A Spatial Analysis of Veteran Healthcare Accessibility

by

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To a very special person, my wife Debra, who reminded me sometimes it’s just too late to turn back. Without her I could never have made it this far.

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List of Abbreviations

2SFCA	Two-Step Floating Catchment Area
ACS	American Community Survey
ARCH	(Project) Access Received Closer to Home
E2SFCA	Enhanced Two-Step Floating Catchment Area
FCA	Floating Catchment Area
FOIA	Freedom of Information Act
FTE	Full Time Equivalent
GIS	Geographic Information System
HCS	Healthcare System
ID	Identifier
LA	Location-Allocation
MFTCC	MAF/TIGER Feature Class Code
OD	Origin-Destination
PtP	Physician-to-Population (Ratio)
PSSG	Planning Systems Support Group
SAIL	Strategic Analytics for Improvement and Learning
SSI	Spatial Sciences Institute
USC	University of Southern California
VA	Veterans Administration
VAST	VA Site Tracking
VHA	Veterans Healthcare Administration
VISN	Veterans Integrated Service Network

Abstract

Healthcare accessibility for veterans are services that are physically accessible, available, and acceptable to the eligible population. This research study examines spatial and non-spatial relationships to assess accessibility of primary care for military veterans. Centered on a Veterans Integrated Service Network, the study begins by developing catchment areas for Veterans Healthcare Administration facilities and using a two-step floating catchment area (2SFCA) model widely adopted in healthcare studies, scores accessibility for populations by census tract. It expands on previous research by focusing on veteran care and modifying the Enhanced 2SFCA (E2SFCA) methodology through the application of impedance factors based on non-spatial measurements, including appointment wait-times and patient satisfaction. These modifications address the requirements of the Veterans Access, Choice, and Accountability Act of 2014 as well as explore analysis based on concepts of acceptability of care. The result is the designation of areas that fall short of delivering primary care services within the context of federal legislation and also a relative scoring of the degree of accessibility to care in areas that meet the federal requirements. The methodology in this paper provides the flexibility for application in different studies and geographic regions, and the results provide information that may prove useful to policy-makers.

Chapter 1 Introduction

The United States government made a promise to its veterans to provide comprehensive healthcare in exchange for military service. The Department of Veterans Affairs (VA) and Veterans Health Administration (VHA) are entrusted with this responsibility. This is a huge undertaking consisting of nearly 7-million total healthcare appointments each year, making it the largest healthcare provider in the United States. In addition, the VA is engaged in providing a range of other benefits including education, job training, and loan guarantees. The aging number of Vietnam War-era patients requiring more resources along with a relatively large share of Post-9/11 veterans requiring long-term medical care has made this challenge even greater for the VA. Meeting these demands has only gotten more difficult for the VHA as an estimated 2.6-billion-dollar budget shortfall has recently been reported (Associated Press 2014).

In 2014, a report surfaced about an investigation that revealed Veterans Administration (VA) healthcare facilities were keeping secret waiting lists, garnering national attention to this challenge. The report identified that the VA was unable to schedule appointments within 30 days, as required by federal law, suggesting a shortage in capacity for care. As federal law regulates the VHA, the United States Congress has attempted to improve care through the passage of the Veterans Access, Choice, and Accountability Act of 2014. This act afforded specific requirements for access to care within the VHA and directed transparency in healthcare performance (VA 2014a).

A key concept in meeting the healthcare needs of any population is accessibility, which is more than just the available supply. It is also measured through the potential utilization based on variables of affordability, physical access, availability, and acceptability of services. To be accessible, healthcare must be relevant and effective for the needs of the population and should result in satisfactory health outcomes for diverse societal groups (Gulliford et al. 2002). For veteran populations, this means eligible individuals must be able to utilize services to avoid out-of-pocket expenses (affordability), receive care in a timely manner (availability), be able to reach centers within a desired distance or time (physical access), and be satisfied with the quality of the services received (acceptability). Therefore, accessibility includes spatial relationships between facilities, providers, and population, characterized geographically, demographically, and through health utilization indices and rates (Klauss et al. 2005). These concepts form the foundation for this research project.

In private sector care, medical facilities historically use a variety of measures to determine if the location is needed and viable. Typically, this is a statistical analysis of the population or by examining patient flow measured by assessment of the overall throughput of patients. Patient care statistics and individual unit performance may also be analyzed (IHCI 2015). Additionally, a facility may use a census of the number of occupied beds to decide if the hospital is supported by the population (FARLEX 2015). Although this may measure the sustainability of a medical facility economically, it does not address the accessibility of medical care. There must be an adequate supply of care to meet demand within a reasonable distance, providing an opportunity for care. Only when these opportunities exist does the population have “access” to services regardless of market factors. Therefore, the extent to which a population has access is a function of both spatial and aspatial factors, which may include not only distance or travel-time, but also financial, social, or cultural barriers, or any other variable that may limit utilization.

Twenty-two Veterans Integrated Service Networks (VISN) divide the VHA into administrative regions to manage its substantial healthcare effort (Figure 1). These networks consist of various sized facilities from large-scale, full-service hospitals and healthcare campuses comparable to civilian medical centers, to outpatient clinics and community-based clinics in an attempt to provide a level of care required by federal law. Management of the system is centered on each of these geographic networks, and for this particular analysis, the scale is limited to the portion of the Sierra-Pacific Region (VISN 21) located within the conterminous United States using Fiscal Year 2015 boundaries and data. VISN 21 also includes facilities in Hawaii, U.S. Pacific Island Territories, and the Philippines; however, these are not included in this analysis. These island locations do not connect to the same transportation network and therefore each would require individual analysis. Therefore, the methodology used only applies to a single transportation network: parts of California, Nevada, and Oregon. However, the same process used in this study is applicable to each of the islands if data were available. The study area covers roughly the northern half of California and one-third of Nevada.

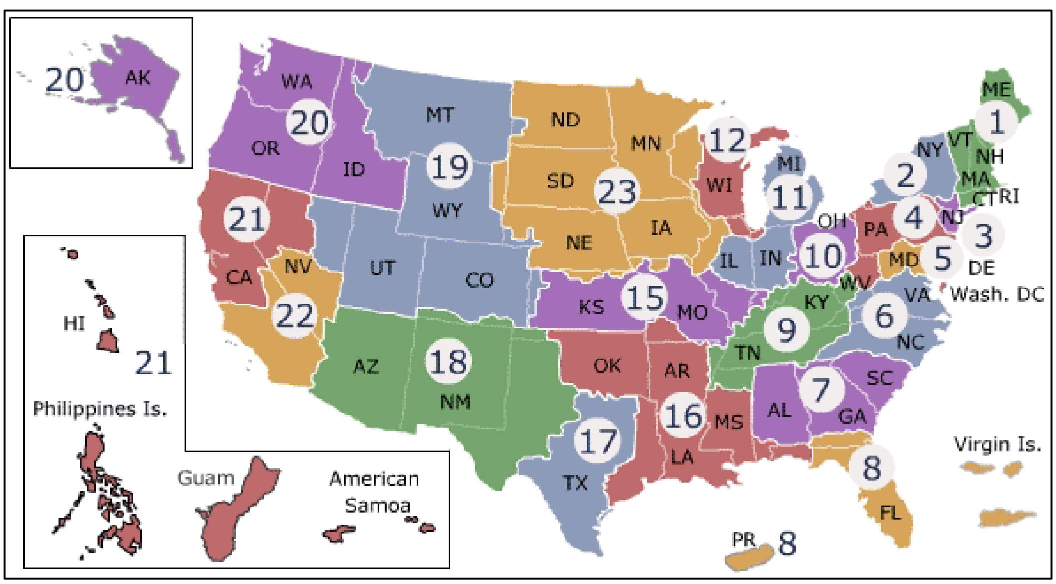

Figure 1 Veterans Integrated Service Networks (VISN) (VA 2010)

The purpose of this study is to identify areas where the VA is able to provide the required care to veteran populations in accordance with federal law for distance and appointment timeliness. For this spatial analysis, a geographic information system (GIS) is used to assess the accessibility to primary care for VISN 21 through the development of catchment areas of facilities and determination of allocation of veterans to facilities. It also looks at travel distance along a network and relationships of appointment wait-times and patient satisfaction. These factors determine overall veteran accessibility to primary care and identify potential healthcare shortage areas. The results of this analysis could inform the VA of the appropriateness of healthcare locations, potential for resource reallocation, and locations where alternatives to VA care may be required.

1.1 Objective

The guiding precept for this study is to improve understanding of healthcare accessibility for veterans by assessing the key principles of physical accessibility and relating it to availability and acceptability of service levels. In this study, affordability is considered, but not as a limiting factor of the population. The burden of affordability is borne by the provider in this case and not the patient and therefore is not a direct objective of this analysis. Although costs certainly have an impact on the ability of the VA to provide access to care, this study focuses on physical access, availability, and acceptability of care. That said, the identification of shortage areas has the ability to provide the VHA a better understanding of how resources may be allocated to meet the healthcare needs of veterans or possibly reduce some costs, making the system more affordable for the federal government.

To achieve these objectives, this thesis builds on previous spatial analysis research in healthcare regarding the determination of markets or service areas and methods for calculating accessibility scores. These principles are then applied to a specific population of veterans in an existing administrative region that provides an understanding of how well the needs of the population are met. Where this study deviates from previous spatial analysis regarding accessibility is the inclusion of additional indices supporting this assessment. These indices achieve two objectives: to analyze healthcare accessibility for veterans according to distance and wait-time requirements of the Veterans Access, Choice, and Accountability Act of 2014 and to apply measures of availability and acceptability as suggested in Gulliford et al. (2002).

Therefore, the key spatial question this study answers is: *Where do shortages of healthcare accessibility for veterans in the Veterans Integrated Healthcare Network (VISN) Region 21 exist for primary care?* To answer this question, several sub-questions are addressed which form the basic analysis. These supporting considerations include:

- Where are the catchment areas for each primary care facility within the study area?
- How do patients and providers interact spatially within catchments?
- What populations reside outside governed distances from a facility for primary care accessibility in accordance with the Veterans Access, Choice, and Accountability Act of 2014?
- Where are appointment timeliness standards not met for populations allocated to a facility in accordance with the Veterans Access, Choice, and Accountability Act of 2014 and how does this affect accessibility?
- How does primary care acceptability influence accessibility with patient satisfaction as an indicator?
- What populations may be experiencing stressed accessibility of primary care supply related to demand based on indices of physician-to-population ratios, wait times, and satisfaction scores?

1.2 Motivation

The Veterans Healthcare Administration system has a responsibility to take care of millions of eligible veterans each year. In 2013, total enrollees in the system reached nearly nine million and outpatient visits were nearly ten-times greater (VA 2015). Sustaining this capability consumes a large quantity of resources and costs continue to rise (Palletta 2014). Despite a decrease in the overall veteran population, the number of VHA enrollees continues to climb because the system is treating a bubble of older, Vietnam-era patients and Post-9/11 veterans (Holder 2010) (Figure 2). In addition, the wars in Afghanistan and Iraq have created a large number of younger veterans requiring long-term care who are more likely to use the VA as their primary healthcare source (Davis 2015; VA 2014b) (Figure 3). Along with these issues, long-term healthcare becomes more expensive as veterans age and require additional or specialized care (VA 2014b).

