over-arching goal of the increased enforcement at selected high crash locations was to deter negative driver behaviors with an increase in issued citations with the goal of decreasing the number of crashes. In order to evaluate the effectiveness of the selective enforcement, Structured Query Language (SQL) and Geographic Information System (GIS) technology were used to integrate police officer patrol patterns, citations issued, crash occurrences, and selective enforcement periods into a relational database and a spatial and temporal analysis framework. The database and GIS map information provides the means to verify selective enforcement



locations and evaluate the increases and decreases in crash frequencies and the number of issued citations before and during selective enforcement.

A relational database of selective enforcement data, citations, and officer patrol routes was created. Selective enforcement data for participating officers was obtained from DPS timesheets and DOT invoices. Additionally, law enforcement officials in the state of Alabama issue approximately 80,000 Electronic Citations (eCitations) per month that are stored in a database. These eCitations do not require GPS coordinates or other structured location data. The eCitations do have an electronic timestamp indicating when the citation was issued. However, each State Trooper vehicle is equipped with a GPS unit that is polled every 30 seconds. The location of the trooper is recorded along with a timestamp in a database. A temporal join methodology was developed to cross-reference timestamps between officer patrol routes and issued citations in order to geolocate citations without GPS coordinates. A methodology to verify selective enforcement locations was developed by comparing officer patrol routes and dates and hours of selective enforcement shifts from DPS and DOT timesheets and invoices. Lastly, the database tables were imported into a GIS, along with crash data, in order to quantify the number of crashes and the number of citations in selective enforcement locations before and during the selective enforcement effort. This methodology is extensible to other states with available officer patrol routes, citation locations, crash data, and selective enforcement time periods.

## 1.2 Thesis Organization

This thesis is organized into six chapters. Chapter 2 Literature Review and Background presents a literature review of the positive effects of general police enforcement and explores examples of effective selective police enforcement campaigns. A data background for this study

is also provided in Chapter 2. Chapter 3 Methodology discusses the developed methodology, referencing SQL queries in Appendix A. The methodology describes a relational database structure capable of organizing participating officers with unique UserIDs, geolocating citations with and without GPS coordinates, and verifying selective enforcement locations by performing a series of summation and grouping analyses. The methodology also covers the use of GIS to incorporate linear referenced route-milepost information, confirm the summation and grouping analyses to verify selective enforcement locations, and incorporate crash data. Chapter 4 Results reports the results of the study, presenting statistical increases and decreases in citation counts and crash frequencies. Chapter 5 Recommendations for Selective Enforcement in 2016 synthesizes several recommendations for ALDOT and other DOTs with selective enforcement campaigns. Chapter 6 Conclusions and Future Work discusses the conclusions of the research project and future work.

## CHAPTER 2. LITERATURE REVIEW AND BACKGROUND

### 2.1 Literature Review

Conventional traffic police enforcement is a proven method to deter negative driver behaviors, decrease crashes, and improve traffic safety (Rothengatter, 1982; Stanojevic, et al., 2013). The first edition of the Highway Safety Manual, while focused on engineering analysis and treatment, states that crash frequencies may be reduced through enforcement efforts (AASHTO, 2010). A comparative study involving driver surveys and roadway observations regarding speeding, driving under the influence, and seatbelt usage was performed in 2012 in Northern Kosovo, a location where there was little, if any, traffic enforcement during the previous 13 years before the study, and in Serbia, a location where traffic enforcement was established. Results showed that drivers in Northern Kosovo had both more reckless driving patterns and driving perspectives than those in Serbia, confirming that traffic police enforcement has a direct effect on driver behavior and traffic safety (Stanojevic, et al., 2013). A theoretical relationship between the level of police enforcement and roadway crash rates, as shown in Figure 2 (Walter, et al., 2011; Smith, et al., 2015), further supports the positive effect that police enforcement has on the number of roadway crashes and traffic safety. Figure 2 illustrates that at zero police enforcement, crash rates will be highest and will not initially decrease with the first increase in police enforcement. However, as the level of police enforcement continues to rise, the rate at which crashes occur will decrease. Furthermore, a saturation point exists where no further increase in selective enforcement will affect crash rates (Walter, et al., 2011; Smith, et al., 2015).

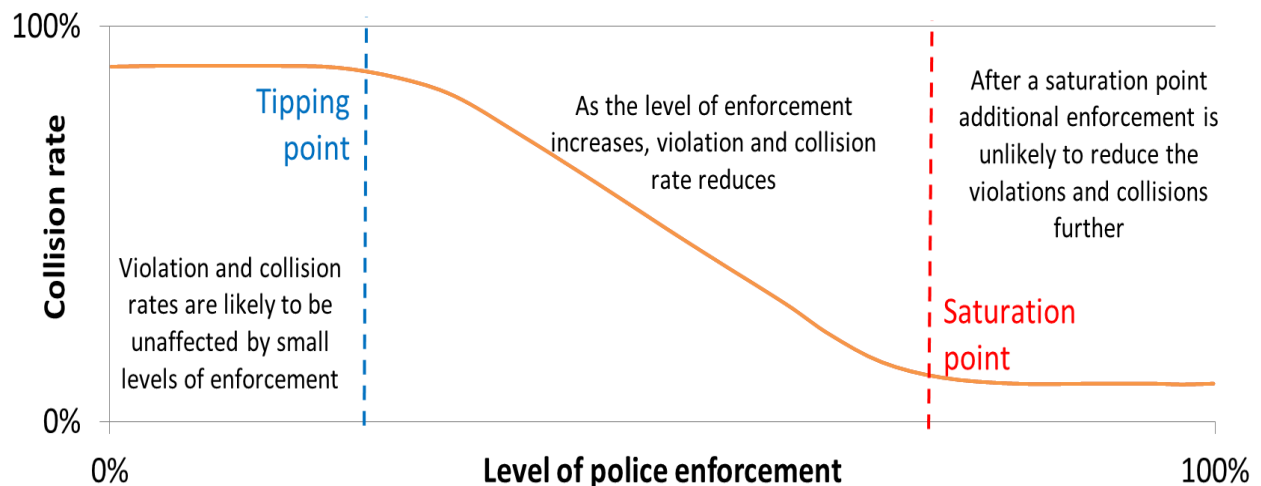


Figure 2. Theoretical relationship between varying levels of police enforcement and roadway crash rates (Walter, et al., 2011; Smith, et al., 2015).

Many case studies show that selective police enforcement, whether for a specific negative driver behavior or for a particular high crash location, can have an influential impact on driver behavior, which can successfully reduce the number of crashes in a location (Jonah and Grant, 1985; Vaa, 1997; Erke, et al., 2009; Walter, et al., 2011). Selective enforcement is a driver-based countermeasure to reduce crash frequency or severity at specific sites (AASHTO, 2010). Historically, the top three negative driver behaviors that increase the number of severe crashes include speeding, driving under the influence, and failing to wear a seatbelt (Peden, et al., 2004; Erke, et al., 2009). Selective enforcement campaigns are being implemented in attempts to deter these dangerous driver behaviors. A meta-analysis comparing and combining findings from 45 evaluation studies from 14 countries including the United States, Australia, the United Kingdom, and Sweden reports that stationary speed enforcement reduced the number of crashes by up to 11%, police patrolling reduced DUI related crashes by 8%, and targeted seat-belt enforcement increased seatbelt usage by 21% (Erke, et al., 2009). A month long study on a six mile stretch of road in South London in May 2008, which utilized static video and speed enforcement, and

mobile police enforcement including a mix of motorcycles, marked, and unmarked vehicles captured varying levels of police enforcement and monitored driver compliance to traffic laws including speeding, mobile phone use, and seatbelt usage. No change in the use of mobile phones was detected and seat belt use remained at an 87% average usage rate. However, the 85<sup>th</sup> percentile speeds of drivers were reduced by as much as 3.4 mph, with reduction effects lasting for at least two weeks after the enforcement effort (Walter, et al., 2011). Studies with static enforcement generally analyze the enforcement campaign in terms of a halo effect (Rothengatter, 1982; Vaa, 1997; Walter, et al., 2011). A halo effect is the length of time and distance away from an enforcement effort that driver behaviors remained effected. Spillover effects, which influence the surrounding network, may also occur (AASHTO, 2010).

Speed-related offenses contributed to 30% of fatal traffic crashes in 2012 in the United States, causing 10,219 lives to be lost (National Center for Statistics and Analysis, 2014). Research shows that at certain high crash locations, selective enforcement is recommended for excessive speed to reduce the number of speeding vehicles and improve traffic safety, as denoted in red in Table 1. Police cannot be present at all times and on all roads with high crash locations. Therefore, various speed management approaches can be substituted for the lack of human presence, such as cameras, signage, and remedial engineering. Table 1 presents additional guidelines for alternate speed management approaches (Taylor, et al., 2000).

Table 1. Recommended speed management approaches for differing situations (adapted from Taylor, et al., 2000).

	Excessive Speed	Inappropriate Speed
High Crash Locations	Fixed Cameras Remedial Engineering <b>Selective Enforcement</b>	Vehicle-activated Signs
General Enforcement Locations	Mobile Cameras Conventional Enforcement Camera Signing	Fixed Warning Signs Vehicle-activated Signs

A widely implemented speed management approach as an alternative to mobile selective enforcement is automatic speed enforcement (Taylor, et al., 2000; Wilson, et al., 2009). Before and after studies at high crash locations conclude that selective speed enforcement detection devices, such as speed cameras and radar and laser devices, are favorable for reducing driver speeds, and in turn, crash rates (Vaa, 1997; Wilson, et al., 2009). The Highway Safety Manual also notes the value of automated speed enforcement using video or photographic identification combined with radar and laser detection devices. This type of enforcement should be considered during the development of safety performance functions and crash modification factors (AASHTO, 2010). With automatic detection, halo effects can be measured by recording real-time vehicle speeds at increasing distances away from the detection device, and at increasing time periods after an automatic detection device is removed. Within automated enforcement areas, different crash reduction effects can be found for different crash severities (Wilson, et al., 2009). While mobile selective enforcement efforts have been studied alongside static enforcement (Walter, et al., 2011), there is an apparent gap in the literature regarding studies of mobile selective enforcement, and citations frequency to evaluate crash reductions. Because static enforcement produces a dataset of actual vehicle speeds, the halo effect analysis is more

straightforward. Therefore, one goal of this research aims to develop a methodology to analyze crash reductions from mobile selective law enforcement in terms of issued citations.

In 2012 in the United States, there were 10,322 alcohol-impaired-driving fatalities, equating to an average of one driving under the influence fatality every 51 minutes (National Center for Statistics and Analysis, 2014). Selective enforcement campaigns for driving under the influence (DUIs) are another prominent police force effort and are proven to be effective in reducing the number of drivers operating vehicles after the consumption of excessive alcohol (Mathijssen and Wesemann, 1993). Before a legal blood alcohol content limit while driving law was passed in the Netherlands in 1974, there was a high percentage of drivers operating vehicles after consuming a high amount of alcohol. A selective enforcement campaign was designed that used checkpoint locations where drivers are stopped at random and police officers administer breathalyzer tests. When publicity efforts and legal consequences were high, only 1% of drivers were operating vehicles under the influence, marking a 14% decrease in one year (Mathijssen and Wesemann, 1993). The National Highway Traffic Safety Administration (NHTSA) funded selective enforcement demonstration projects to reduce DUIs in seven states including Georgia, Louisiana, Pennsylvania, Tennessee, Texas, Indiana, and Michigan. The campaigns involved publicity, statewide implementation, and visible and frequency checkpoints, resulting in significant crash reduction results in four of the seven states, with fatal crash reductions as high as 20% (Fell, et al., 2008).

An estimated 12,174 lives were saved in 2012 in the United States due to the use of seat belts (National Center for Statistics and Analysis, 2014). Some states, municipalities, or organizations do not believe seat belt usage should be a focus for police enforcement (Smith, et al., 2015). Additionally, seat belt use requires individual action and is difficult to enforce as a

countermeasure to improve traffic safety (Williams and Wells, 2004). Yet, increasing seat belt use through education alone is not proven to be effective (Robertson, et al., 1974). Law enforcement and selective law enforcement campaigns targeting seat belt use provide evidence of progress (Williams and Wells, 2004; Jonah and Grant, 1985; Williams, et al., 1987). A selective traffic enforcement program in the regional municipality of Ottawa-Carleton in Canada in 1979 involved up to a tenfold increase in citation counts for failing to wear a seatbelt. In roadside surveys during the program, driver seatbelt usage rose from 58% to 80% for the driver. Over a two year program, causality rates due to a lack of seat-belt usage in Ottawa-Carleton decreased by 13.9%. Two years after the program, seatbelt usage was reportedly at 66%, showing a lasting effect of the program on driver behavior (Jonah and Grant, 1985). A three week long campaign in New York in 1985 increased seat belt use from 49% to 77%, and had lasting effect up to four months later. A control comparison community remained at a constant 40% seat belt usage over the selective enforcement campaign time frame (Williams, et al., 1987).

The complexity and effectiveness of selective enforcement campaigns can increase with the inclusion of publicity and educational outreach. While some believe publicity campaigns in conjunction with selective enforcement make it difficult to determine relative contributions of selective enforcement (Elliot and Broughton, 2005), others believe publicity and outreach play a large role in the deterrence of negative driver behavior (Jonah and Grant, 1985; Mathijssen and Wesemann, 1993). The deterrence theory is defined as the notion that while the general public thinks there is a high probability that an offense will be detected, they will be more inclined to oblige to the law (Walter, et al., 2011; Williams and Wells, 2004).

The Alabama selective enforcement campaign utilized mobile enforcement to target speeding, driving under the influence, and seatbelt usage. The measure of a halo effect was



expressed in terms of citation and crash counts before, during, and after a police selective enforcement effort. Various selective enforcement locations across the state of Alabama were verified and investigated using a SQL query summation and grouping technique, and crash counts and citation counts were studied.

## 2.2 Data Background

The data for officer patrol routes, citations issued, and crash records used in this project were made available by the Center for Advanced Public Safety (CAPS) at The University of Alabama, the Alabama Department of Public Safety (DPS), and the Alabama Department of Transportation (ALDOT). CAPS is a research and development center at the University, dedicating to utilizing information technology to improve public safety. CAPS has developed software used in all 50 states, facilitating data collection and data storage for police officers, transportation and traffic engineers, and other disciplines of business, as well as creating research platforms with the stored data to improve transportation and public safety. CAPS has developed a Mobile Officer's Virtual Environment (MOVE) program, an electronic citation (eCite) program, and an electronic crash (eCrash) program, that automates data entry needs for police officers and produces a comprehensive dataset (Center for Advanced Public Safety, 2009).

Each State Trooper vehicle for law enforcement officials in the state of Alabama is equipped with a Global Positioning System (GPS) unit, which is polled every 30 seconds and recorded in Coordinated Universal Time (UTC). The location of the on-duty trooper is recorded along with a timestamp, which is referred to as officer patrol route data. The officer data and officer patrol route data are stored in 66 tables in a relational database. The tables contain a range of data, including the officer patrol route data, agency codes and relations, courthouse dates and rules, as well as officer information and statistics.

The MOVE program was developed to enable officers to use laptops in law enforcement vehicles to access software tools including citation and crash forms, driver's license scanning devices, and a daily activity log. Law enforcement officials in the state of Alabama issue approximately 80,000 electronic citations (eCitations) per month through the eCite program. The eCite program, which went into production statewide starting in 2007, enables officers to issue eCitations in a matter of minutes, print a copy for the violator, and electronically transmit issued citations to an on-line central server repository (Center for Advanced Public Safety, 2009). The eCitation data is stored in 43 tables in a relational database. The tables contain a range of data, including issued citations, citation and violation codes, offender details, as well as ticketbook sizes and rules. An example of an eCitation form in the eCite program is shown in Figure 3, showing the ticket number location, the electronic timestamp, and the defendant tab of the eCitation. Other tabs include information about the officer, the vehicle information, the location and time, the offense, and court or bond information (Center for Advanced Public Safety, 2009). The eCite program offers GPS coordinate population services, as shown in Figure 3 as a "Populate" option denoted by an image of a globe. However, the eCitations do not require GPS coordinates or other structured location data, so the eCitations do not all have accurate location information. However, the eCitations do have an electronic timestamp indicating when the citation was issued.

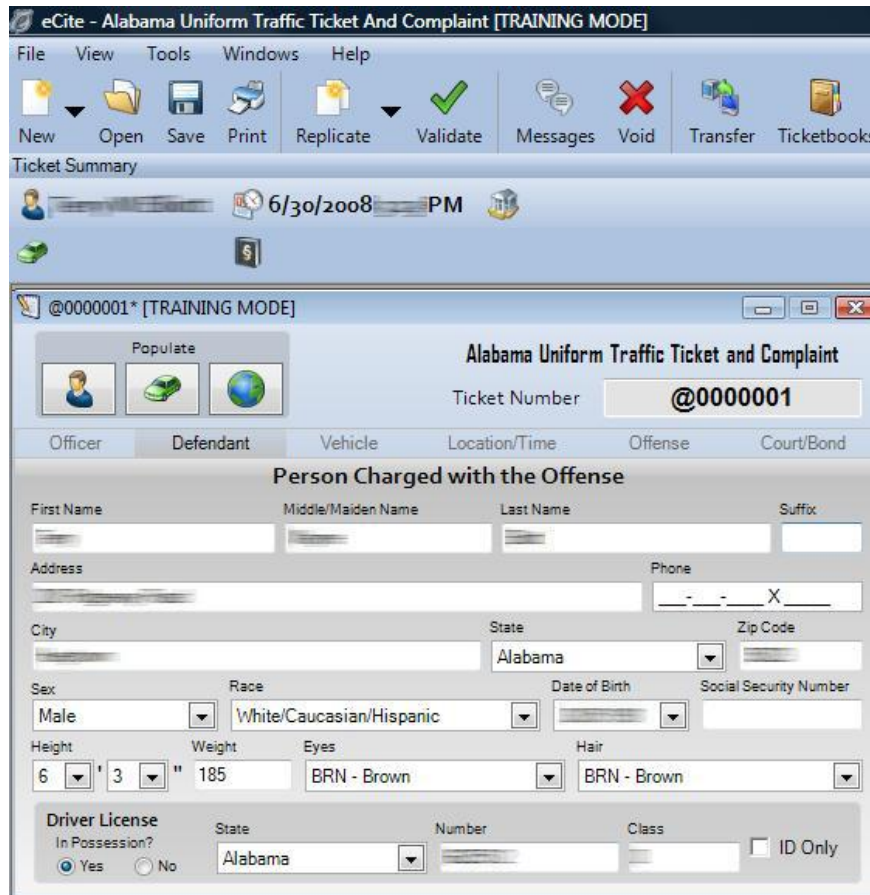


Figure 3. Example of an eCitation form in the eCite program developed by the Center for Advanced Public Safety (Center for Advanced Public Safety, 2009).

Law enforcement officials in the state of Alabama report approximately 10,000 electronic crash (eCrash) reports per month through the eCrash program, containing crash coordinate data as well as crash severity information. The eCrash program has been in production with state troopers since 2009, and a mandated statewide production began in 2010. eCrash supports officers to electronically produce and transmit crash reports, assuring completeness, consistency, and fewer interpretation errors (Center for Advanced Public Safety, 2009). Figure 4 shows an example of an eCrash report and the program capabilities.

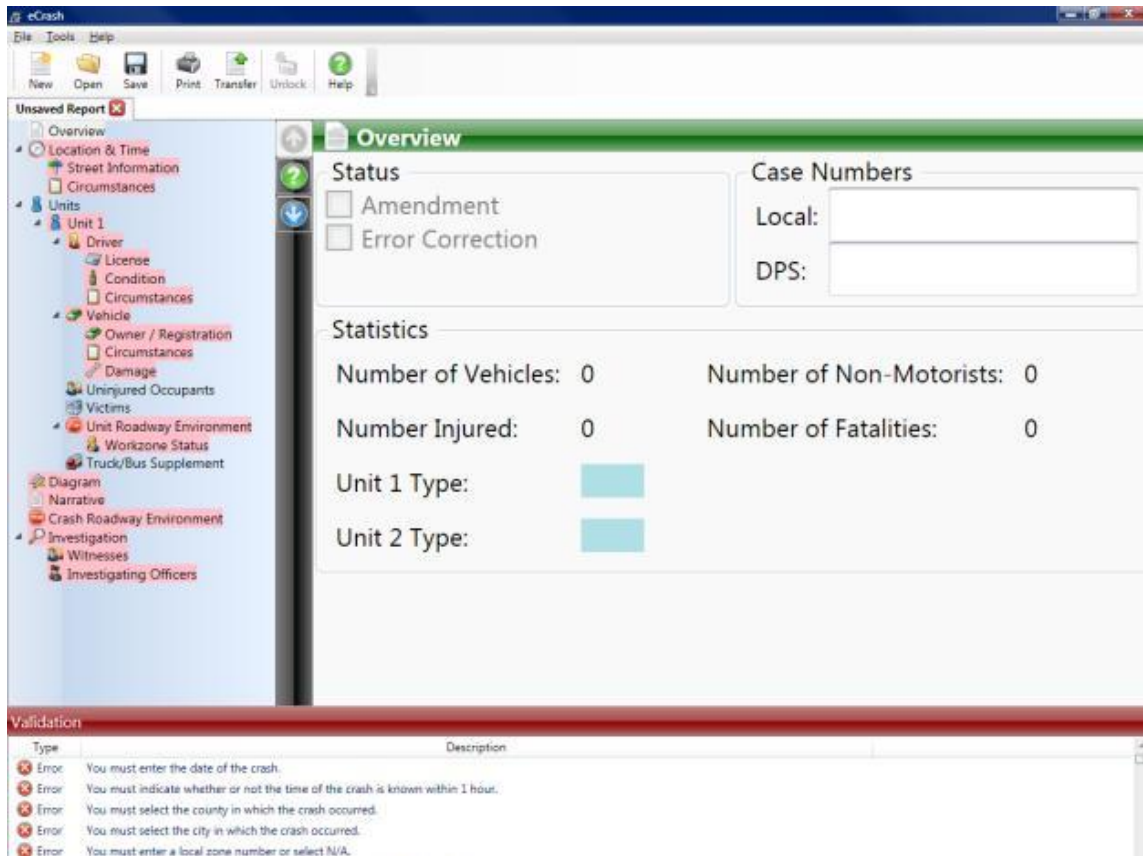


Figure 4. Example of an eCrash report in the eCrash program developed by the Center for Advanced Public Safety (Center for Advanced Public Safety, 2009).

The main portion of the screen in Figure 4 is the data entry screen. The side panel organizes data collection for an eCrash report into appropriate sections that remain highlighted in red until completed. The validation section at the bottom alerts the officer of missing data elements, and will disable the report from being submitted until completed (Center for Advanced Public Safety, 2009). For this project, eCrash data was extracted from the Critical Analysis Reporting Environment (CARE), a data analysis software package with functionalities to export crash report data as a GIS shapefile with GPS coordinates. The data source was a five year crash database of crashes from 2010-2014.

Selective enforcement data was obtained for this project through the DPS timesheets and DOT invoices of officers, dates and hours worked, and funding allocations for the selective enforcement campaign agreement with ALDOT. A large effort was put forth to digitize the data into spreadsheets for relational analysis with the tables in the databases of eCitation and GPS officer patrol route data.

## CHAPTER 3. METHODOLOGY

### 3.1 Introduction

A methodology was developed using relational database and Geographic Information System (GIS) technology in order to verify where selective enforcement efforts took place in Alabama. In addition, the effectiveness of the selective enforcement campaign was evaluated to determine the improvement of traffic safety and the reduction of crash frequencies in high crash locations. Initial work for this project involved digitizing selective enforcement shift information, including the date and hours worked, for each participating officer from DPS extra-duty timesheets and DOT invoice files to spreadsheets for use in electronic analysis. The first task for this project included developing a methodology to cross-reference timestamps between officer patrol routes and issued citations in order to geolocate citations with and without GPS coordinates. Furthermore, a methodology to verify selective enforcement locations was developed by comparing officer patrol routes and dates and hours of selective enforcement shifts from the digitized DOT and DPS files. Relational database tables were imported into a GIS, along with crash data from the Critical Analysis Reporting Environment (CARE), in order to verify selective enforcement locations and quantify the number of citations and the number of crashes in selective enforcement locations before and during selective enforcement efforts. The workflow framework for this research is presented in Figure 5.

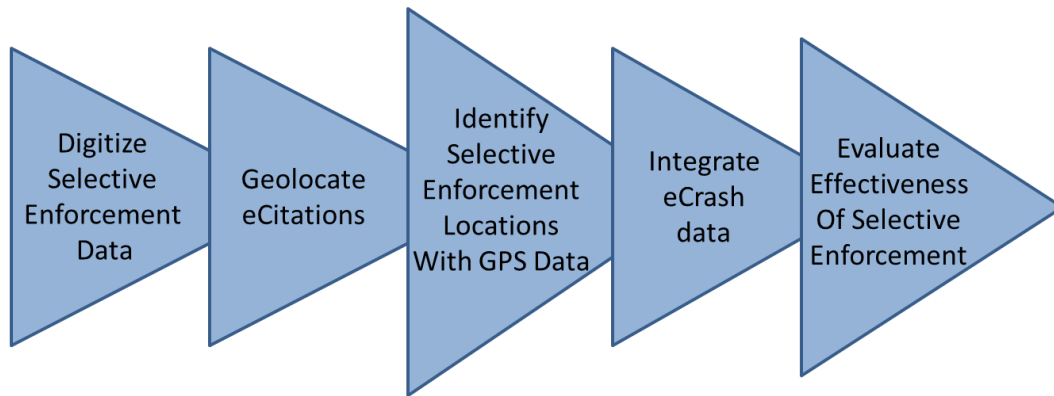


Figure 5. Workflow Framework for Evaluating the Effectiveness of Selective Law Enforcement

Structured Query Language (SQL) is the standard language for working with relational database systems. A relational database is a collection of data, organized in various tables of attributes and rows, that all have a specific, unique relationship with one another. The tables are related through the use of primary keys, a unique attribute in a table, which can be included in other tables as a foreign key. Relationships can be “one-to-one,” “one-to-many,” or “many-to-many” with a linking table. SQL query expressions were written and executed in order to translate data in tables to valuable information (Viescas and Hernandez, 2014). The following sections present the logic behind the executed SQL queries, in combination with GIS tools, which were developed to evaluate the effectiveness of selective law enforcement in Alabama.

### 3.2 Digitizing Selective Enforcement Data

A scanner was used to digitize DPS timesheets and DOT invoices for the Alabama selective law enforcement campaign for one full year from August 1, 2010 to July 31, 2011. Three file types were identified for each invoice: payroll time sheets, extra-duty consolidated activity reports, and in-state travel forms. Optical character recognition (OCR) methods were attempted, but due to the available scanning resolutions and format of the paper files, OCR was not found useful. Therefore, the extra-duty consolidated activity reports were manually entered

into Excel spreadsheets. The attribute headings for the data were as follows: Date Worked, First Name, Last Name, Middle Initial, Suffix, Hours, Salary, Subsistence Pay, Per Diem, Number of Citations, Miles Driven, Initiative, Troop, and Post. The salary and pay information was kept confidential to respect the privacy of individual police officers.

### 3.3 UserIDs and Selective Enforcement Data

Law enforcement officials in the state of Alabama are given a unique UserID, which is used for identification purposes in both the GPS officer patrol route and eCitation databases. In order to incorporate the selective enforcement shift data from the DPS timesheets and DOT invoices, the specific unique UserID associated to each officer was found and recorded by using a sequence of SQL queries, as shown in Appendix A.1. The digitized selective enforcement information, which contains the participating officer names in three fields including First Name, Middle Initial, and Last Name, was imported into SQL Server, and was joined to the Users table, an existing table in the GPS officer patrol route database. The join was based on First Name, Last Name, and an Agency Identification Number (ORI) beginning with 'ALAST', as presented in Appendix A.1.1. Wherever the first and last name of an officer in the selective enforcement data table was equal to the first and last name of an officer listed in the Users table, the selective enforcement data was returned with the unique officer UserID. The agency ORI in the Users table was also required to begin with 'ALAST,' achieved with a WHERE statement in the query. The relationship between the tables and an example dataset with a query result are shown in Figure 6.