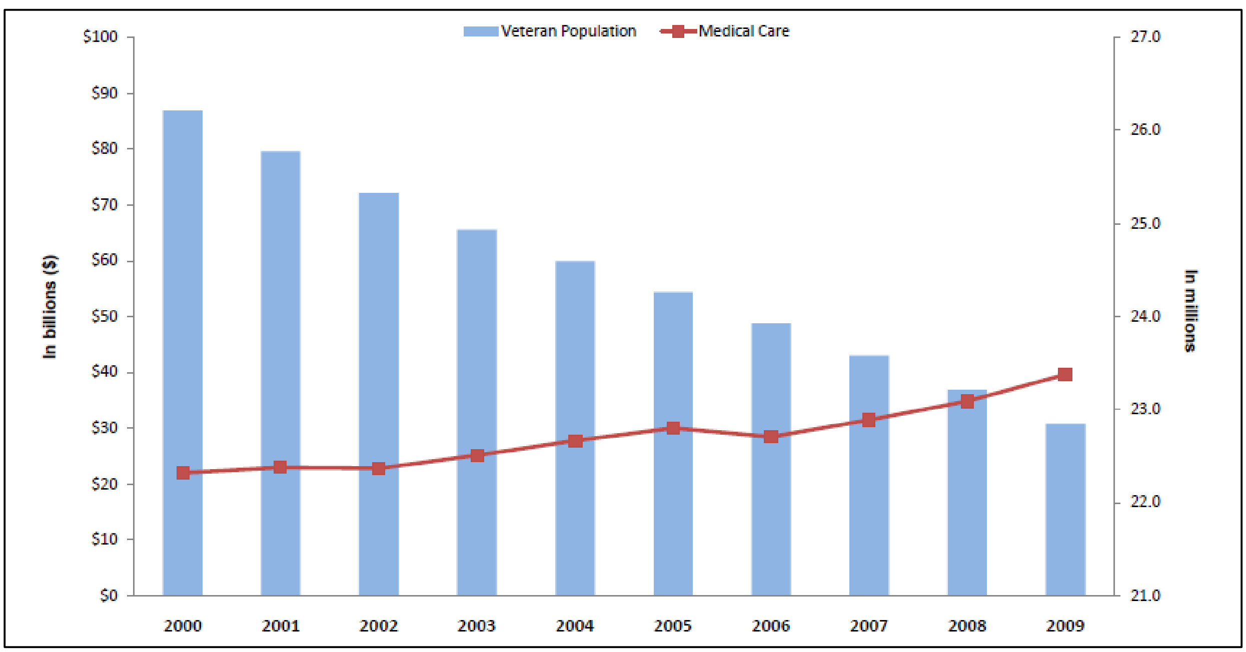

Figure 2 Veteran Population and Medical Care Expenditures (Holder 2010)

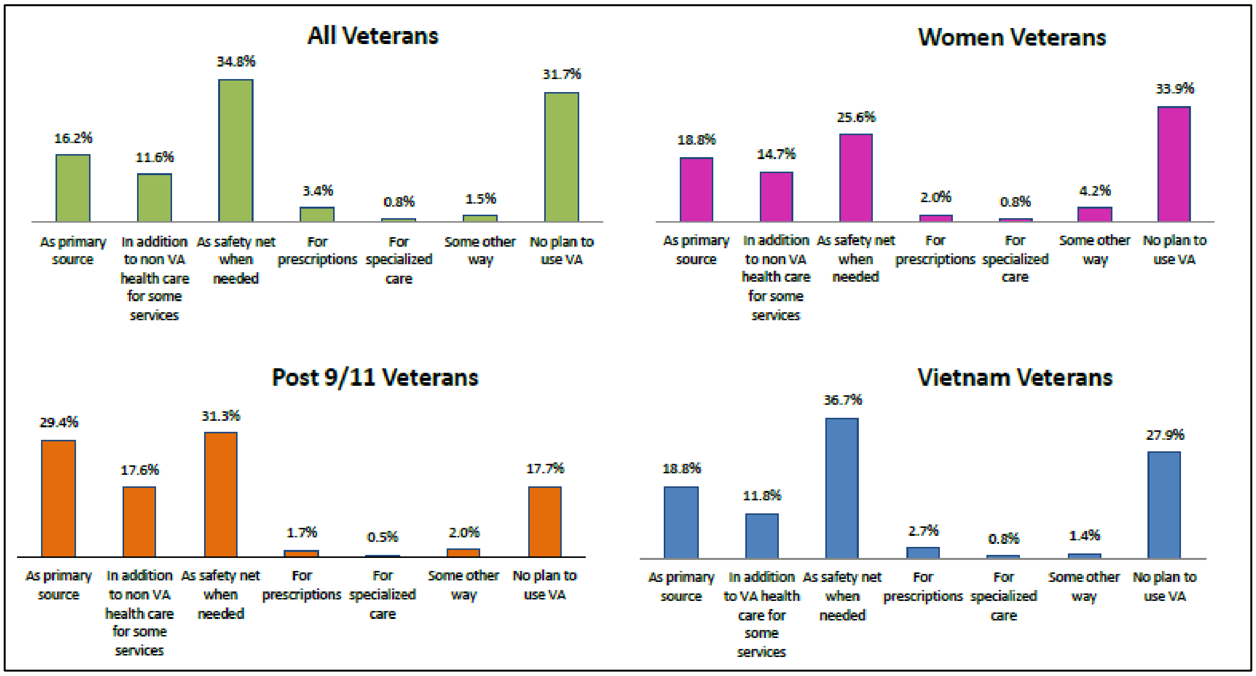

Figure 3 Reported Use of VA Healthcare for Selected Veterans Groups (VA 2014b)

Furthermore, unlike previous conflicts, veterans of Iraq and Afghanistan have survived multiple combat injuries due to advancements in military medicine and improved battlefield care. This means they require extended treatment and medical support, likely for another 30 to 50 years after serving (Davis 2015). Additionally, specialized care as the result of Post-Traumatic Stress Disorder, Traumatic Brain Injury, and the need for multiple prostheses has increased as the nature of conflict has changed over the past 15 years. These factors have converged to cause the cost of VA treatment of Post-9/11 veterans to swell to 2.9-billion dollars in 2012, which only continues to increase every year (Wilde 2013). Although healthcare expenses are increasing for all of society, VA budgets have not kept pace with increased enrollees or expenditures (Palletta 2014).

Medical expenses for the VA have increased over the past 10 years in both total costs as well as individual patient expenditures despite a drop in the veteran population. This project does not attempt to explain trends in expenditures, but focuses on areas where spatial analysis may improve the allocation of resources to improve access to care. Additionally, improved primary care access can reduce long-term expenditures for medical care (Shi 2012). Chapter 5 addresses some potential analysis to address healthcare expenses using this study.

Increased demand compounded by increasing costs stress the VA Healthcare system. The extent of this problem was revealed in an investigative report conducted by Daly and Tang (2014), that identified the problems the Phoenix VA Medical Center had in meeting goals for scheduling appointments in the timeframe required by law. As demand exceeded supply, patients found it difficult to get appointments or referrals at the facility. Since failure reflected poorly on medical center managers, several hospitals kept “unofficial” waiting lists and fraudulently reported meeting appointment timeline requirements. The U.S. Inspector General found that approximately 18 patients at the Phoenix center died while waiting for an appointment, although it was not determined if these deaths were a direct result of this delay. Regardless, the event led to additional scrutiny for the VA and similar incidents found at other facilities led to press deeming it a scandal.

The issue was not just limited to the Phoenix Medical Center though, but was systemic across the nation due to unrealistic pressure put upon healthcare managers to achieve goals for appointment completion. Since the scandal, the VA has implemented oversight and new requirements as part of the Veterans Access, Choice, and Accountability Act of 2014 to publically track timeliness of care. This data is critical in indicating accessibility at a facility in relation to its catchment area population among other measures of capacity and distance. The bill also added $16-billion in supplemental funding with $10-billion for certain veterans to receive private medical care if the VA cannot provide timely care or reasonable access (RTT 2014).

Accessibility is not just a financial problem however, but also a spatial problem. The Veterans Access, Choice, and Accountability Act of 2014 extended a pilot program designated Project Access Received Closer to Home (Project ARCH) (VA 2014). Program eligibility criteria included driving distance to a VA health care facility for primary care, acute hospital care, or tertiary care. As of 2014, this program only applied to five VISNs (1, 6, 15, 18, and 19), but its criteria and analytical approach are applicable to this project. For example, there are over 29,000 veterans enrolled at the Reno hospital and some come from as far away as 280 miles (Wilde 2013). This concept of travel distance or time is a critical part of accessibility recognized by Congress and studies on healthcare accessibility. Expectations as of 2014 are that this program will expand across the VHA in the near future (Gibson 2015).

Therefore, this research is significant as it conducts spatial analyses to determine healthcare accessibility for veterans. Previous studies have primarily dealt with either statistical analysis on physician-to-population ratios, appointments and discharges, or behavioral research. Outside of epidemiology, geographic information systems have yet to be widely used in the health services field (Ngui and Apparicio 2011). It also has a benefit to veterans and the U.S. government since spatial analysis cannot only visualize the situation, but also serve as a decision-making tool to allocate limited resources (Dewulf et. al 2013). This study identifies healthcare shortages in VA regions, improving the understanding of accessibility for this population. It may also benefit society by ensuring federal laws are observed and prevent misleading statistics from influencing managers. Ultimately, the hope is that this study may be of benefit in helping the U.S. keep promises made to veterans.

1.3 Overview of Methodology

In order to address the aforementioned research questions, this study adapts conventional methods for determining healthcare markets and basic accessibility measurements from previous related research using the two-step floating catchment area (2SFCA) model. This model is an accepted method for calculating spatial accessibility scores (Luo and Wang 2003). For this case, execution began with understanding the market associated with healthcare facilities spatially within limits established in the Veterans Access, Choice, and Accountability Act of 2014. From there, it allocates demand to supply by measuring the association of veteran populations with given facilities using ArcGIS software and its Network Analyst tools. Lastly, the 2SFCA method scores the accessibility spatially based on physician-to-population ratios. These scores assign an index to census tracts to gauge whether the populations in that tract have good accessibility to care based on physical distance and availability of primary care.

However, both spatial and non-spatial factors affect accessibility to healthcare providers and facilities (Wang and Tormala 2014). To account for these additional factors, this study applies an improved method for analyzing healthcare accessibility known as the Enhanced 2SFCA (E2SFCA). This model, executed in a GIS, calculates the spatial accessibility scores for the study area weighted by related variables. Typically, E2SFCA methods apply various degrees of impedance to accessibility through distance decay functions to model the probability a population will travel to a facility. For example, Luo and Qi (2009) used distance friction coefficient weights created at predetermined thresholds. Other studies such as McGrail and Humphreys (2009) also enhanced this method by weighting various transportation modes, timetables, bus stop locations, and travel time thresholds in the enhanced 2SFCA models. These researchers emphasized that accessibility to services are a function of supply characteristics and that demand for that service from a population is not just a function of locations, but may experience impedance imposed by finances, time, availability, or quality (Higgs, Langford and Fry 2010).

Therefore, this study uses the principles of E2FCA to measure the impact or impedance to care of non-spatial data through statistics related to the spatial questions. These variables affect the ability to receive necessary care and although are not necessarily spatial in nature, impact spatial relationships of accessibility in the VA healthcare system. Additionally, variables as indices of potential availability and acceptability of care are considered and implemented into modified E2SFCA models.

These processes incorporated census tract centroids containing attributes of veteran population and demonstrate an improved measurement of accessibility for services within VISN 21. Once these models determine accessibility scores, measurements are applied to the census tracts to produce maps representing spatial patterns of accessibility to primary care. Census tracts are the smallest geographic unit available for veteran population distribution from the U.S. Census Bureau and include the best resolution of available data. Furthermore, these maps show not just accessibility scores, but also identify where veteran healthcare shortages exist, providing information to assist more efficient healthcare planning by the VHA.

1.4 Structure of Thesis

There are five chapters in this thesis, each building upon the previous. Chapter 2 describes related studies that provide much of the background required to complete this thesis as well as context for the concepts and decisions made in the development of this research. It also identifies the reasons for choosing and refining particular methods. Chapter 3 presents the methodology for this analysis based on the related work reviewed in Chapter 2. Once methodology is applied, Chapter 4 discusses analytical results. Finally, Chapter 5 covers conclusions from this study as well as limitations, potential improvements, and future research opportunities.

Chapter 2 Related Work

The Veterans Administration is responsible for providing healthcare to honorably discharged veterans who either have retired from service or completed at least 24 months of combat duty. As of 2012, 1.3 million Post-9/11 service members were eligible for care and 713,000 have sought care through the VA. Counting all military conflicts in which the U.S. has been involved, there are approximately 22.5 million veterans eligible to use VA Healthcare in 2015 (VA 2014b). Brownell et al. (2012) noted the uneven distribution of this population geographically causing unbalanced demand on medical facilities.

Previous spatial research on suitability of clinics has focused on distances from patients to facilities; however, the focus of this thesis builds upon previous work by using non-spatial data as indices of barriers or impedance to accessibility. Attributes of particular facilities, such as the number of providers (supply), wait-times for appointments, and patient satisfaction metrics are non-spatial measurements that can be combined with spatial network distance measurements to better assess accessibility. Although previous studies note that GIS can improve assessments of spatial accessibility of facilities, the result of a publication search for applications of GIS for non-spatial impedances for this study was somewhat limited. Several researchers have addressed this issue in limited geographical areas and without similar aspatial indices as in Luo and Wang (2003), Luo (2004), Luo and Qi (2009), McGrail and Humphreys (2009) and Wang and Tormala (2014).

2.1 The Veterans Access, Choice, and Accountability Act of 2014

The recent passage of the Veterans Access, Choice, and Accountability Act of 2014 was an attempt to correct deficiencies in the VHA Scandal of 2014. The biggest impact of this legislation was the establishment of requirements for care based on appointment wait times and distance to facilities. Additionally, the law set standards for transparency though standardized measurement and publication of facility appointment wait-times. It also authorized alternative care options when time or distance requirements cannot be achieved (VA 2014a).