User ID	Rank	First Name	Last Name	Middle Initial	ORI
A124	Trp	John	Smith	E	ALAST0020
B376	Trp	Jane	Jones	K	ALAST0040
C683	Cpl	Dan	Bones	B	AL0056700
C675	Cpl	Dan	Bones	B	ALAST0000

Date Worked	First Name	Last Name	Middle Initial	Hours Worked
08/27/10	John	Smith	E	4
09/15/10	Jane	Jones		5
12/20/10	Dan	Bones	B	8

User ID	Rank	First Name	Last Name	Middle Initial	ORI	Date Worked	Hours Worked
A124	Trp	John	Smith	E	ALAST0020	8/27/10	4
B376	Trp	Jane	Jones	K	ALAST0040	9/15/10	5
C675	Cpl	Dan	Bones	B	ALAST0000	12/20/10	8

Figure 6. Example data for the SQL query to identify UserIDs for participating officers in the selective enforcement data

The agency codes for the majority of the state trooper posts begin with ‘ALAST’ so the criterion that the joined users have the agency ORI ‘ALAST’ was included in order to maximize the semi-automatic method to define UserIDs and minimize duplicate findings of officer names, as shown in Figure 6 with the fictional officer named Dan Bones. The full year dataset came from 13 different invoices and included 431 officers. Using this semi-automatic defining methodology, 93.7% of the participating officers UserIDs were located from the dataset.

The remaining 6.3% of the officers and their respective UserIDs either required a manual addition to a Look Up Table, or required a manual subtraction because of the existence of a duplicate name. Missing officer names were found using a right outer join between the identified selective enforcement officers from the previous query and the complete selective enforcement data, as described in Appendix A.1.2. A right outer join returns all the rows of data from the right table specified in the query (the selective enforcement data), regardless of whether or not there is a match in the left table being joined (the selective enforcement users table).

Therefore, when there is no match in the users table, a NULL value was returned in the UserID column. The UserIDs for the names with NULL values were found in the existing Users table for manual addition, as shown in Appendix A.1.3.

Duplicate UserIDs from the original UserID join were found using the COUNT aggregate function in SQL, as shown in Appendix A.1.4, and the officer UserID chosen to keep was selected based on an order of precedence of additional details. The officer and UserID to keep was selected based on the following details in the following order: the officer Middle Initial matches, the agency ORI is ALAST0000, the officer entry contains city and county information, the officer Rank is Trooper, and lastly, the trace data matches the claimed selective enforcement days worked. Ideally, the use of the trace data for confirmation of UserID would not be used, as the search queries for such are timely and inefficient.

A Look Up table was created simultaneously with the findings and results from the manual additions and subtractions. The Look Up table corrected the located typos, and joined in the manual additions. A query was executed to join and combine the originally identified UserIDs, additions, and subtractions into a final table of officers and unique UserIDs, as shown in Appendix A.1.5. The final table signified the UserIDs and officer names of relevant officers working for the Alabama selective enforcement campaign. The verified UserIDs were joined to the selective enforcement data, and each selective enforcement entry was given a selective enforcement ID (SE\_ID) for relational database purposes. The query for generating SE\_IDs is shown in Appendix A.1.6. Over the course of the year, 99.5% of the selective enforcement shifts were verified with the attachment of a UserID, totaling 5315 selective enforcement shifts. The remaining 0.5% were explained by employees of the DOT and DPS that were paid on the

invoices for administrative purposes, but did not participate in patrol, and therefore do not have UserIDs in the trooper UserID database table.

### 3.4 Geolocating eCitations

Law enforcement officials in the state of Alabama issue approximately 80,000 Electronic Citations (eCitations) per month. These eCitations do not require GPS coordinates or other structured location data. The eCitations do have an electronic timestamp indicating when the citation was issued. Additionally, each State Trooper's vehicle is polled every 30 seconds and the trooper's location is recorded along with a timestamp. Performing a spatial-temporal analysis through a sequence of SQL queries, which are listed in Appendix A.2, the time-stamped eCitations and State Trooper location data were cross-referenced in order to accurately locate an eCitation to the nearest GPS point in time.

The database with eCitation data has a Citation table and a Document table that were joined together based on DocumentID and Ticket Number in order to generate a comprehensive dataset of information about a particular eCitation. For example, the information regarding one particular eCitation includes the officer who issued the citation, city and county location information, a description of the offense and the citation code, and a timestamp for when the citation was issued, recorded in the central time zone. The final selective enforcement users table from the previous sequence of queries was joined to the eCitation data based on UserID, in order to return eCitations written by the relevant officers. The criterion to exclude voided eCitations was also included, as voided eCitations were not officially issued. The query to extract eCitations issued by participating officers is shown in Appendix A.2.1. Over the course of the year being analyzed in this research, including both selective enforcement shifts and regular duty shifts, 475,214 eCitations were issued by the participating officers.

The database with the GPS officer patrol route data has a GPSCoordinates table and a GPSCoordinateGroups table that were joined together based on GroupID in order to generate a comprehensive dataset of information about a particular GPS trace location point. Data for each individual GPS trace point includes the UserID, the latitude and longitude location, and a timestamp recorded in UTC time. The final users table from the previous sequence of queries was joined to the GPS data based on UserID, in order to return GPS location points for the relevant officers exclusively, as shown in Appendix A.2.2. For the year being analyzed in this research, including both selective enforcement shifts and regular duty shifts, 37,628,124 GPS points were recorded for the participating officers. These GPS data points were imported into a relational database table. A GPS\_ID was generated for the GPS trace points in order to have a unique field in the table. The query for generating GPS\_IDs is shown in Appendix A.2.3.

In order to cross-reference the timestamps of the eCitations and the GPS location points, a SQL query was executed to calculate the time differences between GPS location points and eCitations for a particular officer using the DATEDIFF() command. This query only returned eCitations joined to a GPS location point within 600 seconds, as shown in Appendix A.2.4. The time allowance of 600 seconds, or 10 minutes, was chosen to maximize the number of eCitations located while also providing reasonable eCitation location accuracies. Out of the returned results, the minimum time difference between GPS location point and eCitation was chosen to signify the most accurate location of the eCitation, as presented in Appendix A.2.5. An example of this process is shown in Figure 7.

eCitations						GPS Data			
User ID	Ticket Number	Citation Details	Citation Time	Lat	Long	User ID	GPS Time	GPS Lat	GPS Long
C675	V3	DUI	01/02/11 02:27:56 AM	x	y	C675	01/02/11 02:27:42 AM	x1	y1
						C675	01/02/11 02:28:12 PM	x2	y2
						C675	01/02/11 02:29:42 PM	x3	y3
F354	V4	Speed	02/24/11 05:23:16 PM			F354	02/24/11 05:22:36 PM	x4	y4
						F354	02/24/11 05:23:06 PM	x5	y5
F354	V5	No Seatbelt	02/24/11 05:23:16 PM			F354	02/24/11 05:23:36 PM	x6	y6
						F354	02/24/11 05:24:06 PM	x7	y7
Z244	V6	Speed	05/15/11 10:25:38 AM			Z244	05/15/11 10:45:27 AM	x8	y8
						Z244	05/15/11 10:45:57 AM	x9	y9

Geolocated eCitations: Minimized time difference and within 600 seconds							
User ID	Ticket Number	Citation Details	Citation Time	GPS Time	Time Difference	GPS Lat	GPS Long
C675	V3	DUI	01/02/11 02:27:56 AM	01/02/11 02:27:42 AM	14	x1	y1
F354	V4	Speed	02/24/11 05:23:16 PM	02/24/11 05:23:06 PM	10	x5	y5
F354	V5	No Seatbelt	02/24/11 05:23:16 PM	02/24/11 05:23:06 PM	10	x5	y5

Figure 7. Example data for the SQL query to geolocate eCitations

The spatial-temporal analysis through a sequence of SQL queries located 68.6% of eCitations. Further investigation showed that 49 of the officers (11.6%) participating in selective enforcement efforts did not have any GPS trace data associated with their respective UserIDs, potentially due to lack of GPS equipment and/or faulty equipment. With respect to the 88.4% of officers that had trace data associated with their respective UserIDs, 72.6% of eCitations were geolocated using the developed methodology. The resulting dataset was imported into GIS for visual mapping, as well as further refinement. Citations that were not successfully located lacked officer location data or there were breaks in the officer location data due to lost GPS signals.

### 3.5 Identifying Selective Enforcement Locations

The selective enforcement DPS timesheets and DOT invoices provide the following information: Date Worked, First Name, Last Name, Middle Initial, Suffix, Hours, Salary, Subsistence Pay, Per Diem, Number of Citations, Miles Driven, Initiative, Troop, and Post. The salary and pay information was kept confidential to respect the privacy of individual police officers. In order to relate the selective enforcement hours worked with the GPS location data, the total hours worked in a full shift of regular work time was found. By relating the full hours worked by an officer in a shift on a particular day with the claimed selective enforcement hours on that day, specific GPS location points were defined as either “during selective enforcement” or “not during selective enforcement.” The location of the “during selective enforcement,” or overtime work, is vital for the analysis of the effectiveness of selective enforcement. The workflow framework for identifying individual GPS points as during selective enforcement is shown in Figure 8. Figure 8 (a) illustrates the steps to calculate full shifts from the GPS officer patrol route data, in order to establish the necessary relationship to join in the selective enforcement data, denoted by the pink arrow. These steps are described in Section 3.5.1 Calculating Full Officer Shifts from GPS Location Data. Figure 8 (b) illustrates the steps to identify individual GPS points as during or not during selective enforcement shifts after the establishment of the relationship between the data, as noted by the pink arrow. These steps are described in Section 3.5.2 Defining Individual GPS Points During Selective Enforcement Shifts. Even if the original location of a selective enforcement campaign is known, the following steps can be taken to confirm the work was completed in the appropriate locations to ensure a sound analysis.

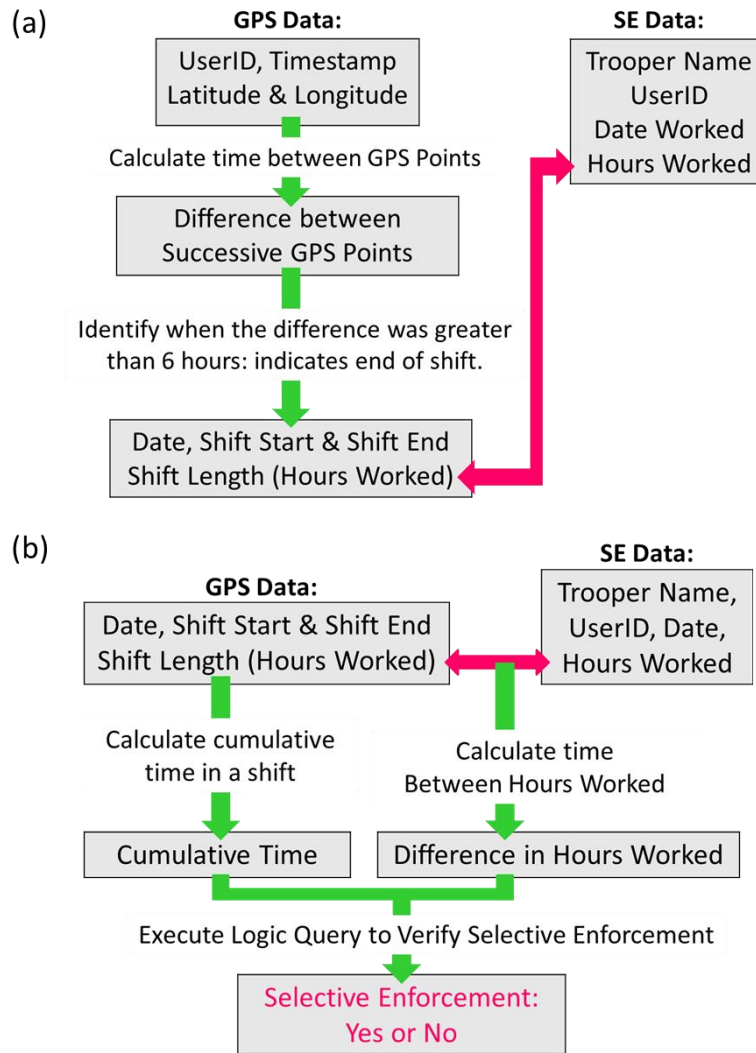


Figure 8. Workflow framework for (a) establishing relationship between the GPS data and selective enforcement (SE) data, denoted by the pink arrow; and (b) identifying individual GPS points as during selective enforcement

### 3.5.1 Calculating Full Officer Shifts from GPS Location Data

A series of SQL queries was used to define the beginning and ending of a full working shift for an officer and calculate the total hours worked for the shift, as described in Appendix A.3. The LEAD function in SQL accesses the previous row in a column of a table, and the LAG function in SQL accesses the next row in a column of a table. To calculate the time difference in seconds between two successive GPS location points, the LEAD function was used partitioned

by UserID and ordered by GPS Time to access the Next GPS Time in the table. The results of the LEAD calculation are stored in a new column in a table. The DATEDIFF() command created an additional column, recording the difference between the GPS Time column and the newly added Next GPS Time column. An example of this query is shown in Figure 9.

UserID	Latitude	Longitude	GPS Time	Next GPS Time	Diff
A	x	y	07/1/09 02:33:58 PM	07/1/09 02:34:28 PM	30
A	x	y	07/1/09 02:34:28 PM	07/1/09 02:34:58 PM	30
A	x	y	07/1/09 02:34:58 PM	07/6/09 06:20:03 AM	445505
A	x	y	07/6/09 06:20:03 AM	07/6/09 06:20:33 AM	30
A	x	Y	07/6/09 06:20:33 AM	NULL	NULL
B	x	y	07/3/09 09:32:47 AM		

Figure 9. Example dataset and query results to calculate the time difference between successive GPS points

The beginning and ending of a shift was identified in the table by using the CASE function in SQL, which enforces a “when-then” statement. *When* the time difference between successive GPS location points was greater than a predetermined time tolerance limit, *then* the GPS location point was considered to be the beginning or end of a shift. An example of a large time difference signifying the beginning of a shift is shown in Figure 9, highlighted with a red circle. On the other hand, *when* the time difference between successive GPS location points was less than or equal to the predetermined time tolerance limit (18,000; 21,600; or 28,800 seconds), *then* the GPS location point was considered to be within a shift. The query that executes this CASE logic for defining the beginning and ending of a shift is presented in Appendix A.3.2. Time difference tolerances of 18,000; 21,600; or 28,800 seconds (five, six, and eight hours) were analyzed using this logic by editing the time tolerance limit value, in seconds, in the query. The



numbers of generated shifts for different shift lengths due to the various time tolerances are shown in Figure 10.