Previously, a geodesic 40-mile buffer assigned a certain population to a specific clinic. This presented a problem for many veterans as it did not account for the terrain or traffic conditions (Walsh 2015). Project Access Received Closer to Home (Project ARCH) identified and corrected this problem and is critical in determining service areas for VA Healthcare (Lawrence 2014; VA 2014). The Veterans Access, Choice, and Accountability Act of 2014 and amendments incorporated and expanded this program. Table 1 shows the criteria for travel distance in determining facility access. As it requires routine visits, primary care has the most limited service-area criteria.

Table 1 Criteria for Qualification under Project ARCH (VA 2014)

Live more than 60 minutes driving time from the nearest VA health care facility providing primary care services, if the Veteran is seeking such service, OR
Live more than 120 minutes driving time from the nearest VA health care facility providing acute hospital care, if the Veteran is seeking such service, OR
Live more than 240 minutes driving time from the nearest VA health care facility providing tertiary care, if the Veteran is seeking such care

2.2 Primary Care

Healthcare consists of several types of services that differ greatly in treatment and the frequency expected for visits. There are four basic categories of healthcare: Primary Care, Secondary Care, Tertiary Care, and Quaternary Care. Primary care is the first and most generalized care. Symptoms are assessed and most treatment occurs for a variety of routine and acute issues within primary care facilities. It is also a form of preventative healthcare not related to public health. Secondary care is care received from a specialist usually referred by a primary care provider and includes more specialized diagnosis and treatment, usually in a narrow field such as cardiology, oncology, and endocrinology. Tertiary care is a higher level of specialized care that usually requires hospitalization. It includes treatments such as coronary bypass, neurosurgery, and severe burn treatment. Quaternary care is an extension to tertiary care and is highly unusual and not available at many medical centers. Often, quaternary care is considered experimental (Torrey 2015).

Primary care is the most common form of medical care. It is also the one form of care used by all potentially eligible veterans since it is for general wellness and diagnosis. All patients require, or are at least recommended for regular primary care visits, but not all patients will require secondary (acute hospital care as defined by the VHA), or tertiary care. Of the types of medical facilities, primary care, whether located within hospitals, medical centers, or outpatient clinics, is the most common type of facility in the VHA system based on this first-line need. Specialized care requires extensively, specifically trained staff and facilities and therefore use is not at the same frequency or used by the same number of potential patients (Friedberg, Hussey, and Schneider 2010).

Primary care should also be the first option for healthcare and its accessibility reduces unnecessary visits to secondary care facilities or hospitals. Friedberg, Hussey, and Schneider (2010) researched the impact of improved primary care and determined that strengthening primary care may reduce costs while increasing quality of care. Access to primary care provides interaction to manage care early, preventing the need to costlier specialized care. Additionally, Bindman et al. (2005) found that required primary care for Medicaid enrollees was associated with fewer hospitalizations in California. They also noted that increased copayments were associated with an increase in hospitalizations as these fees represented a financial barrier to care. For VA healthcare, visits are an entitlement and therefore do not have the same financial barrier. Therefore, increased primary care accessibility is likely to reduce veteran hospitalization as well as healthcare costs over time.

Tracking primary usage within the VHA is an integral part of healthcare management. The VHA defines primary care as outpatients seen in a clinic based on a set of reported stop codes (VA 2013). The VA's Decision Support System is a Managerial Cost Accounting System database that merges input from diverse sources to compile financial and workload data. Data includes a stop code to bin the data according to the type of information. For example, all data collected by the VHA related to primary care services has a stop code ranging from 300-399 (VHA 2013). Data based on this definition was found in the Facility Quality and Safety Report Fiscal Year 2012 Data (VA 2013). VA primary care is designed to provide eligible veterans with access to physicians familiar with their needs through long-term patient-provider relationships. In line with the description in Torrey (2015), VA primary care coordinates treatment across a broad spectrum of healthcare requirements as well as providing health education and disease prevention programs. According to the VA, primary care is the foundation of healthcare and is the first point of contact for veterans receiving care through the system.

Though consideration of these principles and the lack of readily available data, an accurate analysis of accessibility could not be easily conducted for any other type of VA care other than primary care. In addition, based on the principles of care types, assessment of primary care accessibility is most beneficial and accomplishable. The modeling of spatial interaction between patients and providers for primary care does not require specific patient data such as disease or condition not readily available due to privacy concerns. Furthermore, primary care has the greatest use of all care types and the most regular interaction between patients and providers, therefore, assessing primary care accessibility is not only feasible, but has the greatest impact on long-term care and health of the population studied and cost to the provider (Shi 2013; Friedberg, Hussey, and Schneider 2010).

2.3 Accessibility

The concept of healthcare accessibility is nothing new. Hunter, Shannon, and Sambrook (1986) conducted an analysis of 19th Century insane asylums to identify service areas of institutions. They recognized that asylums were generally localized facilities, serving populations closest to the hospital. They also found a universal distance decay from these facilities, whereas, patients were more likely institutionalized the closer they lived to a facility. Their methodology used a non-GIS study to identify relationships between patients and mental health providers. Utilizing data obtained from an 1866 study by statistician Edward Jarvis, the researchers applied what was termed "Jarvis' Law" which proposed those living closer to a facility were more likely to overuse it and those farther would underutilize a facility. Using this principle, Hunter et al. (1986) completed an early analysis of the spatial interaction of patients and providers.

Following this early work, further study of healthcare identified the critical factors that affect accessibility. Researchers, including Wallace (1990) identified these as the interaction among availability, accessibility, and acceptability. Availability was defined as whether a particular service was provided. Accessibility was defined as the population needing a service having the physical and/or financial access to it. Acceptability was determined as a concept that a service is satisfactory to clients so they would not be deterred from use. Where these conditions did not exist together represented a gap in need or a "no-care zone." Wallace (1990) determined that availability, accessibility, and acceptability were each necessary elements of a comprehensive long-term care system; in which primary care would be one example. Therefore, consideration of these factors was important in exploration of primary care accessibility.

Later healthcare research used a GIS to enhance understanding of the relationships of populations with providers. Guagliardo (2004) worried that the majority of healthcare accessibility was primarily a cost concern. The issue was concerned there was surprisingly little understanding about how geographic barriers effect utilization or accessibility of primary care. His paper explored concepts and measurements of geographic accessibility and described the possibilities that GIS and spatial analysis development presented in accessibility research. This research defined key components of primary care accessibility which included availability, access (physical), affordability, acceptability, and accommodation. Guagliardo (2004) identified that such research focused primarily on statistical analysis of affordability, acceptability, and accommodation as these reflect healthcare financing arrangements and cultural issues. The conclusion was a lack of study on spatial relationships that address availability and accessibility and he determined accessibility as the travel distance or time to a service.

Although Guagliardo (2004) focused on spatial accessibility that he defined as the travel distance or time to a service, he explained that there were two dimensions of healthcare access, spatial and aspatial, but that studies did not address both. Searches for previous research on this topic continue to return very few results for studies incorporating both dimensions. Therefore, this potential, shown in Table 2, was a driving factor for this study to attempt to model the interaction of spatial and aspatial variables.

Table 2 Taxonomy of Healthcare Access Studies (Guagliardo 2004)

Stages		**Dimensions**
Potential	**Realized**	
Studies of distance and availability that do not consider utilization measures	Utilization studies that consider spatial factors	Spatial
Studies of affordability, culture, and other non-spatial factors that do not consider utilization measures	Utilization studies that consider affordability, culture, and other non-spatial factors	Aspatial

A review of previously published literature has shown that the idea of healthcare accessibility is well established, but has become an issue of national importance regarding the VA healthcare system only recently. Brownell et al. (2012) analyzed a geographic layout of hotspots of veteran populations to determine those vulnerable to healthcare shortages, but this problem was not limited to population density. Availability is a function of accessibility, so provider capacity and medical center performance is critical. This can be difficult to identify, but various indices may assess the ability of a chosen location to provide available services. Fortney et al. (2002) conducted a series of studies of VA utilization and performance that compared various-sized VA clinics and found consistent levels of care regardless of facility size; an important factor to this study as it allows all clinics be treated equally.

When analyzing the capability of medical facilities to meet a given population's needs, a variety of applied measures determine the viability of a location. Typically, this is completed through a statistical analysis of the population in relation to throughput capacity; an aspect also known as hospital flow (IHCI 2015). This flow measures overall admission and discharge of patients as well as patient treatment statistics and individual unit performance or curative success, minimizing the need for return visits for the same condition. Although hospital flow does not directly relate to primary care, the principle was consistent with the intent of VA metrics for satisfying desired appointment timelines. The Veterans Access, Choice, and Accountability Act of 2014 recognized the requirement to schedule and complete primary care appointments in a timely manner as a critical function of veteran accessibility to care. The law determined that if a veteran cannot complete appointments within 30 days of the desired date, they may qualify for alternative, private care.

Traditionally, a facility may also use a census of the percentage of occupied beds to decide if the hospital is being fully utilized by the population; the supply is balanced to the demand (FARLEX 2015). Although this is an important measurement of sustainability, such a census of occupied beds does not address quality of care for an individual. Surveys on the other hand, measure the perceived care received and hospitals and other medical facilities have used patient surveys to determine whether a hospital is meeting the needs of its patients.

Therefore, patient satisfaction was suggested as an indicator of performance and thus may be related to accessibility. The question could arise however, whether the size of the facility affects patient satisfaction. A study by Chapko et al. (2002) though noted that primary care quality across varying types of VA facilities was indeed comparable. Therefore, despite the differences between VA Medical Centers, Outpatient Clinics, and Community-Based Outpatient Clinics, for this analysis, primary care at all three types of facilities were essentially equal in the ability to provide services (Hedeen et al. 2002; Liu et al. 2010). This study suggested patient satisfaction was not related to the size of the facility, but equally and accurately assessed the satisfaction of care for the individual facility. Therefore, all VA healthcare facilities providing primary care used this variable.

2.4 Markets, Service, and Catchment Areas

The same basic market principles affect healthcare as for any other service. There is a relationship between the demand for healthcare by a population and a supply. Unlike a typical economic interaction however, as healthcare is a critical service, a lack of supply to demand can be detrimental to the population. This is a complicated relationship that this study does not explore in any detail, but understanding the spatial relationships of supply and demand is necessary to ensure accessibility.

Historically, market analysis of the population within an administrative boundary has been the sole factor for determining a service area for healthcare using statistical or aspatial data. This was used to locate a facility on the assumption it would serve the greatest number of people based on expected patient origins. However, this ignored travel patterns as found in Klauss et al. (2005) research on the spatial analysis of utilization of hospitals in Switzerland. Using census and patient data along with topographic information, they studied the spatial distribution of patients and clinics and determined that medical facility use was not strictly a function of distance. Instead, studies focused on analyzing spatial patterns based on patients' home address and choice of healthcare facility. Using these locations, they analyzed the spatial patterns to determine and assess characteristics of facility service areas. Although this study used human behavior for spatial analysis, it did not consider the transportation network.

Additional research in healthcare accessibility focused on the demographic and socioeconomic variables such as the ability to pay. Although this is an important aspect of accessibility to care, veterans are a specific demographic and ability to pay is not a barrier as it was expected the VA would provide care without any attached fees. It is impossible though to address accessibility without analysis of the spatial separation between supply and demand, as either a barrier or facilitator (Ngui and Apparicio 2011).

Although this study does not use gravity models, this type of previous research is important to the development of the methods developed in Chapter 3. Several methods have developed to define a market spatially, but some models and previous research fell short. Several of these previous models used gravity, distance, and impedance to identify access, but ignored the possibility of including other barriers such as traffic and road conditions, social and demographic factors, and patient attitudes toward a facility that may have additional impacts beyond travel and availability of services.

This market interaction was formerly addressed as the service area of a facility. In the past decade, however, the term catchment has become a more common term for the area in which an institution or public service draws a population. A catchment is traditionally a physical geography term used to describe drainage basins. In human geography, it represents an area in which an institution such as a school or hospital draws a population or a population is allocated to a particular institution (FARLEX 2014). The concept of catchments for healthcare accessibility has become standard in research and related literature since about 2000. Therefore, this analysis uses the term "catchment" for the development of methodology and reporting of results for clarity.

As previously identified, the development of catchment areas has become more common as the spatial analysis of healthcare access has evolved, although the origins of this term were unclear. Exploration of literature and previous studies has shown the catchment area assessment was the most common method used in identifying healthcare-facility service areas. This idea has likely grown out of earlier gravity models, hence the idea that a service would draw or attract the population. In other words, the area around an institution would "drain" toward the institution. Barriers or impedance to this gravity flow would exist similarly to that of hydrology.

As of 2016, a widely accepted model using catchments for analysis of the interaction between the population and services or institutions across space has been adopted. Initially, early gravity models attempted to map previously used statistical analysis of physician-to-population ratios. Reality hampered the accuracy of spatial accessibility measurements using this process though. It is uncommon that a predetermined assignment or single pathway exists between potential patients and healthcare providers. Typically, there was some choice involved, making spatial assessments of interaction more challenging. In healthcare, this is particularly valid for primary care and less true for specialized care. Access within primary care usually exists in a network of overlapping, competing catchments in which the population has some choice in utilization (McGrail 2012).