In order to select the time tolerance for shift generation that best represents the GPS data and reasonable shift lengths that officers work, based on data shown in Figure 10, the time difference tolerance of six hours was chosen because six hours minimized shifts of over 24 hours compared to using eight hours, kept an optimum number of seven-, eight-, and nine-hour shifts, and minimized the number of one-hour shifts compared to using five hours.



Figure 10. The comparison of time tolerances for GPS location point shift generation and the number of generated shifts per shift length in hours.

Using the time tolerance of six hours, the beginning and ending timestamps of a particular shift for each officer were selected and compiled into a new table with new columns of Shift Start and Shift End, as shown in Appendix A.3.3. A query was used to calculate the difference between these two timestamps, which resulted in the total hours worked for a particular shift and generating a total of 55,402 GPS location based shifts, as presented in

Appendix A.3.4. The date difference was calculated in seconds and then converted to hours to ensure the precision of the time. A Shift Quality column was generated to define a shift as reasonable (given a value of 1) versus unreasonable (given a value of 2). Shifts with hours worked between 0.5 hours and 17 hours were considered reasonable, as 0.5 hours is the smallest increment possible in the selective enforcement invoices and 17 hours provides a conservative inclusion of a maximum possible shift of two back-to-back 8-hour shifts. There were 94.2% of generated shifts with a reasonable shift length, resulting in 52,179 reasonable GPS location based shifts used in the research. Shift\_IDs were generated to provide a unique field in the table, using the query shown in Appendix A.3.5.

### 3.5.2 Defining Individual GPS Points During Selective Enforcement Shifts

By understanding the GPS point data in terms of full officer shifts, a relationship to the selective enforcement data was established. Using the relationship between shift length of full shifts to the hours worked by an officer for selective enforcement, a series of SQL queries was used to define an individual GPS point as “during selective enforcement” or “not during selective enforcement,” as shown in Appendix A.4. As previously described, the selective enforcement DPS timesheets and DOT invoice data was hand-digitized from paper files into an Excel spreadsheet. The digital format of the selective enforcement data was imported as a table into SQL server, and was joined to a participating officer UserID table and selective enforcement IDs (SE\_IDs) were generated, as described in Section 3.3 UserIDs and Selective Enforcement Data and as listed in Appendix A.1. To relate the selective enforcement shifts to the identified GPS location point shifts, a join was executed in SQL based on UserID and Shift Start date. Any duplicates, due to an officer working two separate shifts starting on the same day, were recognized and signified with a Shift Level of Confidence equal to 2. There were 66% of

selective enforcement shifts that were accounted for and joined to an appropriate GPS location point generated shift. Because of the 49 officers (11.6%) that did not have any GPS trace data associated with their respective UserIDs, 477 selective enforcement shifts were not successfully included. When excluding those particular officers, the GPS generated shifts successfully recognized 72.6% of the logged selective enforcement shifts. This query, presented in Appendix A.4.1, also calculates the difference between GPS shift hours worked and Selective Enforcement shift hours claimed.

Simultaneously, queries to calculate cumulative time worked in a GPS identified shift were executed, as presented in Appendix A.4.2 and Appendix A.4.3. Using the difference between the GPS identified shift hours worked and the claimed selective enforcement hours worked as well as the cumulative time worked, individual GPS location points were denoted as “during selective enforcement” or “not during selective enforcement”, as described in Appendix A.4.4. An example dataset and query result is shown in Figure X. The scenarios for the CASE function, a “when-then” command, used in the SQL query and the necessary assumptions for the methodology are shown in Table 2.

Table 2. The CASE function scenarios, assumptions, and query description for the SQL query used to denote an individual GPS point as during selective enforcement.

Scenario	Assumption	Query
Logged selective enforcement hours < GPS shift hours worked	The last 'x' hours of the GPS shift are the overtime selective enforcement hours	<i>When Diff &lt;= Cumulative Time, then 'Yes'</i>
Logged selective enforcement hours = GPS shift hours worked	Within 0.5 hours is considered "equal"	<i>When Diff is Between -0.5 and 0.5, then 'Yes'</i>
Logged selective enforcement hours > GPS shift hours worked	The whole shift is selective enforcement, and the discrepancy can be explained by a loss of GPS signal	<i>When Diff &lt; 0, then 'Yes'</i>

A final query was executed to create a table of GPS points associated with documented selective enforcement shifts. These points received a "Yes" value in a tracking column, resulting in a total of 1,647,711 GPS points, as described in Appendix A.4.5. The series of SQL queries demonstrates successful data reduction, by turning over 37.6 million GPS points, into approximately 1.65 million points of useful information.

### 3.6 Verification of Selective Enforcement Locations

Officers participating in the Alabama selective enforcement efforts were allowed up to two hours of paid travel time to selective enforcement locations. Therefore, the GPS points during selective enforcement are not all localized at a particular selective enforcement location. Additionally, police presence in a selective enforcement location does not necessarily mean the presence was statistically significant over other areas of patrol. In order to verify selective enforcement locations, a statistical method employing clustering of spatial data was

implemented. In order to employ the location verification process, the GPS points during selective enforcement and eCitation data were integrated into ArcGIS based on Route-Milepost (Route-MP). With Route-MP data associated to each point event, a clustering methodology was executed on the GPS point data using a SQL query technique involving the summation and grouping of point events at various each Route-MP bucket sizes. This technique provides an efficient Hot Spot Analysis.

Hot Spot Analysis is a common technique used to analyze spatial frequencies of data and locate high and low areas of event data, such as crashes. Traditional hotspot analyses uses a complete spatial randomness distribution of data events for a quadrant analysis called Kernel Density Estimation (KDE) and calculates a continuous Euclidean distance between data events and a Ripley's K-function (Borruso, 2008). However, the integrity of the roadway network is lost when using this traditional approach for crash events. Crashes do not occur anywhere in the Euclidean plane of space; they occur along a network. Therefore, a SQL query technique was developed to verify high and low frequency locations for the point event data.

### 3.6.1 Integrating Data Elements into ArcGIS

In order to integrate officer GPS patrol patterns during selective enforcement shifts and eCitations issued over the course of the selective enforcement campaign, SQL Server database connections and ArcGIS commands were utilized in ArcCatalog and ArcMap 10.2.1. By creating database connections in ArcCatalog, the SQL tables with the selective enforcement GPS data and eCitation data were individually selected to create a feature class from an XY table. The output of this tool was a point shapefile in the GCS\_WGS\_1984 geographic coordinate system.

The Alabama DOT maintains a linear referenced route layer for state routes, complete with Route-Milepost (Route-MP) identification. The Route-MP information was used to generate a point shapefile using a point-generation tool, placing a point every 100<sup>th</sup> of a mile (HundredthMP) along all routes in the State. A spatial join of the GPS data identified as selective enforcement data and eCitation data was joined to the HundredthMP. Because the HundredthsMP shapefile was in a projected coordinate system, WGS\_1984\_UTM\_Zone\_16N, the selective enforcement points and eCitation data shapefiles were projected before the spatial join to ensure a generated distance column in understandable units of meters. The spatial join defined a Route-MP for each point event, which is vital for the location of significant clusters of points. A cluster of point events verifies a selective enforcement location.

The Route-Milepost information is only available along state routes, which coincides with this research and investigation of only selective enforcement efforts occurring on state routes. However, every driven GPS location and eCitation in the data was joined to a Route-MP. Therefore, using the distance field generated during the spatial join, a selection of point events joined within 400 meters was employed in order to optimize the inclusion of GPS location points and eCitations located along wide ramp interchanges and terminals across the state. The selection resulted in 1,283,211 GPS points during selective enforcement and 243,800 eCitations along state routes over the course of the year. The points within 400 meters of a state route were exported to an alternative shapefile.

### 3.6.2 SQL Server Query Technique to Verify Selective Enforcement Locations

A series of SQL Queries using GPS point data identified as selective enforcement was implemented to verify selective enforcement locations by finding clusters of points at identifiable Route-Milepost locations, as listed in Appendix A.5. The Route-MP data was incorporated by

summarizing the number of selective enforcement points that were identified at Route-MP locations using the COUNT aggregate function, as shown in Appendix A.5.1. Bucket sizes of one-tenth of a mile, one-half of a mile, and one mile were evaluated. In order to standardize the bucket sizes and confirm appropriate lengths along a particular route in the network, queries to calculate the difference between successive Mileposts and the cumulative difference of Mileposts were employed. The queries used to organize the milepost data and buckets for analysis are listed in Appendix A.5.2 and Appendix A.5.3. The summation of Selective enforcement points in groups of the three bucket sizes was centered in the middle of each bucket size and recorded in a SQL table, as shown in Appendix A.5.4. The LEAD and LAG function were used to calculate the number of selective enforcement points prior to and after a particular row of data. A hypothetical example of the logic for the summation query is shown in Figure 11.

Route	MP	Number of Events	Sum
A	3.0	0	486
A	3.1	49	1131
A	3.2	1	1192
A	3.3	6	1197
A	3.4	0	1198
A	3.5	430	1198
A	3.6	645	1198
A	3.7	61	1149
A	3.8	5	1156
A	3.9	1	1150
A	4.0	0	1150
A	4.1	0	720
A	4.2	0	75
A	4.3	8	14

Figure 11. SQL Query summation analysis logic: centering the summation on a particular milepost by LEAD and LAG functions

The Sum column in Figure 11 was executed for all three bucket sizes used in the analysis: one-tenth of a mile, one-half of a mile, and one mile. The sum data was imported back into ArcGIS for thematic mapping using natural jenks for statistical recognition of large sums, or clusters, of selective enforcement locations. Natural jenks organize the data into groups, or classes, that exclusively minimize the variance of the data points included in all classes. While the located selective enforcement points may not be the exact area law enforcement was directed to patrol with extra-duty hours, the largest natural jenk was used to identify the areas with statistically high levels of selective enforcement and was therefore considered a selective enforcement location for the analysis.

Three natural jenk classes were used on the one mile summation and grouping analysis values in order to optimize the length of the located and verified selective enforcement locations. The one-tenth of a mile and one-half of a mile analyses generated locations of smaller length, which were stacked relatively close together, whereas the one mile analysis recognized the small, close locations as one whole location. Figure 12 (a) shows highlighted locations using the largest natural jenk class limit for the one-half of a mile analysis as a location indicator. The lowest value was 1877 selective enforcement points at a particular Route-MP. Figure 12 (b) shows highlighted locations using the largest natural jenk class limit for the one-mile analysis. The limit value for the one-mile analysis was 2885 selective enforcement points at a particular Route-MP.



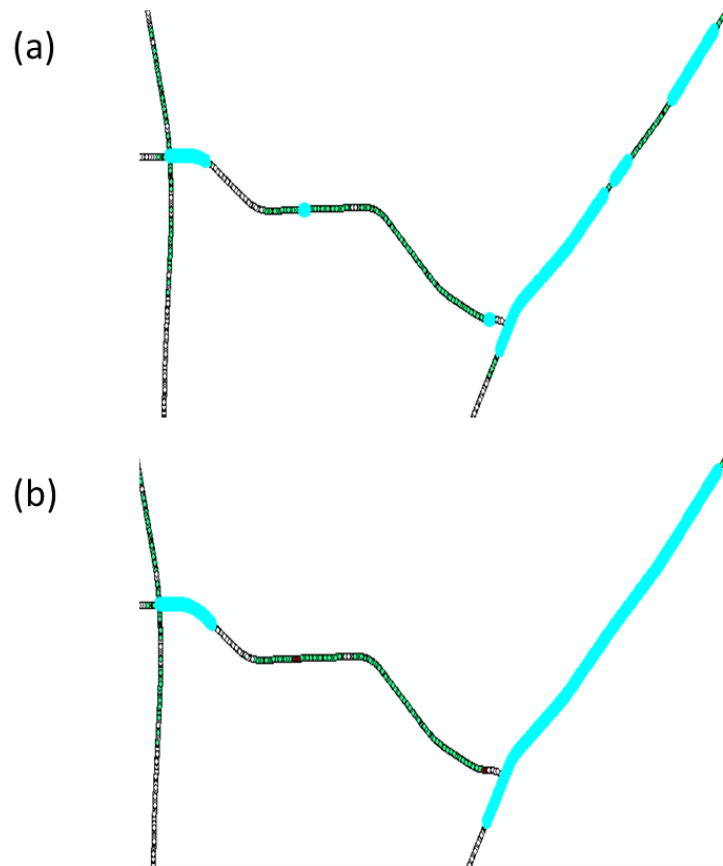


Figure 12. (a) Utilizing one-half of a mile analysis summation values for selective enforcement location verification, (b) Utilizing one-mile analysis summation values for selective enforcement location verification.

A SQL query was executed to extract only the Route-MP combinations that met the requirement of the natural jenk class limit of 2885 selective enforcement points from the one-mile analysis, as listed in Appendix A.5.5. This query also utilized the LEAD and LAG functions to create two columns of information to serve as Quality Assurance/Quality Control checks for defining the beginning and ending Route-MP of a selective enforcement location. An additional query was used to select only the start and end of the selective enforcement locations to define the sections of route that were considered selective enforcement across the state, as shown in Appendix A.5.6. Using the one-mile analysis and largest natural jenk class, 26 locations were considered selective enforcement areas across the state of Alabama.

### 3.7 Incorporating eCrash Data from CARE

The Critical Analysis Reporting Environment (CARE) is data analysis software developed by The Center for Advanced Public Safety at The University of Alabama. A data source of crash records from 2009-2013 were imported into CARE, and filters were created to export crash report data for the research time period as a GIS shapefile with GPS coordinates. Two exports were completed: crashes during one year before the selective enforcement year and crashes during the selective enforcement year. The created filters also incorporated highway classifications, and only exported crashes along Interstate, Federal and State routes. A spatial join of the GIS shapefiles of the exported crash data to the Route-Milepost information (HundredthMP shapefile) was performed to ensure consistency of location identification with the selective enforcement points and eCitations. An attribute selection of crashes joined to Route-MP points within 400 meters was also executed for consistency.

## CHAPTER 4. RESULTS

### 4.1 Introduction

The Alabama Mobile Selective Law Enforcement Campaign was in effect under an agreement between the Alabama Department of Public Safety (DPS) and the Alabama Department of Transportation (ALDOT) between October 2007 and September 2011. While selective enforcement efforts may still be ongoing, available data ranged over these five years. For a one year study from August 1, 2010 through July 21, 2011, data for selective enforcement shifts worked, police officer vehicle GPS trace data, eCitations, and eCrashes were integrated into one spatial and temporal map by data manipulation using SQL queries with relational databases and spatial mapping tools in Geographic Information Systems (GIS). Selective enforcement efforts were located at 26 areas along state routes across the state of Alabama. After further investigation of each location using ArcMap and Google Maps, three locations that were found to have high selective enforcement presence were located at state trooper posts and were omitted from further studying. Additionally, two different areas were found to have two separate defined locations of selective enforcement high points, separated by 0.2 miles, and were therefore merged. The respective lengths in miles and area type for the resulting 21 locations are shown in Table 3. The locations are referred to by a number to respect the privacy of crash and citation location information, but the specific location information has been presented to the Alabama Department of Transportation. The effectiveness of the selective enforcement efforts were evaluated in terms of crash frequencies and the number of issued citations using paired difference t-tests. The 21 locations were also analyzed by area type. Locations were considered

rural if the population of the location municipality was less than 5000, while locations were considered urban if the population of the location municipality was greater than 5000.

Table 3. The located and verified selective enforcement locations

Location	Length	Area Type
1	0.71	Urban
2	0.977	Urban
3	4.2	Rural
4	0.863	Urban
5	1	Rural
6	0.983	Rural
7	0.737	Urban
8	0.29	Rural
9	3.1	Urban
10	3.301	Rural
11	0.56	Urban
12	1.68	Rural
13	1.43	Rural
14	2.45	Urban
15	1.93	Rural
16	0.49	Urban
17	0.662	Urban
18	2.37	Rural
19	2.16	Rural
20	0.82	Rural
21	1.16	Urban

In practice, it is reasonable for law enforcement officials to be directed to selectively enforce locations referred to by full integer mileposts for segments of a route, or by route to route crossings based on intersections. The 21 locations along state routes in Alabama, while not entirely covering a potential area where an officer was instructed to patrol, were found to have high selective enforcement presence and can be considered the focused point of enforcement for that particular location.

#### 4.2 Number of Crashes and Citations Before and During Selective Enforcement

Based on the one mile summation and grouping analysis in SQL, as shown in Appendix A.5.4, in conjunction with the natural jenk symbology classification in GIS, 21 locations were recognized with a statistically high amount of selective enforcement presence and confirmed logical for selective enforcement efforts using engineering judgement. The natural jenks classification in GIS, also known as the goodness of variance fit, is used to minimize the variance within a specified number of groups, or classes. Three classes were used for the location process, as described in Section 3.6.2 SQL Server Query Technique to Verify Selective Enforcement Locations. The number of crashes and the number of issued citations were evaluated at the 21 locations before and during the selective enforcement research year, including both regular and overtime shifts. The number of crashes and citations for each location over the course of the before and during year are shown in Table 4, along with the percent change between the before and during selective enforcement crash and citation counts for each location. A negative percent change for crashes marks a decrease in the number of crashes during the selective enforcement research year, and a positive percent change for citations marks an increase in the number of issued citations during the selective enforcement effort. Table 4 is ordered by the percent change in the number of crashes at each location, and is sectioned off by negative and positive percent changes. There were 11 locations that experienced a decrease in the number of crashes. These locations had variable changes in the number of issued citations. Notably, Location 9, an enforcement effort between two interchanges, experienced a citation increase of 2015%.

Table 4. Crash and Citation Data for the Selective Enforcement Locations, organized by percent change on crashes before and during selective enforcement

Location	Crashes			Citations			Equivalent C Level Crashes	
	One Year Before	One Year During	Percent Change	One Year Before	One Year During	Percent Change	One Year Before	One Year During
7	2	0	-100.00%	93	153	64.52%	0	0
8	2	0	-100.00%	31	23	-25.81%	0	0
12	33	19	-42.42%	1512	963	-36.31%	27	5
21	22	14	-36.36%	91	257	182.42%	10	14
11	10	7	-30.00%	180	180	0.00%	6	4
19	17	14	-17.65%	75	505	573.33%	5	11
10	24	20	-16.67%	268	1133	322.76%	0	9
5	15	13	-13.33%	4	41	925.00%	8	1
13	16	14	-12.50%	916	511	-44.21%	8	9
9	16	15	-6.25%	33	698	2015.15%	4	4
15	16	15	-6.25%	214	826	285.98%	10	10
3	22	22	0.00%	886	1243	40.29%	11	8
16	2	2	0.00%	33	46	39.39%	6	2
20	9	9	0.00%	144	343	138.19%	2	2
1	13	15	15.38%	311	223	-28.30%	7	7
4	43	50	16.28%	35	170	385.71%	21	15
6	7	9	28.57%	371	365	-1.62%	1	1
18	13	19	46.15%	229	568	148.03%	7	9
2	19	30	57.89%	140	161	15.00%	7	11
17	3	5	66.67%	27	91	237.04%	0	0
14	13	34	161.54%	868	1599	84.22%	8	10

Severity weighted crash counts are also presented in Table 4. The weighted crash counts were included in the analysis of the effectiveness of selective enforcement in order to draw conclusions on any changes in the severity of crashes at the various locations. For instance, the number of severe crashes may have decreased, while the number of total crashes may have increased. The severity weighted crash counts for the 21 selective enforcement areas before and during the selective enforcement year are presented in terms of equivalent C level crashes. The

severity of vehicular crashes is often classified by law enforcement officials using the “KABCO” injury scale. The classifying injury levels are denoted by a letter in the acronym, KABCO: the letter K stands for a fatal injury, A for incapacitating injury, B for non-incapacitating injury, C for possible injury, and O for no injury (Federal Highway Administration, 2011). The letter classifications can also be utilized to weigh crashes by severity by calculating the number of equivalent C level crashes, which have a weight value of one. Weight values for the worst injury levels in a crash are shown in Table 5. The number of persons involved in a crash does not affect the severity weighting factor (Center for Advanced Public Safety, 2013).

Table 5. Crash severity level weighting values (Federal Highway Administration, 2011)

KABCO Letter	Injury Severity Level	Severity Level Weighting Value
K	Fatal Injury	5 C injuries
A	Incapacitating Injury (visible/carried from the scene)	3 C injuries
B	Non-incapacitating Injury (bruises/abrasion/swelling)	2 C injuries
C	Possible Injury (minor/pain/fainting)	1 C injuries
O	Property Damage Only	0 C injuries

#### 4.3 Evaluating the Effectiveness of Selective Enforcement

A paired difference t-test was used to determine whether the mean, or expected value, of the differences between the before and during crash frequencies and citation counts yielded a significant change. A positive value change for crashes will conclude that the number of crashes decreased during the selective enforcement efforts.

The null and alternative hypotheses for the before and during crash number tests are

$$H_0: \mu_d \leq 0 \quad \text{and} \quad H_1: \mu_d > 0$$

where  $H_0$  is the null hypothesis,  $H_1$  is the alternative hypothesis, and  $\mu_d$  is the difference in the means. A negative value change for citations will conclude that the number of issued citations went up during selective enforcement. The null and alternative hypotheses for the before and during citations number tests are

$$H_0: \mu_d \geq 0 \quad \text{and} \quad H_1: \mu_d < 0$$

If the null hypothesis is rejected based on the t-test statistic and a corresponding P value less than a particular significance level, then the alternative hypothesis is accepted, meaning there was a statistical change in the number of crashes or citations at the various selective enforcement locations. For example, at a significance level of 0.10, the null hypothesis is rejected with 90% confidence. The Paired Difference t-test results for the total number of crashes, the number of equivalent C injury level crashes, and the number of issued citations, are shown in Table 8.

The crash and citation data was analyzed by separating the 21 selective enforcement locations by urban and rural area types in order to account for large variances and potential “noise” in the data. There were 10 selective enforcement areas located in urban areas, and 11 selective enforcement areas in rural areas. The paired difference t-test results for the total number of crashes, the number of issued citations, and the number of equivalent C injury level crashes for urban selective enforcement locations are shown in Table 6. The paired difference t-test results for the total number of crashes, the number of issued citations, and the number of equivalent C injury level crashes for rural selective enforcement locations are shown in Table 7.



Table 6. Paired Difference t-test Results for 10 Urban selective enforcement locations along state routes in Alabama.

	Crashes		Citations		Equivalent C Crashes	
	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>
Mean	14.3	17.2	181.1	357.8	6.9	6.7
Variance	151.122	257.956	66137.21	222289.1	34.9889	30.9
Observations	10	10	10	10	10	10
Hypothesized $\mu_d$	0		0		0	
Deg. of Freedom	9		9		9	
t-Statistic	-1.111		-1.967		0.198	
P-value	0.148		0.040		0.424	

Table 7. Paired Difference t-test Results for 11 Rural selective enforcement locations along state routes in Alabama

	Crashes		Citations		Equivalent C Crashes	
	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>
Mean	15.818	14	422.727	592.818	7.182	5.909
Variance	72.564	39.8	227955.4	166447	58.964	17.491
Observations	11	11	11	11	11	11
Hypothesized $\mu_d$	0		0		0	
Deg. of Freedom	10		10		10	
t-Statistic	1.237		-1.353		0.525	
P-value	0.122		0.103		0.305	

For both urban and rural selective enforcement locations along state routes in Alabama from August 1, 2010 through July 21, 2011, for urban selective enforcement locations, the p-value for the crash frequency data was 0.148. The null hypothesis (the number of crashes remained constant or increased) can be rejected at a significance level of 0.15, or with 85% confidence. For rural selective enforcement locations, the p-value for the crash frequency data was 0.122. The null hypothesis (the number of crashes remained constant or increased) can be

rejected at a significance level of 0.15, or with 85% confidence. The results confirm that crash frequencies were reduced at both urban and rural selective enforcement locations, with 85% confidence. The number of issued citations increased during selective enforcement for both urban and rural locations, with rejections of the null hypotheses with low-p values of 0.040 and 0.103, respectively. The results confirm that the number of issued citations at selective enforcement locations was increased during the campaign. The results for the equivalent C severity level crashes test between the before and during selective enforcement frequencies at both urban and rural locations did not constitute the rejection of the null hypothesis. Therefore, when analyzing urban and rural locations exclusively, it is plausible that selective enforcement was not effective in reducing the severity of crash occurrences.

The 21 selective enforcement locations along state routes in Alabama for the year of August 1, 2010 through July 21, 2011 were also analyzed as a whole for comparison. The p-value of 0.390 for the test between the number of crashes one year before and one year during, as listed in Table 8, does not constitute the rejection of the null hypothesis with substantial certainty. Therefore, when looking at the selective enforcement locations collectively, it is plausible that selective enforcement was not effective in reducing crashes in these areas. However, when comparing the analysis of the equivalent C crash counts to the total number of crashes, the p-value decreased, going from 0.390 to 0.287. Additionally, the variance values were decreased. The p-value of 0.018, for the test between the number of issued citations one year before and one year during, as listed in Table 8, means the null can be rejected with 99% confidence. Therefore, the number of issued citations statistically increased during the selective enforcement year as compared to the year before.

Table 8. Paired Difference t-test Results for 21 selective enforcement locations along state routes in Alabama.

	Crashes		Citations		Equivalent C Crashes	
	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>	<i>One Year Before</i>	<i>One Year During</i>
Mean	15.095	15.524	307.667	480.905	7.048	6.286
Variance	104.891	138.662	159030.4	197719.5	45.248	22.814
Observations	21	21	21	21	21	21
Hypothesized $\mu_d$	0		0		0	
Deg. of Freedom	20		20		20	
t-Statistic	-0.282		-2.261		0.573	
P-value	0.390		0.018		0.287	

In summary, there is evidence of trends between selective enforcement and the decrease of crashes by analyzing urban and rural locations separately, as opposed to collectively. Analyzing the locations by area type seems to explain some of the variance of the data, and shows some improvement to understanding the effectiveness of selective enforcement. However, the decrease in the severity of crashes was better understood when analyzing all 21 selective enforcement locations together. In each paired difference test performed, the results confirm that the number of issued citations increased during the selective enforcement efforts. Overall, there was a statistically significant increase in citations at all identified selective enforcement locations, while there was a marked decrease in the number of crashes.

## CHAPTER 5. RECOMMENDATIONS FOR SELECTIVE ENFORCEMENT IN 2016

### 5.1 Introduction

Selective enforcement efforts in Alabama have shown trends such as a significant increase in the number of citations and a marked decrease in the number of crashes in selective enforcement areas, as shown in Chapter 4. In order to further improve the positive impacts that selective enforcement efforts provide for crash reductions and traffic safety, an updated selective enforcement campaign is described using lessons learned from the literature and the analyzed selective enforcement campaign.

### 5.2 Guide for the Development and Implementation of a Selective Enforcement Campaign

1. Define the scope and intent of the selective enforcement campaign.

The Alabama selective enforcement campaign data from August 1, 2010 to July 31, 2011 was used as the basis for the recommended campaign. Therefore, the proposed selective enforcement campaign targets speed, driving under the influence (DUI), and failure to wear a seatbelt along state routes in Alabama. The proposed selective enforcement efforts are also split among urban and rural locations. In order to stay consistent with the evidence of selective enforcement in Alabama from this research, approximately 20 locations will be chosen along various state and federal roads, highways, and interstates, with a desired even distribution between urban and rural locations. The locations chosen will also be areas with a statistically high frequency of speed- or DUI-related crashes. Both segments of road and intersections will

be considered. The following steps will follow this scope, however the steps provided can be tailored and implemented by other states and/or DOTs with different selective enforcement targets.