The development of catchment area analysis continued to grow out of existing gravity models and statistical analysis of healthcare services. Luo (2004) recognized the floating catchment area model as a method to overcome previous approaches that were unable to account for spatial variations of physician supply and demand. He identified the important factors for healthcare as standard market variables of physicians (supply) and population (demand). Both variables occur spatially, but distributions were seldom normal and do not necessarily match each other, especially in rural areas, an attribute of VISN 21 as well.

The floating catchment area model developed from potential spatial measures of accessibility that included regional availability (the availability of providers) and regional accessibility (the ability to reach reasonably those providers). Regional availability was easy to measure using standard supply versus demand within a region, expressed as the physician-to-population ratio. The catchment areas overcame the key criticism of physician-to-population ratios. In previous studies, this measurement assumed populations within the region have equal regional accessibility to physicians and that populations within the region do not go beyond their assigned region to seek care. These assumptions made the traditional method highly susceptible to modified areal unit problems that smaller administrative units did not solve as borders were treated as impervious to movement (Luo 2004).

Therefore, using a GIS, Luo (2004) implemented a floating catchment area methodology to demonstrate the principle applied to healthcare. The process was implemented in a GIS using buffer and overlay functions. There were four basic steps involved. First, a circle was drawn centered on the centroid of a census tract with a radius equal to the reasonable distance a person is willing to travel for care. The circle is that census tract's catchment area. Second, the circle was overlaid with the population and physician data to determine the number of each that fall within the circle. Third, the physician-to-population ratio was computed within the circle and assigned to the census tract being considered. Fourth, the first three steps were repeated for the remaining census tracts. In other words, the catchment floats over space providing a measure of accessibility to each population by chosen areal unit.

Figure 4 demonstrates this process with census tract centroids representing a single person. When the circle is centered on the centroid of census tract #2, it encompasses seven persons and one physician for a physician-to-population ratio of 1:7, which is assigned to census tract #2. For census tract #3, there are five persons and two physicians in the circle so the physician-to-population ratio for census tract #3 is 2:5.

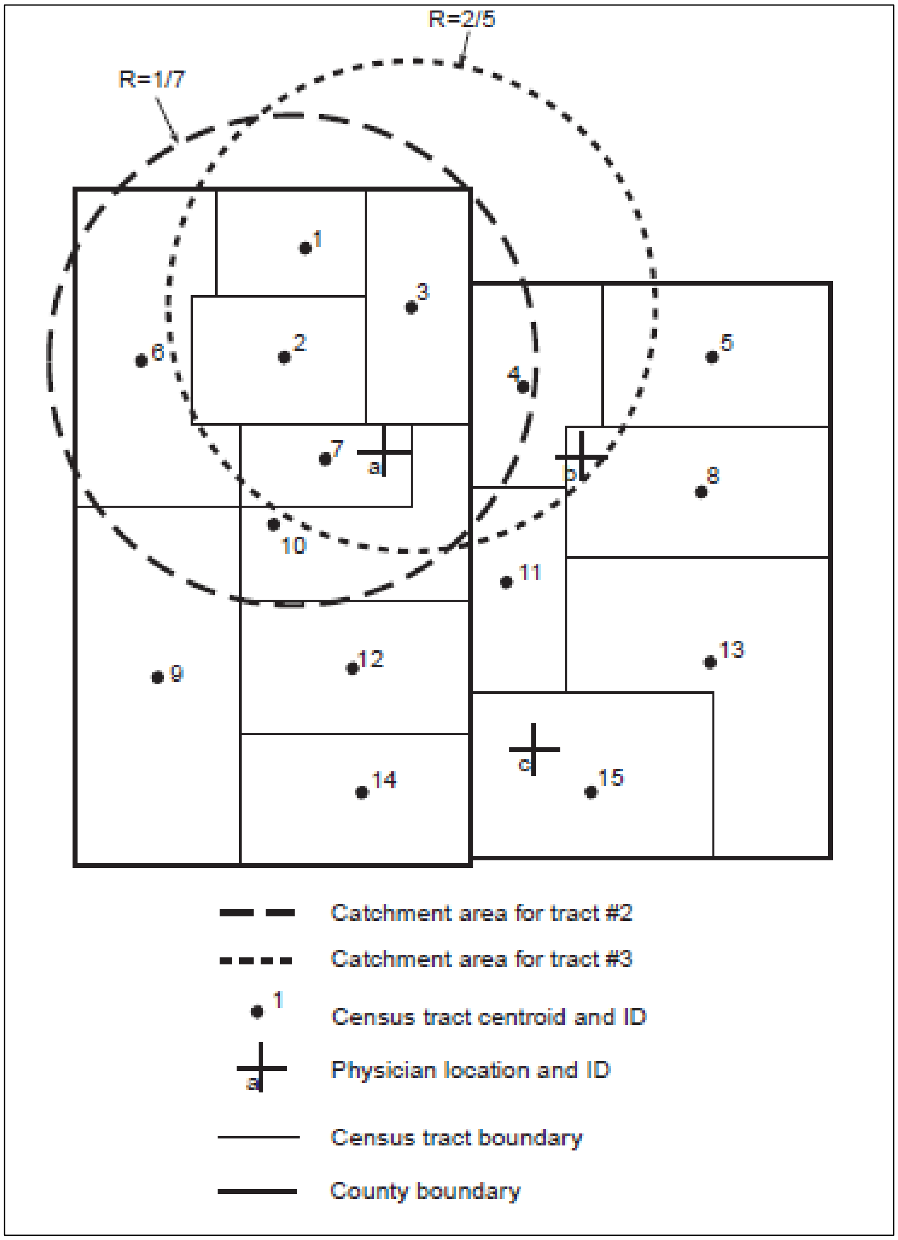

Figure 4 Floating Catchment Method (Luo 2004)

This process continues until all census tracts have had available physicians for the populations measured. In the actual calculation, the sum of the available physicians for a census tract was applied, accounting for travel across boundaries. The only problem with this basic method was that it still assumed equal access within each census tract and did not account for other characteristics, such as transportation networks or socio-economic factors. Visualized through the classification of tracts based on the physician-to-population ratio, the result of this process designated areas with a ratio of less than 1: 3,500 as a Health Professional Shortage Area based on Department of Health and Human Services criteria. Figure 5 shows the result of this analysis, although Luo only presented this as an example of the method (Luo 2004).

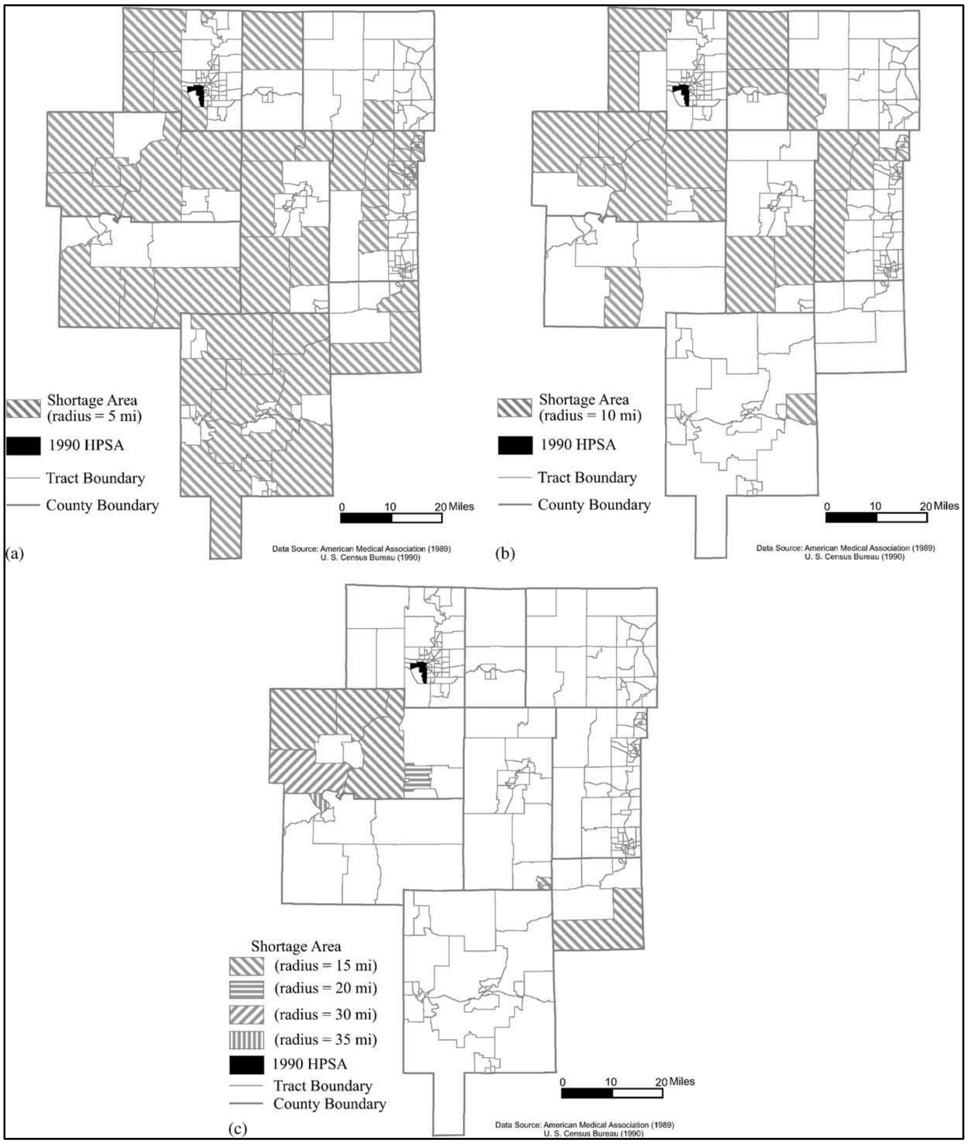

Figure 5 FCA Method with a Threshold Physician-to-Population Ratio of 1:3500 (Luo 2004)

Catchment areas have additional benefits over geographic distance or use of administrative units to define populations for utilization. As noted, they consider availability to better characterize supply and demand. More importantly, they allow for the crossing of administrative borders. Furthermore, the development of catchment areas can be analyzed with regard to transportation networks, an important feature of geographic barriers as well as the ability to satisfy requirements of the Veterans Access, Choice, and Accountability Act of 2014 and Project ARCH.

Building on this research, Wang and Luo (2005) published an improved version of the original floating catchment area model. In this model, they added a second step and termed this the two-step floating catchment area (2SFCA) model. It proposed using circles of a reasonable radius around census tract centroids to identify variability in accessibility of patients to healthcare providers. This method also accounted for interaction across administrative boundaries, traditionally ignored as planning was done at the administrative unit level (Ngui and Apparicio 2011).

An underlying assumption in previous models was that services that fall within the population catchment area are fully available to any residents within that catchment. However, not all services within a catchment are reachable by every resident in the catchment. In addition, it ignored physicians on the periphery of the catchment who may also serve nearby residents outside the catchment, creating competition within a neighboring catchment. Using travel-time on a network rather than Euclidian distance partially overcame these issues (Wang and Luo 2005).

The 2SFCA proposed by Wang and Luo (2005) hoped to address some of these fallacies. It analyzed relationships through population-weighted centroids to assess accessibility by integrating spatial and non-spatial data such as demographics and used travel time instead of straight-line distance to reduce some errors of previous studies. Building on the previous research, the improved model repeated the floating catchment process twice: once on physician locations and once on population locations. The first step assigns an initial ratio to each of the service areas centered on physician points to measure availability of supply. For each physician location, a search of all population locations that were within a threshold travel time from the physician location (within the catchment area) was conducted and the physician-to-population ratio was computed within that catchment area.

The second step sums up the ratios in overlapping service areas to measure accessibility of a demand location. Therefore, for each population location, a search was conducted for all physician locations within the threshold travel time from the area centroid (within the population catchment area) and sum up the physician-to-population ratios for each of those locations. Thus, in areas were populations have access to multiple supply locations, the model considered the interaction across borders based on travel times. Accessibility measurements thereby vary from one tract to another. The second step is essentially a comparison of physician-to-population ratios for each population center filtered by travel time and, unlike previous research, it is demand-centered and not supply-centered (Wang and Luo 2005).

The formula for the first step is:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \tag{1}$$

Where P_k is the population of tract k whose centroid falls within the catchment ($d_{kj} \leq d_0$), S_j is the number of physicians at location j; and d_{kj} is the travel time between k and j (Wang and Luo 2005).

The formula for the second step is:

$$A_i^F = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} \left(\frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \right) \tag{2}$$

Where A^F_i represents the accessibility at resident location *i* based on the 2SFCA method, R_j is the physician-to-population ratio at the physician location *j* whose centroid falls within the catchment centered at *i* (i.e., $d_{ij} \leq d_0$), and d_{ij} is the travel time between *i* and *j* (Wang and Luo 2005). The result is an indexed score of accessibility by areal unit within distance threshold of the population, as shown in Figure 6.

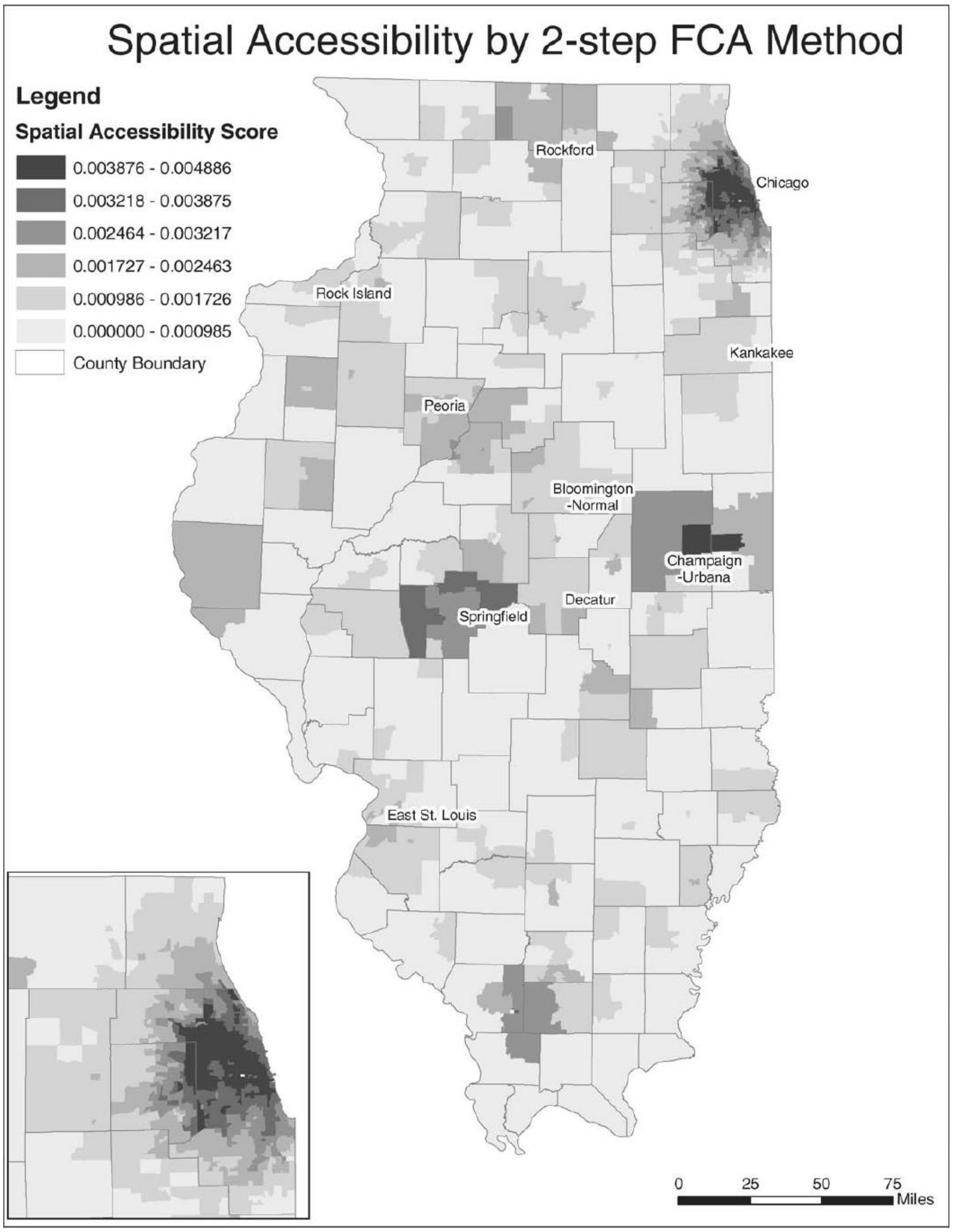

Figure 6 2SFCA Results (Wang and Luo 2005)

Wang and Luo (2005) also began to explore new possibilities for changes to their 2SFCA model. The first supposition was to modify the model with new gravity factors to better account for travel time. Design of a revised formula made closeness to one physician more attractive than a distant one. The idea presented that instead of using an arbitrary distance threshold, friction or impedance could be added to the formula. One possible formula is:

$$A_i^G = \sum_{j=1}^{n} \frac{S_j d_{ij}^{-\beta}}{V_i}, \text{ where } V_j = \sum_{k=1}^{m} P_k d_{kj}^{-\beta} \quad (3)$$

Where *n* and *m* indicate the total number of physician and population locations respectively, *b* is the travel friction coefficient and all other variables were the same as the second step of the 2SFCA equation (Wang and Luo 2005). This formula allowed examination of the relationships of spatial data and was easily tailorable to this thesis. Therefore, it was selected as the foundation for methodology development for assessment of VA clinic catchment areas for this research and discussed in Chapter 3.

Wang and Luo (2005) also spent part of their study discussing the integration of aspatial social-economic factors into the process. The idea recognized tracts with “disadvantaged” populations as areas identified as lacking accessibility to aid in the decisions related to the allocation of resources. This integration of external, non-spatial factors affecting healthcare accessibility, along with the researchers’ observations, led to the determination that friction or impedance can be added into the equation without affecting its framework. This meant other possible modifications to conduct spatial analysis of healthcare could be executed through modified 2SFCA models using a variety of variables.

The original 2SFCA model continued being improved upon. Luo and Qi (2009) added weights to the two steps to add a distance decay as distance from the census tract centroid increased. One of the main limitations with the 2SFCA is it treats accessibility equally across all populations within a catchment. DeWulf et al. (2013) further studied this problem by adding a resistance coefficient to add impedance weights to the formula and travel-time catchments. These methods constituted an Enhanced 2SFCA (E2SFCA) methodology. Small-scale calculations in ArcMap accounted for the interaction not just between physicians and patients, but also distance. Figure 7 demonstrates how the incorporation of networks and distance weighting changes the shape of a catchment area from a simple circle as was used in Luo (2004) (DeWulf et al. 2013).

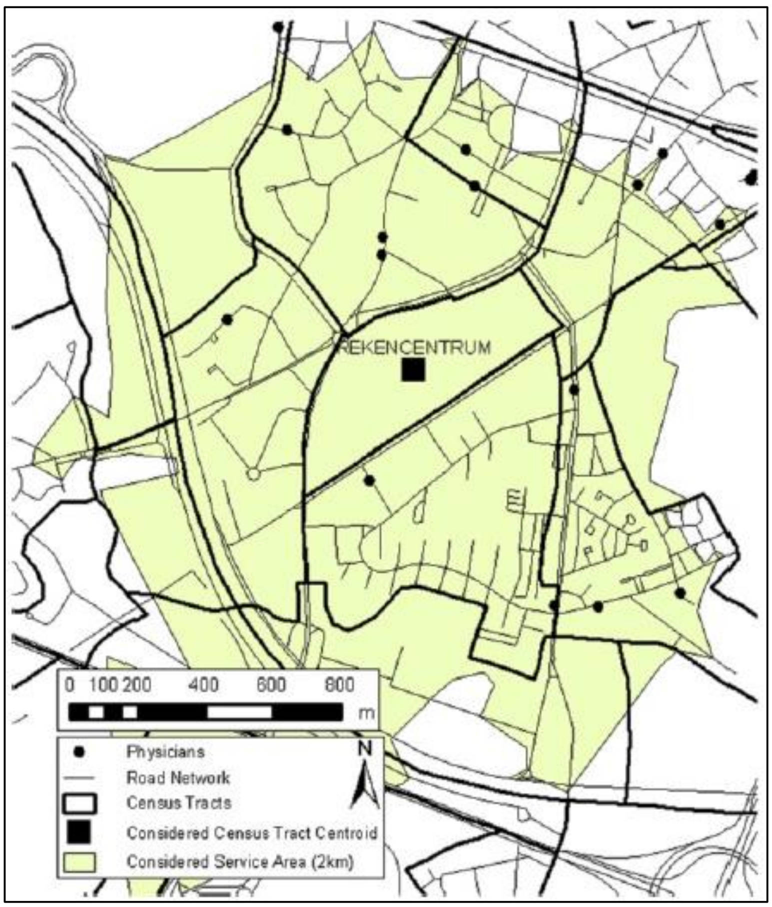

Figure 7 Service Area around a Census Tract Centroid (DeWulf et al. 2013)

Several studies have been conducted since to evaluate and compare the 2SFCA and E2SFCA models. Notable literature on this comes from McGrail (2012) who studied and assessed the usefulness of adding a distance decay or stepped decay to the original 2SFCA model. Using a case study in Victoria, Australia, McGrail (2012) conducted an analysis using the 2SFCA and two E2SFCA models. Figure 8 shows his initial 2SFCA (a) result and changes using E2SFCA (b-d). McGrail (2012) found that flexibility in the 2SFCA models was both a strength and a weakness. It was easily modifiable within its framework, a finding also noted by Wang and Luo (2005), but he believed it underestimated the realities of the impact of geography on accessibility, such as population densities and local patterns, especially when assessing both urban and rural areas. His biggest concern was that catchment sizes should be variable for different geographies. These weaknesses however, were not an issue for this thesis as the law sets the maximum catchment size.

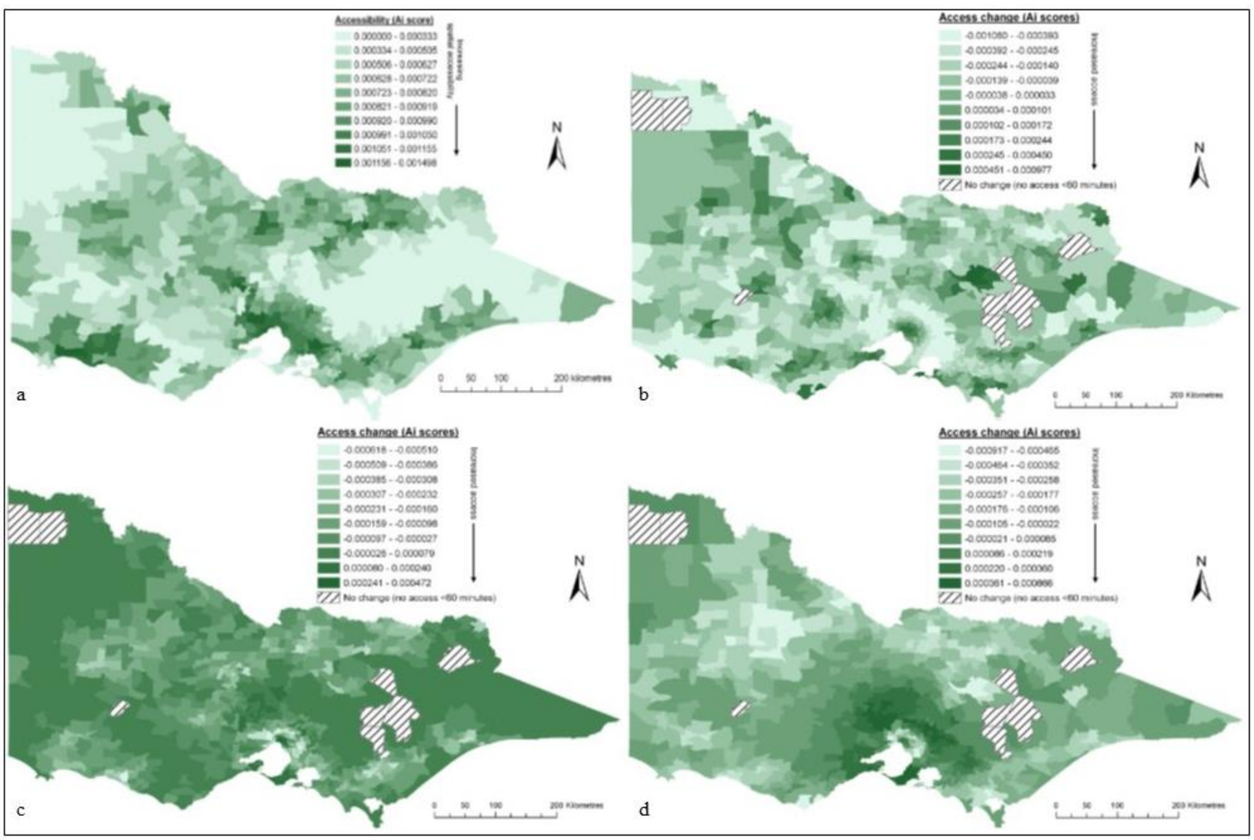

Figure 8 2SFCA and E2SFCA Comparison (McGrail 2012)