2. Identify high-crash locations eligible for selective law enforcement patrol
  - a. Access three years of crash data
  - b. Filtered crashes for speed- or DUI-involvement in both urban and rural locations
  - c. Perform hotspot analysis on filtered crashes
  - d. Confirm appropriateness of the locations for final location selection
  - e. Use a safety performance function to confirm over-representation of crash frequency

High crash locations are generally the starting points for the selection of locations to increase law enforcement and target particular negative driver behaviors that tend to lead to more severe crashes. Based on lessons learned from the Ticketing Aggressive Cars and Trucks (TACT) project by the Federal Motor Carrier Safety Administration (2007), three years of crash data provides the optimum data source in order to locate high crash hotspots and select enforcement locations. A crash dataset from 2012-2014 from The Critical Analysis Reporting Environment (CARE) developed by the Center for Advanced Public Safety (CAPS) at The University of Alabama was used for hotspot identification.

The crash dataset was filtered by speeding or DUI involvement in urban and rural locations. Only crashes with contributing circumstances or issued citations as a result of the crash related to speed offenses or driving under the influence of alcohol or drugs situations were used in the hotspot analysis. The crash dataset was filtered in order to narrow down the hotspot

search to high crash locations due to negative driver behaviors including speeding and driving under the influence, while still evenly distributing locations across urban and rural locations along state routes across the state. Crash hotspots were located by specifying a minimum number of crashes within a certain hotspot length, in miles. For urban locations, the hotspot parameters specified were 75 crashes in 5 miles, and the rural locations, the hotspot parameters specified were 50 crashes in 5 miles. These hotspot parameters were chosen by trial and error to result in approximately 20 locations for each area type for further investigation before the final selection of 20 recommended enforcement location areas. The crash filtering workflow and desired output is shown in Figure 13.

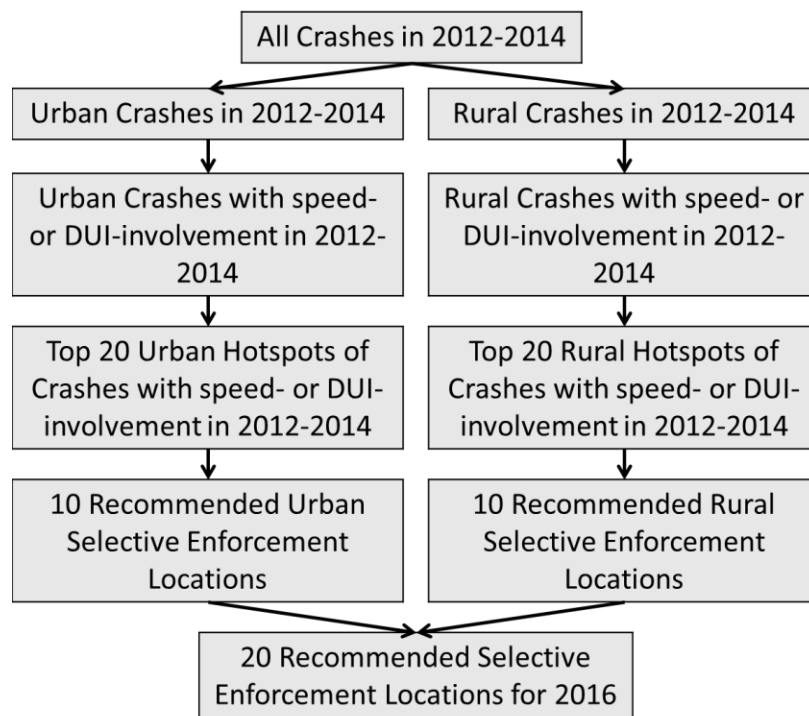


Figure 13. Crash Filtering Workflow for 20 Recommended Selective Enforcement Locations

The hotspot analysis identified 37 locations, 18 urban locations and 19 rural locations, which were investigated in GIS for appropriateness and safety. All locations were compared by

additional considerations including the number of equivalent C severity crashes per million vehicle miles (see Table 5), shoulder width, and the number of lanes to ensure the potential location is safe for participating officers. Additionally, some locations were merged into 10 or 15 mile segments, or recognized as an intersection. The specific Route-Milepost or intersection information for the suggested 10 urban locations and 10 rural locations for selective enforcement was provided to ALDOT. The 20 recommended locations were described in terms that would appropriately direct a police officer to patrol an area in practice. For example, a suggested area from CARE may have been defined as State Route 1 from Milepost 109.1 to Milepost 119.1. This description would have been refined to State Route 1 Milepost 110 to Milepost 120.

Safety performance functions (SPF) from SafetyAnalyst, a software tool from the American Association of State Highway and Transportation Officials, were used to confirm the over-representation of crashes at the identified locations. Safety performance functions predict the average number of crashes that are expected at a location, based on the length of the segment and the annual average daily traffic (Federal Highway Administration, 2014). If the actual number of crashes at the identified location is greater than the predicted number of crashes from the SPF, the location is over-represented with crashes and is suitable for selective enforcement. The standard equation for a SPF (Federal Highway Administration, 2014) is:

$$\text{Predicted Crashes} = \exp[\alpha + \beta * \ln(AADT) + \ln(\text{segment length})]$$

where  $\alpha$  and  $\beta$  are regression coefficients that vary for different roadway characteristics. The  $\alpha$  and  $\beta$  values shown in Table 9 were obtained from the default SPFs from SafetyAnalyst (Federal Highway Administration, 2010). Each recommended location was categorized into the different site code groups presented in Table 9 in order to use the appropriate  $\alpha$  and  $\beta$  for the crash

prediction. These values were developed using data from the states identified in the third column of the table, and were not calibrated to Alabama roadway data. However, the approach effectively normalizes the expected crash frequency at each location by traffic exposure.

Table 9.  $\alpha$  and  $\beta$  coefficients for Safety Performance Functions for Segments (Federal Highway Administration, 2010)

Site Code	Site Subtype Description	State	Regression Coefficient ( $\alpha$ )	Regression Coefficient ( $\beta$ )
101	Rural 2-lane highway segments	OH	-3.63	0.53
102	Rural multilane undivided highway segments	NC	-3.17	0.49
103	Rural multilane divided highway segments	MN	-5.05	0.66
104	Rural freeway segments – 4 lanes	MN	-6.82	0.81
105	Rural freeway segments – 6+ lanes	CA	-8.28	0.94
106	Rural freeway segments within an interchange area – 4 lanes	MN	-7.76	0.97
107	Rural freeway segments within an interchange area – 6+ lanes	CA	-9.63	1.06
151	Urban 2-lane arterial segments	OH	-7.16	0.84
152	Urban multilane undivided arterial segments	WA	-10.24	1.29
153	Urban multilane divided arterial segments	OH	-11.85	1.34
154	Urban one-way arterial segments	MN	-3.53	0.60
155	Urban freeway segments – 4 lanes	WA	-7.85	1.00
156	Urban freeway segments – 6 lanes	WA	-5.96	0.78
157	Urban freeway segments – 8+ lanes	WA	-16.24	1.67
158	Urban freeway segments within an interchange area – 4 lanes	WA	-11.23	1.30
159	Urban freeway segments within an interchange area – 6 lanes	WA	-11.25	1.28
160	Urban freeway segments within an interchange area – 8+ lanes	WA	-26.76	2.58

The recommended locations were identified based on a high frequency of speed- or DUI-related crashes over three years; however, the SPFs predict a total crash count for one year. The actual total crash count for three years was found in CARE and divided by three to get an average total number of crashes per year at each location. The recorded average was used for



comparison to the SPF predictions. Only one of the identified locations recommended for selective enforcement had a lower actual crash count than the predicted crash count. The SPF predictions confirmed the suitability of 95% of the recommended selective enforcement locations.

It is requested that DPS provide a proposed budget following the final selection and approval of the selective enforcement locations. Additionally, all locations should be mutually agreed upon by the DOT and DPS, as these lines of communication are vital for the optimum organization of the campaign. For instance, law enforcement officials have knowledge of the roads that will be patrolled as well as knowledge of recurring citizen complaints about roads with frequent speeding or drunk driving activity, and can provide valuable insight during planning (National Highway Traffic Safety Administration, 2008).

3. Plan the timing and logistics of the campaign.
  - a. Define the time span for the selective enforcement campaign
  - b. Perform crash frequency analysis by month for all locations
  - c. Perform crash frequency analysis by time of day for each location

A one year campaign is proposed for the Alabama selective enforcement campaign beginning on January 1, 2016 through June 30, 2017. It is recommended that intensification of enforcement presence be dispersed across the calendar, but frequently enough that drivers feel a deterrence effect (National Highway Traffic Safety Administration, 2008). The TACT project recommends planning for three waves of enforcement in each enforcement location during a year campaign (Federal Motor Carrier Safety Administration, 2007). The presence of school zones,

planned construction projects and work zones, major celebratory holidays, and other enforcement countermeasure programs going on at the same time should be considered.

Frequency analysis for all the selective enforcement locations was completed in CARE to identify the months over the three years that the filtered crashes were most frequent. January, December, and July were the top three months over the three years with the most speed- or DUI-related crashes. Additional months with high crash frequency in the selective enforcement locations included November, February, and March. In order to disperse selective enforcement across the calendar while targeting months with higher crash risk, March, July, and December should be used as the months for waves of selective enforcement in Alabama. If funding for selective enforcement overtime work is subsidized over the entire year, it is recommended that March, July, and December have an increase in selective enforcement over the other months of the year.

Each selective enforcement locations have varying crash risk circumstances. Therefore, frequency analysis for each selective enforcement location suggestion was used in CARE to identify the top three times of day at each location with the most crashes from 2012-2014. While the scheduling of selective enforcement efforts is at the discretion of DPS, increased enforcement should occur at the time of day when crashes are most frequent in attempts to mitigate the risk. This was done for all 20 recommended selective enforcement locations, and the information was provided to ALDOT. It is during those times of day that selective enforcement should occur most prominently at each location.

4. Organize community outreach and media publicity
  - a. Create lines of communication with community officials
  - b. Implement community outreach and publicity activities

Publicity and outreach of a selective law enforcement campaign play a large role in the deterrence of negative driver behavior, and the effectiveness of the campaign in reducing crashes (Jonah and Grant, 1985; Mathijssen and Wesemann, 1993). The general public is more inclined to follow the law when they believe there is a high probability that an offense will be detected and a citation will be issued against them (Walter, et al., 2011; Williams and Wells, 2004). Personal contact, as simple as an email or phone call, should be made between three parties in order to spread the word about the selective enforcement campaign: a representative from ALDOT, such as a traffic safety engineer, a representative from DPS, and a representative from the mayor's office of each local community identified with a recommended selective enforcement location. Additionally, a letter to send to local community officials requesting support of community outreach and media coverage is presented in Appendix B. If possible, an opening press conference should be hosted in order to engage community officials, local community members, the media, and other external participants. A Steering Committee should be formed, as a result of the press conference, to organize outreach and media publicity across the State to spread the word about the program and develop the proper message of the campaign.

Planned community outreach and publicity activities will help portray to the community, and the State as a whole, the importance of selective enforcement to reduce traffic crashes and improve public safety, as well as potentially make the campaign more successful. Table 10 provides multiple examples for community outreach and publicity activities and specifies the appropriate host, audience, and purpose of each. These have been adapted from The Speed

Enforcement Program Guidelines (National Highway Traffic Safety Administration, 2008). A blanket message to air to the media in public service announcements, billboards, and paper advertising will provide the summary details of the campaign to remind vehicle users of the selective enforcement locations and negative driver behaviors being targeted.

Table 10. Community Outreach and Publicity Activity Examples (adapted from National Highway Traffic Safety Administration, 2008)

Activity	Host	Audience	Purpose
Opening Press Conference	Police Chief, Representatives from Mayor's office, District Attorney's office	Media, community leaders and officials, active community members, parents, high school teachers	Announce the program, describe the intent, reveal equipment, state the goals, give specifics on locations of targeting patrol
Public Service Announcements	Local media or police personnel	Radio listeners; 3 per week per station	Remind vehicle users of the campaign while they are driving
Billboards	Department of Transportation; Potential donations from transportation companies	Drivers and passengers	Remind vehicle users of the campaign while they are on the road
Media Events/Special News Coverage	Local media	TV/News viewers	Reinforce the importance of the campaign during tragic news reports related to reckless driving (e.g. speed-related crash scene)
Paper Advertising (Posters, brochures, leaflets, etc.)	Department of Transportation; Potential donations from transportation companies	Community at large	Provide details of the campaign from background information about selective enforcement to specific details (where, how, why)

5. Train participating law enforcement officers
  - a. Explain the timing and logistics of the campaign
  - b. Train officers on new equipment (if applicable)

With the establishment of an annual budget for the proposed selective enforcement campaign in Alabama, the program will be initiated with the training of law enforcement officials and potential purchase of new equipment. The selective enforcement campaign timing and logistics will be explained to participating officers. For efficiency and best utilization of available funding, DPS should solicit extra-duty work from Troopers to Sergeants. The specific locations that will be selectively enforced should be discussed with participating officers, and instruction for who will cover certain areas and times of intensified patrol should be explicitly defined. Particular trooper posts should cover nearby surrounding regions to minimize unnecessary travel times and increase productivity.

Radar equipment is vital to accurately and reliably monitor traffic speeds and provide the evidentiary support necessary to sustain a speed citation. Devices range from hand-held radar, which uses electromagnetic signals, to LiDAR, which uses infrared laser light wave emissions should be used (National Highway Traffic Safety Administration, 2008). State and local law enforcement agencies should stay current with methods and technologies. Therefore, new equipment should be included in the proposed selective enforcement budget, if needed. If included, necessary training of the new equipment should ensue.

## 6. Implement and Document Selective Enforcement Activities

- a. Increase law enforcement at selected locations across the state, coupled with media and outreach
- b. Populate GPS coordinates on issued eCitations
- c. Ensure functionality of GPS equipment in officer vehicles
- d. Document selective enforcement efforts

The new selective enforcement campaign in Alabama should be deployed in 2016, with intensified surges of law enforcement in the located high crash areas and planned selective enforcement locations. Just as the training of the equipment is essential to the campaign, so too is the training of the use of the Electronic Citation (eCite) program, Electronic Crash (eCrash) program, and documentation of enforcement activities during the campaign. Based on the evaluation of the selective enforcement campaign efforts in Alabama ranging from August 1, 2011 through July 31, 2012, there are multiple lessons learned in regard to the documentation of selective enforcement activities.

To reduce processing time and the current necessary task to geolocate Electronic Citations (eCitations), participating officers should populate GPS coordinates for every issued eCitation in the eCite program. It is suggested that the Center for Advanced Public Safety add programming code to the eCite program to include eCitation GPS coordinates as a validation step, in which the eCitation will not be successfully completed without the inclusion of location information. Additionally, incentives such as awards for outstanding performance should be incorporated (National Highway Traffic Safety Administration, 2008). The Electronic Crash (eCrash) location data and access from the Critical Analysis Reporting Environment (CARE) was successful and beneficial in this research, and therefore should continue to be recorded and

conducted in accordance with standard DPS reporting and operational procedures. Additionally, to improve upon the location accuracy and inclusion of eCitations and selective enforcement shifts in the analysis of this research, GPS units in each law enforcement patrol vehicle should be routinely maintained. The GPS unit should be turned on during shifts, and off when the officer is not working.

Lastly, selective enforcement effort data should be recorded with more detail to reduce processing time for the evaluation of the effectiveness of the campaign in the specified locations. Currently, per the collaborative agreement between DPS and ALDOT, the DPS maintains officer work records and accounting in accordance to the applicable State and Federal Acquisition Regulations and sends billing information and invoices to ALDOT. In addition to the invoices and consolidated extra-duty officer timesheets, it is suggested that the files for participating officers also record the start and end time of the selective enforcement effort, in addition to the total hours worked on a given day. The particular selective enforcement location that was enforced during each extra-duty shift is also desired.

The new, proposed selective enforcement campaign for Alabama is intended to (1) improve upon the positive trend that with an increase in enforcement presence and issued citations in various locations comes a decrease in crashes, (2) include community outreach and media activities, and (3) organize the data necessary for a successful evaluation of the effectiveness of selective enforcement efforts.

## CHAPTER 6. CONCLUSIONS AND FUTURE WORK

### 6.1 Conclusion

The results of this research show that selective law enforcement efforts and the increase of issued citations along state routes in Alabama have started to improve public safety and decrease the number of crashes at select areas. For the analysis of the effectiveness of selective law enforcement in Alabama, Structured Query Language (SQL) and Geographic Information System (GIS) technology were used to:

- pre-process selective enforcement data,
- geolocate 72.6% of Electronic Citations (eCitations),
- verify and locate 21 selective enforcement areas across the State,
- incorporate Electronic Crash (eCrash) data, and
- evaluate the increases and decreases in crash frequencies and the number of issued citations before and during selective enforcement.

Officer patrol routes, geolocated citations, crash data, and selective enforcement time periods were integrated into one cohesive source of spatial and temporal data for the analysis. The processing tasks in this research were essential to the evaluation of selective law enforcement and the results. Relational database tables were created to efficiently organize participating officer information and selective enforcement data. eCitations were geolocated via a temporal join between the timestamps of the officer patrol routes and issued eCitations. Queries in SQL were written and executed to perform a summation and grouping analysis of



spatial selective enforcement data in order to locate areas for analysis. Paired difference t-tests confirm the decrease of crash frequency with 85% confidence, at urban and rural locations separately. Crash severity improved compared to the overall crash frequency when analyzing the selective enforcement locations collectively, however is not statistically conclusive. The analysis of the number of issued citations at the locations confirmed that citations increased during the selective enforcement year by an average of 254%. While a statistical increase in the number of issued citations does not necessarily cause a statistically decrease in the number of crashes, the increase seems to have some effect. In order to improve the initial positive trends observed, a new selective enforcement campaign step-by-step guide was developed for implementation in 2016.

## 6.2 Future Work

The developed methodology in this research was applied to selective enforcement efforts occurring between August 1, 2010 and July 31, 2011. The citation and crash data used in the analysis covered citation and crash occurrences during and outside of selective enforcement shifts. Future work should include performing the analysis of increases and decreases in citations issued and crash frequencies before and during selective enforcement using only citations and crashes occurring during selective enforcement shifts. Time-space clustering would facilitate this work.

Additional future work should include applying the developed methodologies in this research to analyze the effectiveness of varying levels of general enforcement efforts. There are currently big data issues in regard to working with the large officer patrol route dataset. However, once overcome, this recommended research would provide results for the necessary

policing levels to obtain a certain response or potentially locate a saturation point of enforcement efforts.

Although locations with high selective enforcement presence were identified in this research, further verification is needed to confirm the effects of selective enforcement efforts. The proposed selective enforcement campaign presented in Chapter 5 Recommendations for Selective Enforcement in 2016 should be implemented in order to evaluate the positive impacts that selective enforcement efforts provide for crash reductions and traffic safety along state routes in Alabama. Improved evaluations and results will enable research for the development of crash modification factors and the calculation of a return of investment.

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## APPENDIX A: SQL QUERIES

### A.1 UserIDs

*(A.1.1) Query to join DPS timesheet/DOT invoices officer names to the Users table in the AURA database to locate unique UserIDs*

```
SELECT DISTINCT [UserID]
      ,[Rank]
      ,tblUsers.[FirstName] AS MainFirst
      ,tblUsers.MiddleInitial
      ,tblUsers.[LastName] AS MainLast
      ,Troopers.FirstName
      ,Troopers.LastName
      ,[BadgeNum]
      ,[CodeCity]
      ,[CodeCounty]
      ,[ORI]
FROM [AURA].[dbo].[tblUsers]
JOIN [AURA].[dbo].[SEData_True] AS Troopers
ON tblUsers.LastName = Troopers.LastName AND tblUsers.FirstName = Troopers.FirstName
WHERE ORI LIKE 'ALAST%'
```

*(A.1.2) Query to locate names without UserIDs from the original join in query A.1.1*

```
SELECT DISTINCT Users.FirstName
      ,Users.MI
      ,Users.LastName
FROM [AURA].[dbo].[SEDataUsers1] AS Troopers
RIGHT OUTER JOIN [AURA].[dbo].[SEData_True] AS Users
ON Users.FirstName = Troopers.FirstName AND Users.LastName = Troopers.LastName
WHERE UserID IS NULL
```

*(A.1.3) Query to find manual UserID additions*

```
SELECT UserID
      ,Rank
      ,FirstName
      ,MiddleInitial
      ,LastName
      ,BadgeNum
      ,CodeCity
      ,CodeCounty
      ,ORI
FROM [AURA].[dbo].[tblUsers]
WHERE LastName = 'jarrett'
ORDER BY FirstName
```

(A.1.4) Query to locate duplicate UserID joins from original join in query A.1.1

```
SELECT COUNT(T.UserID)
      ,T.FirstName
      ,T.LastName
FROM [AURA].[dbo].[SEDataUsers1] AS T
GROUP BY T.LastName, T.FirstName
ORDER BY COUNT(T.UserID) DESC, T.LastName
```

(A.1.5) After creating a Look Up Table and setting Level of Confidences, this final query can be used to combine original joins, additions, and subtractions, and finalize UserIDs for the selective enforcement dataset

```
SELECT DISTINCT UserID
      ,[DateWorked]
      ,Users.[FirstName]
      ,Users.[LastName]
      ,[MI]
      ,[Other]
      ,[Hours]
      ,[Salary]
      ,[SubPay]
      ,[PerDiem]
      ,[Contacts]
      ,[Miles]
      ,[Initiative]
      ,[Troop]
      ,[Post]
      ,LOC
FROM [AURA].[dbo].[SEData_True] AS SE
JOIN [AURA].[dbo].[SEData_LookUpTable] AS Users
ON SE.LastName = Users.LastName AND SE.FirstName = Users.FirstName
ORDER BY LastName
```

(A.1.6) Set Selective Enforcement Shift ID's (SE\_ID) for each SE entry

```
ALTER TABLE [AURA].[dbo].[SEDataFinal]
ADD [SE_ID] INT IDENTITY (1,1)
```

## A.2 Geolocating eCitations

(A.2.1) Query to organize and combine eCitation data

```
SELECT DISTINCT tblCitation.[DocumentID]
      ,tblCitation.[TicketNum]
      ,CreatorUserID AS UserID
      ,CreatorBadgeNum
      ,CreatorORI
      ,[CitLocation1]
```



```

    ,[CitLocation2]
    ,[CitPlace]
    ,TicketCity
    ,TicketCounty
    ,[Description]
    ,[Citation]
    ,DateIssued + 0.25 AS CiteTime
    ,[GPSLatitude]
    ,[GPSLongitude]
    ,WorkStatus
    ,LOC
FROM ([ECITATION].[dbo].[tblCitation]
JOIN [ECITATION].[dbo].[tblDocument]
ON [ECITATION].[dbo].[tblCitation].DocumentID =
[ECITATION].[dbo].[tblDocument].DocumentID AND [ECITATION].[dbo].[tblCitation].TicketNum
= [ECITATION].[dbo].[tblDocument].TicketNum
JOIN [AURA].[dbo].[SEDataFinal]
ON [ECITATION].[dbo].[tblDocument].CreatorUserID = [AURA].[dbo].[SEDataFinal].UserID)
WHERE [ECITATION].[dbo].[tblDocument].DateIssued BETWEEN '2010-08-01' AND '2011-07-31'
AND [ECITATION].[dbo].[tblDocument].VoidReason IS NULL

```

*(A.2.2) Query to organize and compile GPS location data*

```

SELECT DISTINCT GpsC.GroupID
    ,GpsG.MachineID
    ,GpsG.UserID
    ,Users.FirstName
    ,Users.MI
    ,Users.LastName
    ,GpsC.Latitude
    ,GpsC.Longitude
    ,GpsC.GPSTimeUTC
    ,GpsC.ReportTimeUTC
    ,Users.LOC AS TraceLOC
FROM (([AURA].[dbo].[GpsCoordinatesArchive] AS GpsC
JOIN [AURA].[dbo].[GpsCoordinateGroupsArchive] AS GpsG
ON ID = GroupID)
JOIN [AURA].[dbo].[SEDataFinal] AS Users
ON GpsG.UserID = Users.UserID)
WHERE GpsC.GPSTimeUTC BETWEEN '2010-08-01' AND '2011-07-31'

```

*(A.2.3) Set GPS IDs (GPS\_ID) for each GPS location point*

```

ALTER TABLE [AURA].[dbo].[SEGPSData]
ADD [GPS_ID] INT IDENTITY (1,1)

```

*(A.2.4) Query to calculate time differences between eCitations and GPS location points, and return only those joined within 600 seconds*

```

SELECT LocatingMethod.DocumentID, LocatingMethod.TicketNum, LocatingMethod.Latitude,
LocatingMethod.Longitude, LocatingMethod.GPSTimeUTC, MIN(LocatingMethod.TimeDiff) AS
MinTimeDiff
FROM (SELECT DISTINCT Cites.*

```

```

,Locations.Latitude
,Locations.Longitude
,Locations.GPSTimeUTC
,TraceLOC
,(ABS(DATEDIFF(s, Locations.GPSTimeUTC, Cites.CiteTime))) AS TimeDiff
FROM AURA.dbo.SEGPSData AS Locations
RIGHT JOIN ECITATION.dbo.SE_AllCitations AS Cites
ON Locations.UserID = Cites.UserID
WHERE (ABS(DATEDIFF(s, Locations.GPSTimeUTC, Cites.CiteTime)) <= 600) AS LocatingMethod
GROUP BY LocatingMethod.DocumentID, LocatingMethod.TicketNum, LocatingMethod.Latitude,
LocatingMethod.Longitude, LocatingMethod.GPSTimeUTC

```

(A.2.5) *Query to select the minimum time difference and accurately locate eCitations*

```

SELECT ECITATION.dbo.JSCiteLocatingMethod.DocumentID
,ECITATION.dbo.JSCiteLocatingMethod.TicketNum
,Latitude
,Longitude
,GPSTimeUTC
,MinTimeDiff
FROM ECITATION.dbo.JSCiteLocatingMethod
INNER JOIN
(SELECT DocumentID, TicketNum, MIN(MinTimeDiff) AS MinPoint
FROM ECITATION.dbo.JSCiteLocatingMethod
GROUP BY DocumentID, TicketNum) AS Located1
ON Located1.DocumentID = ECITATION.dbo.JSCiteLocatingMethod.DocumentID AND
Located1.TicketNum = ECITATION.dbo.JSCiteLocatingMethod.TicketNum
WHERE Located1.MinPoint = ECITATION.dbo.JSCiteLocatingMethod.MinTimeDiff

```

### A.3 Calculating Full Officer Shifts

(A.3.1) *Query to calculate difference between successive GPS location points*

```

SELECT [UserID]
,[Latitude]
,[Longitude]
,[TraceLOC]
,[GPSTimeUTC]
,LEAD([GPSTimeUTC], 1, NULL) OVER (PARTITION BY [UserID] ORDER BY [GPSTimeUTC]
ASC) AS [NextTime]
,DATEDIFF(second, [GPSTimeUTC], LEAD([GPSTimeUTC], 1, NULL) OVER (PARTITION BY
[UserID] ORDER BY [GPSTimeUTC] ASC)) AS Diff
FROM [AURA].[dbo].[SEGPSData]

```

(A.3.2) *Query to denote the beginning and ending of GPS location point shifts with a value of 0, using a six hour time difference tolerance*

```

SELECT UserID
,Latitude
,Longitude
,TraceLOC
,GPSTimeUTC

```

```

,NextTime
,Diff
,(CASE WHEN (LAG(Diff,1,NULL) OVER (PARTITION BY [UserID] ORDER BY [GPSTimeUTC]
ASC)) <= 21600
THEN 1
WHEN (LAG(Diff,1,NULL) OVER (PARTITION BY [UserID] ORDER BY [GPSTimeUTC]
ASC)) > 21600
THEN 0
ELSE 0 END) AS [Shift]
,(CASE WHEN [Diff] IS NULL
THEN 0
WHEN [Diff] > 21600
THEN 0
ELSE 1 END) AS [Shift2]
FROM [AURA].[dbo].[JS_CalcDiffBetweenNextGPSpts]
ORDER BY UserID, GPSTimeUTC