The strength of these methods is the ability to study relationships between variables and apply them spatially; however, it only applies sub-zone distance weights applied in the steps. Luo (2014) began exploring additional gravity improvement using this concept as a measure of accessibility, but included additional measurements to study integration of the Huff Model into service area assessments. The Huff Model is a method for quantifying the probability of selection of a service site from multiple choices (Huff 1963, 1964). This application added the probability that populations will use a specific facility when there is more than one option. Luo (2014) noted that a selection weight could be added to these methods to improve spatial analysis of whether a population was actually using the facility, creating a better representation of the service area. As noted in other studies, it was possible to improve understanding of service area and accessibility using additional variables related to patient care. This calculation builds on 2SFCA methods to address accessibility factors through inclusion of attractiveness of a facility, a variable which could be drawn from various measurements and is calculated as:

$$Prob_i = \frac{C_j d_{ij}^{-\beta}}{\sum_{s \in D_0} C_s d_{is}^{-\beta}} \tag{4}$$

This was defined by Luo (2014), where $Prob_i$ is the probability of population location i visiting service site j; d_{ij} is the travel time between i and j, and β is the distance impedance coefficient; C_j is the capacity/attractiveness of service site j and s is any service site within the catchment D_0 of i. Theoretically, attractiveness is not limited to one variable. This method proposes a third step to the 2SFCA model that was a version of the E2FCA model. Luo (2014) coined this probability inclusion as a Three-Step Floating Catchment Area model. This idea represented a viable option for incorporating the variables of wait time and patient satisfaction in this study to increase the likelihood of either greater demand on a facility, or with increased wait times, decreased desirability of a facility. In the end, if a facility is more probable for use, this could over-stress the supply at the chosen location and reduce accessibility scores for the population assigned to that location. Although this thesis did not use gravity models, these concepts form the basis for improvements to the original 2SFCA, E2SFCA, and modified E2SFCA models inspire the methods developed in Chapter 3.

2.5 Optimization

Other researchers continued to modify the E2SFCA through the inclusion of additional variables in either new steps or new weighting. Li, Serban, and Swann (2015) conducted multiple modifications to the 2SFCA method to create new E2SFCA formulas by weighting based on indices that may affect competition between institution and services. These indices would increase or decrease the demand on a particular facility and thereby effect accessibility within the catchments. These modifications were termed optimization models and they found many variations were possible through the addition of constraints or objective function values. Their modified models address inclusion of patient "experience" such as experienced congestion at a facility. Although this study only tried to address modifications to identify ways to increase accessibility, the researchers also noted the ability to adapt 2SFCA models to account for patient experience and not only actual utilization.

The 2SFCA and E2SFCA models have also been adapted for accessibility studies outside of healthcare. Kuai (2015) conducted a study of healthy food accessibility in Baton Rouge, Louisiana. He also departed from standard 2SFCA method through modification using the Huff model, Kernel Density, and socio-economic factors. Each modification was designed to provide better understanding of the supply and demand relationships and improve the likelihood the model represents actual interaction. The inclusion of non-spatial factors affecting accessibility was a common theme of literature related to improvements of the 2SFCA model. As noted earlier in this chapter, studies of affordability, culture, and other non-spatial factors that do not consider utilization measures are a potential for accessibility studies of which there was "surprisingly little" (Guagliardo 2004). Studies to achieve this potential are a relatively recent phenomenon.

Determining accessibility has a relationship with optimization of services. Veterans experienced a higher satisfaction with care than non-VA patients did, but access to care was not equal for all populations (Ibrahim et al. 2014). To correct this imbalance, populations need not only be able to get to a facility, but must receive care when needed. Since accessibility includes functions of availability, performance, cost, time, and distance, more than just one aspect must be assessed. Furthermore, the large number of eligible veterans and limited resources mean that the VA must optimize availability while constraining costs (Maciejewski et al. 2002).

In addition, since travel patterns were a function of medical facility utilization, optimization is a spatial problem and not just a question of patient throughput. Klauss et al. (2005) suggested there may also be socio-economic choices involved such as education, income, and race that represent barriers to movement playing a key role in the use of particular facilities by the population. These are all areas previously studied separately, but rarely in relation to one another. Finally, since the passage of the Veterans Access, Choice, and Accountability Act of 2014, geographic accessibility has not been studied under the new rules nor has it been applied to this specific population, at least outside the VA or published publically. This was another area in which this study can provide the VA the knowledge to make informed resource allocation decisions.

2.6 Summary of Related Work

A review of previous literature and research on the subject of healthcare accessibility provided the foundation for the methodology of this thesis. First, understanding the Veterans Access, Choice, and Accountability Act of 2014 provided insight into the issues the U.S. Congress hoped to improve regarding VA healthcare. It set some of the measurements used in developing this analysis as well opportunities to explore modifications to the model. This, combined with concepts and definitions on healthcare accessibility helped refine the spatial questions and guide the methodology. Literature surrounding 2SFCA, ES2FCA, and modified 2SFCA development proved critical to identifying standard practices related to this topic while also identifying new possibilities applicable to this study. Overall, a review of related work guide and inspire the methods in Chapter 3 and research on optimization and location-allocation helps to inform opportunities for follow-on study, as discussed further in Chapter 5.

Chapter 3 Data Sources and Methodology

This study seeks to identify areas in VISN 21 in which the ability to provide promised care was either available within Federal law or where there may be degrees of shortages. Based on accessibility measurements, areas of concern were identified for more in-depth study, allowing determinations to better situate facilities or manage resources. In addition, results could support a model created to optimally situate facilities to reduce potential healthcare shortages. Therefore, data for this project included spatial information for the analysis of relationships across the study area as well as attributes of VA primary care facilities for the determination of catchment areas and as indices of possible stressors on healthcare accessibility. Data selected for this thesis was used to build upon the theories and previous research analyzed in Chapter 2. Therefore, data selection was focused on demand, supply, and indices of acceptability of care (timeliness of care and patient satisfaction).

Relevant data was identified, collected, and imported into ArcGIS through download from U.S. government GIS portals, data received from the VA, or from VA reporting available online. Much of the data was only available in spreadsheets or text and was processed into a format useful in ArcGIS for spatial analysis. From this, a network was created, catchment areas were developed from census tracts and facilities, network analysis refined the study area, and models were created to determine accessibility for each population. Once these initial catchments were assessed, the attributes of each facility provided impedance based on appointment wait-times and patient satisfaction to better portray accessibility assessments and identify possible healthcare shortages spatially.

3.1 Data Sources

Veterans Administration and census data for this thesis were available, but not in ArcGIS formats such as geospatial databases. Much of the required data was only available in tables, spreadsheets, and reports and had to be manually manipulated. This included population, demographic, and facility attribute data. Additionally, upon joining the veteran population data to census tract polygons, ArcMap did not recognize the data as integers. Therefore, executing simple cartographic operations such as creating a choropleth map of total veteran population was impossible from direct import. Instead, tables were produced and heavily edited in ArcMap before they were joined to shapefile attribute tables. Processing is detailed later in this chapter.

The VA collects and archives a great deal of data, both spatial and non-spatial, as part of its operations and mandate; however, it does not make this data readily available to the public. Much of this data is contained in the Veterans Administration Site Tracking (VAST) database. This is a central repository for VA data and may also include spatial data files, but was not publically accessible. Also, the Veterans Administration Healthcare Planning System and Support Group (PSSG) has a GIS office for the purpose of managing and studying VA healthcare issues, and several additional departments dedicated to the collection of veteran data and statistics also produce ArcGIS maps of veteran data. This activity was evident from Esri reports (Harp 2010), but there was no VA GIS data download page or server for public information gathering. Therefore, data must be obtained by direct request to the VA.

To acquire data for this project, Freedom of Information Act (FOIA) requests were submitted to each applicable VISN: VISN 20, VISN 21, and VISN 22. The two additional VISNs were required to include facilities near the borders of the VISN 21 study area. Additionally, a search was executed for alternate data sources and previous studies related to this topic, however, it was impossible to determine the accuracy of some data. Therefore, VA-provided data was preferred. The requirement to submit the FOIA request was not unexpected, but lengthened the time required to receive the information. A review of the FOIA website was used to determine that the request did not violate any of the exemptions under the act and thus would be fulfilled (Table 3). Simple requests are usually filled quickly if the data already exists. For this study, the requests were kept simple with basic primary care information and patient satisfaction data the VA indicates it collects based on published reports and documentation.

Table 3 Freedom of Information Act Exemptions (Justice 2015)

Exemption 1: Information that is classified to protect national security. **Exemption 2:** Information related solely to the internal personnel rules and practices of an agency. **Exemption 3:** Information that is prohibited from disclosure by another federal law. **Exemption 4:** Trade secrets or commercial or financial information that is confidential or privileged. **Exemption 5:** Privileged communications within or between agencies, including: Deliberative Process Privilege Attorney-Work Product Privilege Attorney-Client Privilege **Exemption 6:** Information that, if disclosed, would invade another individual's personal privacy. **Exemption 7:** Information compiled for law enforcement purposes that: (A). Could reasonably be expected to interfere with enforcement proceedings (B). Would deprive a person of a right to a fair trial or an impartial adjudication (C). Could reasonably be expected to constitute an unwarranted invasion of personal privacy (D). Could reasonably be expected to disclose the identity of a confidential source (E). Would disclose techniques and procedures for law enforcement investigations or prosecutions (F). Could reasonably be expected to endanger the life or physical safety of any individual **Exemption 8:** Information that concerns the supervision of financial institutions. **Exemption 9:** Geological information on wells.

For us in this thesis, requested data was returned for VISN 21 within seven weeks, but exact timing for a response is always unknown (Justice 2015). Furthermore, requests for information were never acknowledged from VISN 20 and no data was received in response to the request from VISN 20 and VISN 22. Physician data for these VISNs were interpolated using the VISN 21 data during processing. Even though data was not returned as a part of the FOIA request for the adjoining VISNs, much was available publically, but not in a format for easy use in ArcMap, making it necessary to transpose data from spreadsheets, tables, and reports into tables that could be joined in ArcMap as attributes.

3.1.1. Study Area

As outlined in Chapter 1, the focus of this study was accessibility in VISN 21; however, it was necessary to consider inclusion of areas on the edges of that administrative boundary. As the population of veterans and location of facilities occur across space, there is the ability of a population to move across boundaries. Spatial data includes the geographic location representing the area of study; in this case, the area was limited to VISN 21 and border areas in VISN 20 and 22 where the supply or demand may influence the analysis in VISN 21.

VISN 21 was functional as it represents a variety of conditions, urban and rural, as well as areas experiencing increases and decreases of veteran populations. These variances in the landscape meant the process should provide a noticeable difference in some areas, making analysis worthwhile. Therefore, for the collection of data, it was determined that spatial data was required for the entirety of VISN 21, and areas of VISN 20 and 22 within a potential drive-time of 60 minutes in accordance with the Veterans Access, Choice, and Accountability Act of 2014. This area and associated data were refined during processing.

Within this area, vector data were obtained for all spatial data within the areas anticipated for use. The largest areas of vector data gathered were state boundaries. For this project, three states comprised the necessary coverage; however, the states in their entirety were not used. Although VISN 21 is located exclusively in parts of Northern California and Nevada, parts of

Oregon were also added to the vector data to avoid edge effects where veterans may travel across administrative boundaries for care. As long as they are enrolled in the VA, they can choose which facility they prefer or find more convenient. This is one reason wait time and patient satisfaction were important variables to accessibility for this study. A veteran may have more access if multiple facilities were available despite the closeness of a single facility. There is nothing to prevent them from traveling to a different VISN for care either because it is closer or more desirable as many borders are not an impediment to care. Understanding these relationships may affect accessibility and a desire to travel to a better performing facility represents an opportunity for more in-depth analysis as this may negatively affect balances between supply and demand.

Census tracts were chosen based on review of related work, which commonly used this as the primary areal unit for determination of markets and catchment areas at the scales as were explored in this study. Census tracts were readily available for download from the U.S. Census Bureau. In addition, census tracts were the smallest division available for the veteran population and demographic data. These were also easily processed as the centroids required for this type of analysis. Additionally, veteran data was readily available by census tract, avoiding the need to interpolate the population to fit a different, perhaps smaller areal unit. Unfortunately, there are few data layers specifically for veterans that would allow such a dasymetric interpolation. For census tracts that border the VISN, buffers calculated an estimated percentage of the population within the intersection to reduce the number of downloads prior to actual processing as much as possible.

3.1.2. Veteran Population

The next spatial data requirement was veteran population and demographics. These were downloaded from the American Community Survey (ACS) in a comma-delimited file imported into Excel. The resulting spreadsheet contained a large amount of veteran data by census tract. ACS data is created from statistical sampling based on surveys from residents. The results are demographic data based on one-, three-, or five-year sampling periods. In this project, five-year estimates from the most recent end date, 2013, were used as they contain the lowest margin of error. In addition, they were produced from statistical trends calculated from data obtained over a five-year period and the closest period available to 2015 VA data used for facilities in this study. The source files were imported into ArcMap using the data conversion tools, however, most fields were translated as strings, which could not be used to conduct analysis or classify maps. Therefore, fields were added for each column as either a short or long integer or float for an attribute, and the field calculator was used to translate the numbers saved as text to numbers in the new column. The old column was then deleted from the table, preventing confusion during later processing.

All veteran demographic data was retained from the ACS file, however, only the total veteran population was used for this study. The complete list of fields for this data are shown in Appendix A and include not only population data, but classifications by service era for veterans serving during designated conflicts (e.g. Gulf War, Vietnam, or World War II), age, race, education, disability, and employment. Retaining the additional demographics provides the ability to model accessibility patterns for specific groups such as by age, gender, service era, or socio-economic characteristics. Therefore, it was worthwhile to retain the data in case the project was modified or follow-on analysis was desired. The ACS data were converted into tables usable in ArcMap and joined to U.S. Census Bureau shapefiles. There were three files, one for each state, joined to the census tracts polygon by a census tract identifier. Figure 9 shows the total veteran population by census tract for the three state files once merged.

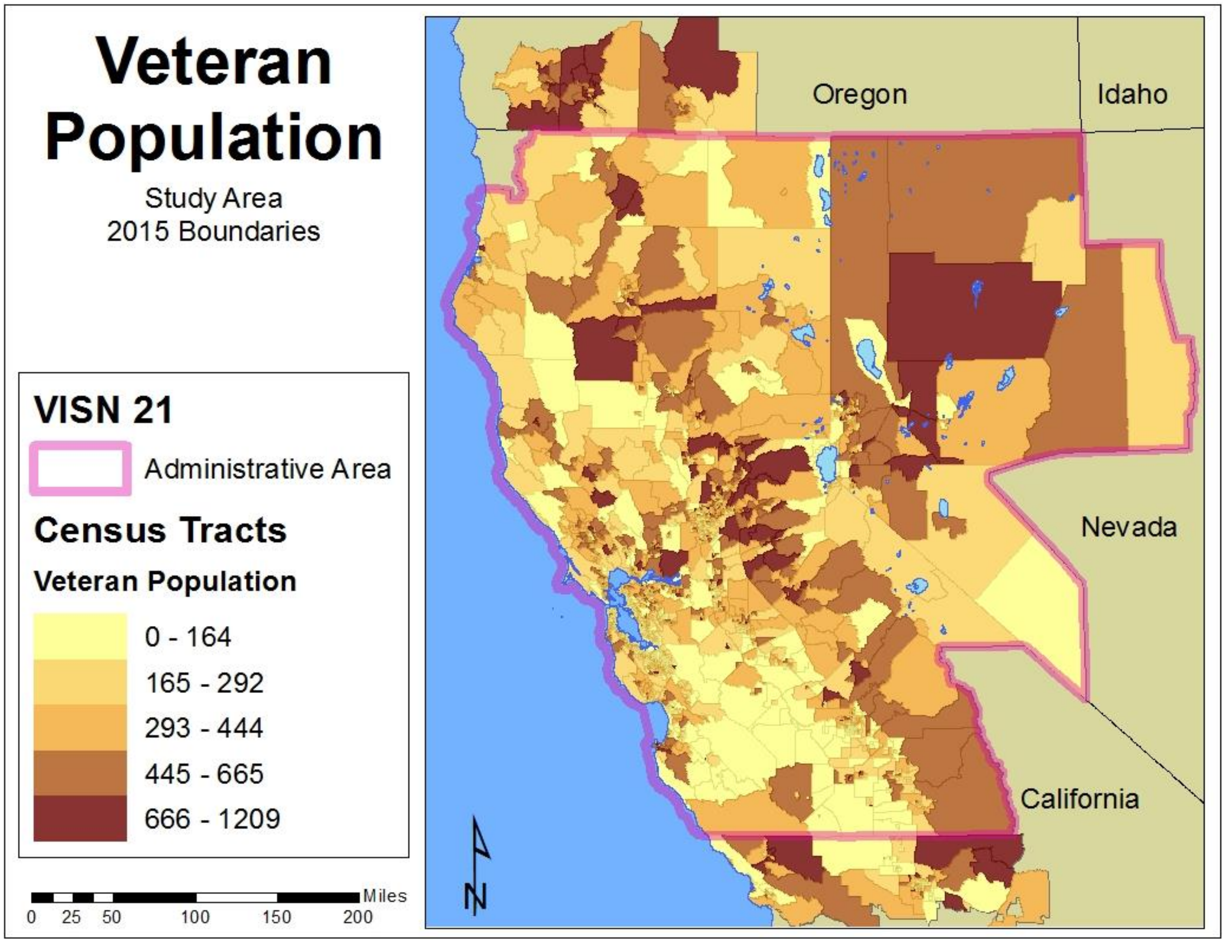

Figure 9 Total Veteran Population by Census Tract

3.1.3. VA Healthcare Facilities

To understand data associated with veteran primary care clinics, it is necessary to first understand the organization of VA healthcare systems. Facilities within the Department of Veterans Affairs are organized under a hierarchy that begins at the top level with the department having overarching responsibility for all matters related to veterans. These are managed under three administrations: Veterans Health Administration, Veterans Benefits Administration, and National Cemetery Administration. All health care facilities are run by the Veterans Healthcare

Administration and managed administratively under Veteran Integrated Service Networks (VISN). Each VISN contains several Healthcare Systems (HCS) that include large medical centers and hospitals, outpatient clinics, nursing homes, veteran centers, veteran canteens, and mental health facilities. This study used the organization of VISN 21 based on Fiscal Year 2015 boundaries as all other data collected was for the same period. The VISN 21 boundaries expanded to include the Las Vegas area beginning with Fiscal Year 2016.

As with the census tracts, facilities in a neighboring VISN were included if in close proximity to the administrative boundary as populations may be within a catchment of these facilities if they are closer. An initial examination of the map showed that there were five facilities that border VISN 21, but belong to neighboring VISNs. Since these might well be the closest facilities to veterans in the VISN 21 based on the 60-minute distance threshold, they were included in the analysis.

For this project, only information from facilities related to primary care was considered. Hospitalization and specialized care has many limitations in availability and capacity. It was not expected that the same level of accessibility be provided for this type of care. This difference was evident in varying rules included in the Veterans Access, Choice, and Accountability Act of 2014. The VA expects that travel and wait times for appointments would be extended for specialized care. Also, each specialization has different criteria and services for different populations and demographics whereas primary care is used by the population as a whole.

Healthcare facilities of interest for this research were developed as point data, based on geocoding the address of each facility denoted as providing primary care in the VA data. A table of addresses was created from the VA healthcare website and validated against provider information from the FOIA response. The table of address is included in Appendix B. Other user-created shapefiles were available online, however, it was impossible to assess data validity. To insure accuracy, the table of addresses was modified and then geocoded using ArcGIS Online to place clinics into a shapefile containing all the points. The facilities for the study are shown in Figure 10.

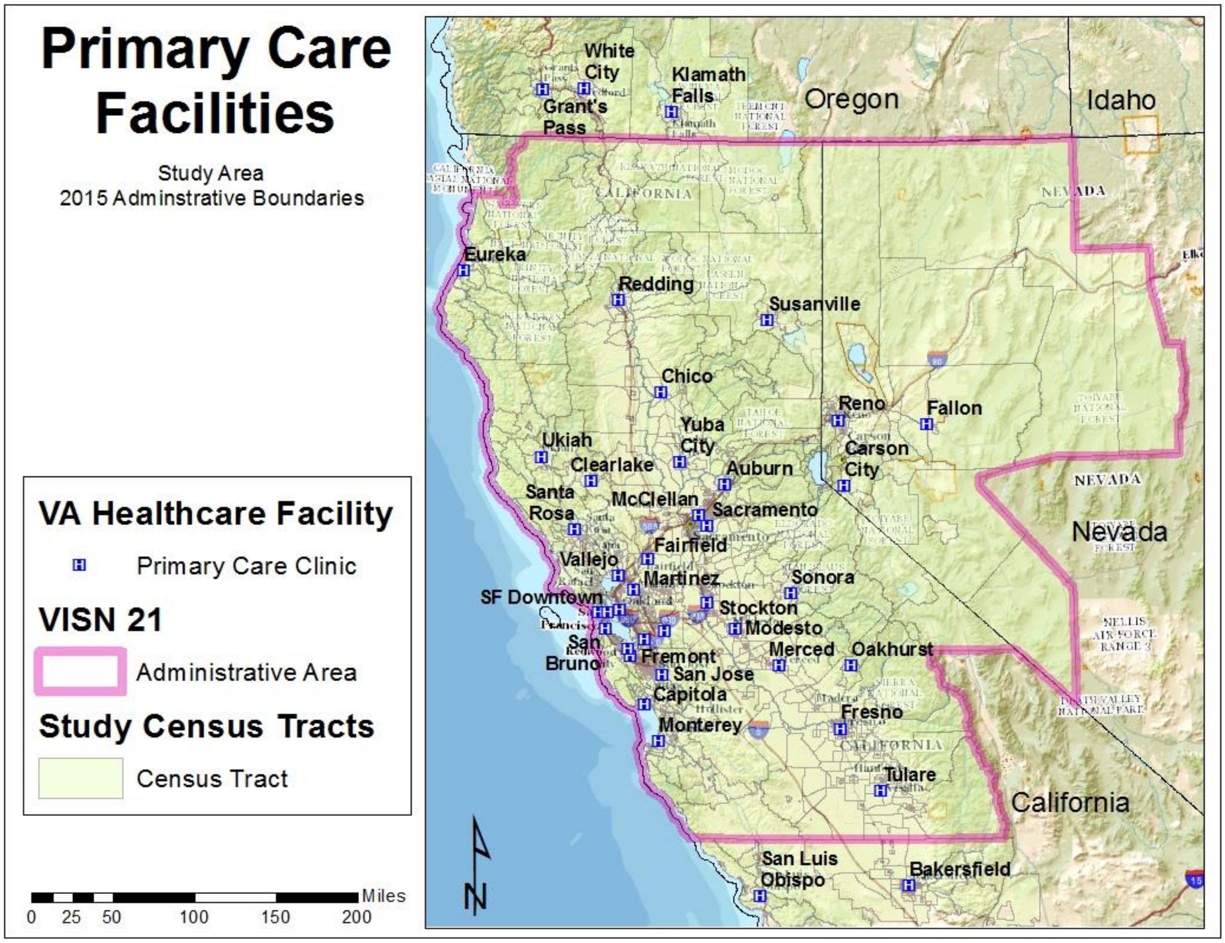

Figure 10 Selected Healthcare Facilities

3.1.4. Primary Care Supply

For each facility to be assessed, attributes of the number of available primary care providers (i.e. physician and physician assistants) were joined to each facility. Primary care provider numbers were an important aspect of determining accessibility as this represents the supply side for care. Information on the number of providers was provided in an e-mail from

Rebecca J. Dominy, VISN 21 FOIA manager, December 17, 2015, for each of the facilities within VISN 21 as a measure of Full Time Equivalent (FTE); a standard heath care industry measurement. An FTE is the hours worked by an employee on a full-time basis. This converts the hours worked by several part-time employees into full-time employees.

VISN 21 provided information because of the FOIA request, but no response was received for the three facilities located in VISN 20 and two in VISN 22. Therefore, using the data from VISN 21, the FTE was interpolated for these facilities. The FTE median was identified for each facility type and applied as the provider attribute for each of the VISN 20 and VISN 22 facilities. This was needed to execute the model and account for accessibility along the edges of VISN 21. The number of primary care providers at each facility was necessary to assess physician-to-population ratios to assess primary care supply.

3.1.5. Road Networks

In order to determine catchment areas and assess travel time in accordance with the Veterans Access, Choice, and Accountability Act of 2014, it was necessary to build a road network. TIGER Line Files were downloaded from the U.S. Census Bureau website and stored in a geodatabase. TIGER Line Files with a sufficient level of detail for the study area were contained in .zip files by county. Therefore, each file was downloaded based on the assessed maximum extent of the study area and included 106 files. These files were uncompressed and then merged into one shapefile.

There are 14 features in the TIGER files Road/Path Features Superclass designated by a MAF/TIGER Feature Class Code (MTFCC) shown in Table 3. Of these, only the feature classes easily traversed by automobile were used for this study and include the MTFCC: S1100, S1200, S1400, S1630, and S1640. Therefore, a selection by attributes was executed to only use segments containing these codes. The exclusion of S1500 (4WD Vehicular Trail), S1740 (Private Roads), S1780 (Parking Lot Road) caused some segments to be isolated from the rest of the network depending on how they were classified when digitized. This limitation is discussed in Chapter 5.