```

(A.3.3) Query to compile a table of shift start times and shift end times

```

SELECT UserID
,Latitude
,Longitude
,Shift
,Shift2
,TraceLOC
,GPSTimeUTC AS ShiftStart
,(CASE WHEN [Shift] = 0
THEN (LEAD([GPSTimeUTC], 1, NULL) OVER (PARTITION BY [UserID] ORDER BY
[GPSTimeUTC] ASC))
ELSE 0 END) AS ShiftEnd
FROM [AURA].[dbo].[JS_DenoteBeginEndShift]
WHERE [Shift] = 0 OR [Shift2] = 0

```

(A.3.4) Query to calculate hours worked for the generated GPS location point shifts, and define a Shift Quality value

```

SELECT UserID
,MainFirst
,MainMI
,MainLast
,ORI
,TraceLOC
,ShiftStart
,ShiftEnd
,DATEDIFF(second,ShiftStart,ShiftEnd) AS MinsWorked
,ROUND((CAST(DATEDIFF(second,ShiftStart,ShiftEnd) AS float) / 3600),2) AS Hrs
,(CASE WHEN ROUND((CAST(DATEDIFF(second,ShiftStart,ShiftEnd) AS float) / 3600),2)
<= 0.5
THEN 2
WHEN ROUND((CAST(DATEDIFF(second,ShiftStart,ShiftEnd) AS float) / 3600),2)
>= 17
THEN 2
ELSE 1 END) AS ShiftQual
FROM [AURA].[dbo].[JS_UseBeginEndShift]

```

```
WHERE ShiftEnd <> '1900-01-01 00:00:00.000' AND NOT ([Shift]= 0 AND [Shift2] = 0)
```

(A.3.5) Set Shift IDs (Shift\_ID) for each GPS location point generated shift

```
ALTER TABLE [AURA].[dbo].[SE_GPSShifts6Hrs]
ADD [Shift_ID] INT IDENTITY (1,1)
```

## A.4 Defining GPS Location Points as Selective Enforcement

(A.4.1) Query to join Selective Enforcement data to GPS shift data based on UserID and Shift Start Date, while calculating differences in the hours worked and claimed and creating a Shift LOC field

```
SELECT DISTINCT SE.*
    ,CONVERT(DATE,GPS.ShiftStart) AS StartDate
    ,CONVERT(DATE,GPS.ShiftEnd) AS EndDate
    ,GPS.ShiftStart
    ,GPS.ShiftEnd
    ,GPS.Hrs
    ,GPS.Shift_ID
    ,(CASE WHEN LEAD([Shift_ID],1,NULL) OVER (PARTITION BY SE.[UserID] ORDER BY
CONVERT(DATE,GPS.ShiftStart) ASC) = [Shift_ID]
        THEN 2
        WHEN LAG([Shift_ID],1,NULL) OVER (PARTITION BY SE.[UserID] ORDER BY
CONVERT(DATE,GPS.ShiftStart) ASC) = [Shift_ID]
        THEN 2
        WHEN LEAD([SE_ID],1,NULL) OVER (PARTITION BY SE.[UserID] ORDER BY
SE.DateWorked ASC) = [SE_ID]
        THEN 2
        WHEN LAG([SE_ID],1,NULL) OVER (PARTITION BY SE.[UserID] ORDER BY
SE.DateWorked ASC) = [SE_ID]
        THEN 2
        ELSE 1 END) AS ShiftLOC
    ,ROUND(([Hrs] - [Hours]),2) AS HourDiff
FROM [AURA].[dbo].[SE_GPSShifts6Hrs] AS GPS
JOIN [AURA].[dbo].[SEDataFinal] AS SE
ON (SE.UserID = GPS.UserID) AND (SE.[DateWorked] = (CONVERT(DATE,GPS.ShiftStart)))
WHERE ShiftQual = 1
```

(A.4.2) Query to calculate cumulative time worked in a GPS location point driven shift

```
SELECT GPS.[UserID]
    ,[Latitude]
    ,[Longitude]
    ,GPS.[TraceLOC]
    ,[GPSTimeUTC]
    ,[NextTime]
    ,[Diff]
    ,[Shift]
    ,[Shift2]
    ,[ShiftQual]
    ,[Shift_ID]
```

```

        ,(CASE WHEN ([Shift] = 1 AND [Shift2] <> 0)
            THEN ROUND((CAST(SUM([Diff]) OVER (PARTITION BY GPS.[UserID],Shift_ID ORDER
BY [GPSTimeUTC] ASC) AS float) / 3600),2)
            ELSE 0 END) AS [CumulativeTime1]
FROM [AURA].[dbo].[JS_DenoteBeginEndShift] AS GPS
JOIN [AURA].[dbo].[SE_GPSShifts6Hrs] AS Shifts
ON GPS.UserID = Shifts.UserID AND (GPS.GPSTimeUTC BETWEEN Shifts.ShiftStart AND
Shifts.ShiftEnd)
ORDER BY GPS.UserID, GPS.GPSTimeUTC

```

(A.4.3) Query to correct the cumulative time worked in a GPS location point driven shift by including the last GPS point in the shift

```

SELECT [UserID]
      ,[Latitude]
      ,[Longitude]
      ,[TraceLOC]
      ,[GPSTimeUTC]
      ,[NextTime]
      ,[Diff]
      ,[Shift]
      ,[Shift2]
      ,[ShiftQual]
      ,[Shift_ID]
      ,[CumulativeTime1] + (CASE WHEN [Shift2] = 0
            THEN LAG([CumulativeTime1],1,NULL) OVER (PARTITION BY [UserID],Shift_ID
ORDER BY [GPSTimeUTC] ASC)
            ELSE 0 END) AS [CumulativeTime]
FROM [AURA].[dbo].[JS_CumulativeTime1]
ORDER BY UserID, GPSTimeUTC

```

(A.4.4) Query to define 'Yes' or 'No' for During Selective Enforcement

```

SELECT GPS.[UserID]
      ,[Latitude]
      ,[Longitude]
      ,[TraceLOC]
      ,[GPSTimeUTC]
      ,[ShiftQual]
      ,[ShiftLOC]
      ,GPS.[Shift_ID]
      ,[CumulativeTime]
      ,Shifts.Hours AS SEHours
      ,Shifts.Hrs AS GPSHours
      ,HourDiff
      ,(CASE WHEN (Shifts.[Hours] < Shifts.[Hrs]) AND ([HourDiff] <= [CumulativeTime])
            THEN 'Yes'
            WHEN [HourDiff] BETWEEN -0.5 AND 0.5
            THEN 'Yes'
            WHEN [HourDiff] < 0
            THEN 'Yes'
            ELSE 'No' END) AS SE
FROM [AURA].[dbo].[JS_GPSByShift] AS GPS
JOIN [AURA].[dbo].[SEJoinedShifts] AS Shifts

```

```
ON GPS.Shift_ID = Shifts.Shift_ID
ORDER BY UserID, GPSTimeUTC
```

(A.4.5) Query to create table of only 'Yes' (During Selective Enforcement) GPS Points

```
SELECT [UserID]
      ,[Latitude]
      ,[Longitude]
      ,[TraceLOC]
      ,[GPSTimeUTC]
      ,[ShiftQual]
      ,[ShiftLOC]
      ,[Shift_ID]
      ,[CumulativeTime]
      ,[SEHours]
      ,[GPSHours]
      ,[HourDiff]
      ,[SE]
FROM [AURA].[dbo].[SEShiftDaysGPSPoints]
INTO [AURA].[dbo].[SEYesShiftDaysGPSPoints]
WHERE [SE] = 'Yes'
```

## A.5 Hotspot Analysis Technique

(A.5.1) Query to summarize the number of Selective Enforcement 'yes' points at each Route-MP

```
SELECT Total.RouteID
      ,Total.MP
      ,ISNULL(NumSEPts,0) AS NumSEPts
FROM
(SELECT [RouteID]
      ,[MP]
      ,Count(*) AS NumSEPts
FROM [ECITATION].[dbo].[SEYes_RtMP_400m]
GROUP BY RouteID, [MP]) AS SE
RIGHT OUTER JOIN [ECITATION].[dbo].[SE_RtMPUnion] AS Total
ON Total.RouteID = SE.RouteID AND Total.MP = SE.MP
ORDER BY Total.RouteID, Total.MP
```

(A.5.2) Query to calculate the difference between successive Mileposts

```
SELECT *, LEAD([MP], 1, NULL) OVER (PARTITION BY [RouteID]
ORDER BY [RouteID], [MP] ASC) AS [NextMP], (ROUND((LAG([MP], 1, NULL) OVER (PARTITION BY
[RouteID]
ORDER BY [RouteID], [MP] ASC) - [MP]), 2)) * - 1 AS Diff
INTO [ECITATION].[dbo].[SEYesRtMPDiff]
FROM [ECITATION].[dbo].[SEYesRtMP]
```

(A.5.3) Query to calculate the cumulative difference between mileposts along a route

```
SELECT RouteID
```

```

,MP
,NumSEPts
,NextMP
,Diff
,ISNULL(ROUND(SUM([Diff]) OVER (PARTITION BY RouteID ORDER BY [MP] ASC),3),0) AS
CumulMP
FROM [ECITATION].[dbo].[SEYesRtMPDiff]
WHERE Diff = 0.01 OR DIFF IS NULL
ORDER BY RouteID, MP

```

(A.5.4) Query to perform a summation and grouping analysis of Selective Enforcement points using 3 “bucket” sizes: One-Tenth of a mile, One-Half of a mile, and One mile

```

SELECT RouteID
,MP
,NumSEPts
,NextMP
,ISNULL(Diff,0) AS Diff
,CumulMP
,([NumSEPts] + (LEAD(NumSEPts,1,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP]
ASC)) + (LEAD(NumSEPts,2,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,3,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,4,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,5,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,1,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,2,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,3,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,4,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,5,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))) AS OneTenth
,([NumSEPts] + (LEAD(NumSEPts,1,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP]
ASC)) + (LEAD(NumSEPts,2,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,3,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,4,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,5,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,6,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,7,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,8,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,9,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,10,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))
+ (LEAD(NumSEPts,11,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))
+ (LEAD(NumSEPts,12,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,13,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,14,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,15,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,16,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,17,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,18,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,19,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,20,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))
+ (LEAD(NumSEPts,21,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP]
ASC)) + (LEAD(NumSEPts,22,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,23,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,24,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LEAD(NumSEPts,25,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))
+ (LAG(NumSEPts,1,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC))
+ (LAG(NumSEPts,2,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,3,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +

```







```

(LAG(NumSEPts,45,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,46,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,47,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,48,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,49,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) +
(LAG(NumSEPts,50,NULL) OVER (PARTITION BY [RouteID] ORDER BY [MP] ASC)) AS OneMile
FROM [ECITATION].[dbo].[SEYesRtMPCumulDiff]
ORDER BY RouteID, MP

```

*(A.5.5) Query to extract the Route-MP points within the limits of the one-mile analysis for selective enforcement points, and calculate necessary checks to locate the beginning and ending of the location segments*

```

SELECT [RouteID]
      ,[MP]
      ,[NumSEPts]
      ,[NextMP]
      ,[CumulMP]
      ,[OneTenth]
      ,[HalfMile]
      ,[OneMile]
      ,LEAD([MP], 1, NULL) OVER (PARTITION BY [RouteID] ORDER BY [RouteID], [MP] ASC)
AS See
      ,LAG([MP], 1, NULL) OVER (PARTITION BY [RouteID] ORDER BY [RouteID], [MP] ASC)
AS See2
      ,(ROUND((LAG([MP], 1, NULL) OVER (PARTITION BY [RouteID] ORDER BY [RouteID],
[MP] ASC) - [MP]),2))*-1 AS Diff
INTO [ECITATION].[dbo].[SE_HSALocator]
FROM [ECITATION].[dbo].[SE_HSA]
WHERE [OneMile] >= 2885
ORDER BY RouteID, MP

```

*(A.5.6) Query to select the beginning and ending of selective enforcement location segments*

```

SELECT [RouteID]
      ,[MP]
      ,[NumSEPts]
      ,[NextMP]
      ,[CumulMP]
      ,[OneTenth]
      ,[HalfMile]
      ,[OneMile]
      ,[See]
      ,[See2]
      ,[Diff]
FROM [ECITATION].[dbo].[SE_HSALocator]
WHERE ([NextMP] <> [See]) OR ([See] IS NULL) OR ([Diff] IS NULL) OR ([Diff] <> 0.01)

```

APPENDIX B: LOCAL COMMUNITY OFFICIAL OUTREACH SAMPLE LETTER

*(Insert Organizational Letterhead)*

Alabama Department of Transportation

Alabama Department of Public Safety

*(Insert Address)*

Subject: Requesting Involvement in the  
  
Alabama Selective Law Enforcement Campaign  
  
Media Outreach and Publicity

Dear *(Insert City/Community Official name/s)*:

The Alabama Department of Transportation and the Alabama Department of Public Safety have renewed a collaborative agreement to implement a selective law enforcement campaign for the increase of traffic law enforcement efforts for patrolling on various state and federal roads, highways, and interstates. The Center for Advanced Public Safety at The University of Alabama has reported that in 2011 in Alabama, speeding and driving under the influence contributed to 54% of fatal crashes. The selective law enforcement campaign will target these negative driver behaviors at high-crash locations across the state. The Federal Highway Administration has approved the program as part of the Highway Safety Improvement Plan for Alabama.

The results from recent research on selective law enforcement in Alabama present a statistical increase in the number of issued citations and a slight decrease in the number of crashes in the selected locations. The Alabama Department of Transportation and the Alabama Department of Public Safety believe these results can be improved with the inclusion of a media outreach and publicity element to the campaign. *(Insert Route Name and Milepost or Intersection)* in *(Insert City/County)* has been chosen as a selective enforcement location for the campaign starting in 2016. We would like to invite you or one of your representatives to join the Steering Committee for the program, as your perspective and understanding of the area is invaluable. Additionally, any publicity activities such as public service announcements, billboard or paper advertisements, or news coverage that can be deployed around and within your community will be essential to the success of the campaign. Steering Committee involvement will help to facilitate the media aspect of the campaign.

Your support would be greatly appreciated, and would contribute to the Strategic Highway Safety Plan goal to reduce crashes, injuries, and fatalities in Alabama by 50% over the next twenty years. Please contact *(Insert Program Director name)* at *(Insert Phone)*.

Sincerely,

*(Insert Name and Title)*