Table 3 MAF/TIGER Feature Class Code (MTFCC) Definitions (U.S. Census Bureau 2013)

MTFCC	FEATURE CLASS	DESCRIPTION
S1100	Primary Road	Primary roads are generally divided, limited-access highways within the interstate highway system or under state management, and are distinguished by the presence of interchanges. These highways are accessible by ramps and may include some toll highways.
S1200	Secondary Road	Secondary roads are main arteries, usually in the U.S. Highway, State Highway or County Highway system. These roads have one or more lanes of traffic in each direction, may or may not be divided, and usually have at-grade intersections with many other roads and driveways. They often have both a local name and a route number.
S1400	Local Neighborhood Road, Rural Road, City Street	Generally, a paved non-arterial street, road, or byway that usually has a single lane of traffic in each direction. Roads in this feature class may be privately or publicly maintained. Scenic park roads would be included in this feature class, as would (depending on the region of the country) some unpaved roads.
S1500	Vehicular Trail (4WD)	An unpaved dirt trail where a four-wheel drive vehicle is required. These vehicular trails are found almost exclusively in very rural areas. Minor, unpaved roads usable by ordinary cars and trucks belong in the S1400 category.
S1630	Ramp	A road that allows controlled access from adjacent roads onto a limited access highway, often in the form of a cloverleaf interchange. These roads are unaddressable.
S1710	Walkway/ Pedestrian Trail	A path that is used for walking, being either too narrow for or legally restricted from vehicular traffic.
S1640	Service Drive usually along a limited access highway	A road, usually paralleling a limited access highway that provides access to structures along the highway. These roads can be named and may intersect with other roads.
S1720	Stairway	A pedestrian passageway from one level to another by a series of steps.
S1730	Alley	A service road that does not generally have associated addressed structures and is usually unnamed. It is located at the rear of buildings and properties and is used for deliveries.

S1740	Private Road for service vehicles (logging, oil fields, ranches, etc.)	A road within private property that is privately maintained for service, extractive, or other purposes. These roads are often unnamed.
S1750	Internal U.S. Census Bureau use	Internal U.S. Census Bureau use.
S1780	Parking Lot Road	The main travel route for vehicles through a paved parking area.
S1820	Bike Path or Trail	A path that is used for manual or small, motorized bicycles, being either too narrow for or legally restricted from vehicular traffic.
S1830	Bridle Path	A path that is used for horses, being either too narrow for or legally restricted from vehicular traffic.
S2000	Road Median	The unpaved area or barrier between the carriageways of a divided road.

Additionally, to refine the study area and reduce the number of census tracts outside the VISN and road segments needed for the network, a few processes were executed. First, all layers were projected to the same California (Teale) Albers US (Feet) projection. This ensured that all measurements were the same. Next, using the ArcGIS Online Service Area tool, 60-minute drive-time polygons were created. The ArcGIS Desktop map was then intersected with these 60-minute service areas drawn outward from each VA primary care facility to streamline the number of census tracts. The purpose was to identify for inclusion only those census tracts or VA facilities outside the VISN 21 boundaries which might possibly factor into the analysis on the edges of the study area. Shapefiles from ArcGIS Online were imported to ArcGIS desktop to facilitate this. Once all factor census tracts and facilities were selected, the road segments from the MAF/TIGER shapefile was clipped to the same area. This reduced the number of line segments in the shapefile from over 1,270,000 to 673,362.

Once the road segments were selected, a field was added to assign travel speeds for each type of feature. California identifies basic speed limits in the California Driver Handbook (2011) based on the road type. In this manual, highways have a maximum speed of 65 miles-per-hour in most cases and business and residential streets have a basic speed of 25 miles-per-hour unless otherwise posted. Alleys and blind or unmarked intersections are limited to 15 miles-per-hour. These speed limits are the maximum and are reduced depending on weather and visibility. As these roughly coincide with the MFTCC, the Field Calculator was used to assign specific values to each segment based on the MFTCC value. Therefore, Primary Roads, based on the description stated in Table 3, were assigned a value of 65. Secondary Roads, usually U.S. and state highways, were given a speed of 45 to account for the fact that the speed will vary based on location and grade. Service Roads were given a value of 35 as there was no corresponding description in the California Driver Handbook (2011). Local Neighborhood Roads, Rural Roads, and City Streets were assigned a value of 25 based on the guidelines in the driver handbook. Finally, ramps were given values of 15.

To create a network capable of distance and time calculation, a field was added for travel time. The length of each segment was calculated in feet to populate a Shape_Length field. A Travel_Time field was also added to assign the total time in minutes it would take to travel that segment and a field calculation was used to assign a value based on road class by MFTCC. The formula divides the shape length by feet per minute as follows:

$$Travel\_Time = \frac{Shape\_Length}{(Speed \times 88)} \tag{5}$$

Where Travel_Time is the time in minutes required to travel the line segment based on the speed limit. The [Shape_Length] is the length of the segment in feet. [Speed] is the assigned speed limit for the segment in miles-per-hour based on the MFTCC. The *88 is the result of 5280/60 and is used to convert miles per hour speed into feet per minute. The result of the Field

Calculator is the Travel_Time field which is populated with the number of minutes required to travel each segment. This provided the necessary data to determine travel time to facilities.

After the speeds were applied and travel time for each segment calculated, a topology was created to identify problems with the shapefile before building the network. Since this is a simple network which does not account for turn or travel restrictions, only the “Must Not Overlap” rule of ArcMap was applied. This was necessary as several segments had duplicates due to having multiple names or feature class relationships. For example, a single road segment may exist in multiple entries based on MTFCC with a local have a name, as well as a county road, state highway, and U.S. highway designator.

Also, due to the duplication of designators, the MFTCC were often different for overlapping segments. Therefore, there were areas where the speed was duplicated such as where a U.S. highway passed through a town. The highway may have been assigned a 45 mile-per-hour speed limit, yet the road was also listed as Main Street, with a 25 mile-per-hour speed limit. This caused 67,323 overlap errors. Each was quickly evaluated and a choice was made based on the location. For example, if a road was listed both as Main Street (S1400) and as U.S. Highway 50 (S1200), the U.S. Highway was subtracted leaving the S1400 feature and applicable speed. This prevented higher speeds through towns. The opposite was done outside of what appeared to be more populous areas. This reduced the number of features in the network shapefile to 605,796 segments.

The next step in building the network was to run the Integrate tool. This created coincident vertices where the lines intersected. Before running the tool, it was impossible to properly run tools using Network Analyst as many segments had no connectivity. This tool ensured all segments were connected.

The final step to building the network was to create the network dataset using the Network Analyst toolbox and the optimized shapefile of road features. Since elevation data was not available, a simple dataset was created using only the default global turns option. Additionally, the dataset does not include information on one-way streets or other restrictions. Although this data would add more detail to the dataset, it was not readily available and did not make a substantial difference due to the size of the study area. Finally, once the network dataset was processed, the topology was executed again to ensure there were no new errors and several runs were made using the New Route tool to ensure connectivity of roads.

Once the network was built, a service area calculation was executed using the Network Analyst tools to test the validity of the network. For validation, the result using the network developed for this study was compared to the 60-minute service area result completed using ArcGIS Online services. The results of the two service area calculations were close in most cases, but had some differences, particularly in rural areas due to the how speed limits were assigned to each segment. ArcGIS Online has greater resolution for each road segment in its database whereas the study area network could only assign speeds based on MFTCC Feature Class. Therefore, several S1400 Feature Class, particularly in rural areas, were assigned speeds of 25 miles-per-hour; however, in reality, these roads may have actual speed limits up to 55 miles-per-hour. Specific differences are noted in Chapter 5. The result of the study area network processing was a network that is slightly more conservative with regard to the Veterans Access, Choice, and Accountability Act of 2014, but was satisfactory within the scope of this project.

Although some census tracts have limited primary or secondary roads, the use of census tract centroids allowed snapping centroids along the road lines at the closest point to the network for the analysis. This is a common practice for determining network distance measurements from facilities (DeWulf et al. 2013). The census tract centroid becomes the center of the demand point for the veteran population contained within the census tract polygon. This point was then used along with the facility point to calculate the network distance. As previously stated, this distance determines which populations are within the 60-minute drive-time threshold. Accessibility models use point-to-point calculations during processing.

3.1.6. Availability and Acceptability Indices

Availability and acceptability indices are non-spatial data on facility performance used to weight some models. For this study, wait-time, patient satisfaction, and a composite of these were chosen for this purpose. Wait-time thresholds for appointments are dictated by the Veterans Access, Choice, and Accountability Act of 2014, publically available, and published monthly. Patient satisfaction data is collected by the VA from surveys which are scored as a percentage of satisfaction of care. Patient satisfaction scores were obtained via the FOIA request, but since January 2016, this data is published quarterly online by Fiscal Year, beginning in the 4th Quarter, Fiscal Year 2015. Therefore, the data published online was used as it was readily available and consolidated using a single method for all VHA facilities in one place and includes data that was not returned for the FOIA request for VISN 20 and 22. These two major indices were used as impedance to accessibility.

Data on wait times for appointments and primary care satisfaction was available online, but in Excel or .pdf format. For this study, spreadsheets from the Strategic Analytics for Improvement and Learning Value Model (SAIL) website were used, which is a VA system that summarizes VHA system performance. SAIL assesses 25 quality measures, including patient satisfaction, as a measure of overall efficiency at individual VA medical facilities. Data tables are updated quarterly (VA 2016). Reports were downloaded in a single spreadsheet for each facility and used to modify attributes.

Wait times were transcribed from these reports provided online in accordance with the rules of the Veterans Access, Choice, and Accountability Act of 2014. Wait times were provided as groupings of time from the initial desired date to appointment completion date and indicated availability of services. Patient satisfaction data was an indicator of acceptability and was provided by the FOIA request was also included based on the metrics, but were also available as part of the SAIL spreadsheets. The SAIL reports were used as they standardized the reporting of metrics and time periods for all facilities including those for which FOIA responses were not received. For each of these, an additional column was added to the table used for geocoding through the creation of new fields and the table editor function of ArcMap. The relatively limited number of facilities made this manageable.

Information on wait times was collected for July, August, and September 2015 and then averaged by quarter to match the timeframe available for primary care satisfaction. Table 4 shows the percentage of appointments completed in 30 days (wait-time) and patient satisfaction scores taken from monthly and quarterly performance reports for facilities included in this study. All measurements from SAIL are on a 0-100 percent scale.

Table 4 VA Primary Care Facility Metrics

VISN	**ADMIN CODE**	**NAME**	**PERCENT COMPLETED**	**PATIENT SATISFACTION**
20	692	WHITE CITY HCS	98.41	56.548
20	692	SORCC	98.20	56.548
20	692GA	KLAMATH FALLS	99.83	56.548
20	692GB	GRANTS PASS	100.00	56.548
21	570	FRESNO HCS	96.27	62.576
21	570	FRESNO	96.00	62.576
21	570GA	MERCED	98.28	62.576

21	570GB	TULARE	97.64	62.576
21	570GC	OAKHURST	98.94	62.576
21	612	N. CALIFORNIA NCS	95.63	61.902
21	612A4	SACRAMENTO	94.76	61.902
21	612B4	REDDING	95.63	61.902
21	612BY	OAKLAND	97.52	61.902
21	612GD	FAIRFIELD	98.57	61.902
21	612GE	VALLEJO/MARE ISLAND	95.61	61.902
21	612GF	MARTINEZ	95.54	61.902
21	612GG	CHICO	95.36	61.902
21	612GH	MCCLELLAN	95.74	61.902
21	612GI	YUBA CITY	98.35	61.902
21	640	PALO ALTO HCS	97.29	71.873
21	640	PALO ALTO	97.89	71.873
21	640A0	MENLO PARK	98.23	71.873
21	640A4	LIVERMORE	96.35	71.873
21	640BY	SAN JOSE	97.57	71.873
21	640GA	CAPITOLA	99.76	71.873
21	640GB	TUOLUMNE	95.24	71.873
21	640GC	FREMONT	98.75	71.873
21	640HA	STOCKTON	96.16	71.873
21	640HB	MODESTO	95.26	71.873
21	640HC	MONTEREY	96.93	71.873
21	654	RENO HCS	96.79	64.098
21	654	SIERRA NEVADA	96.49	64.098
21	654GA	SIERRA FOOTHILLS	99.60	64.098
21	654GB	CARSON VALLEY	99.20	64.098
21	654GC	LAHONTAN VALLEY	96.91	64.098
21	654GD	DIAMOND VIEW	99.92	64.098
21	662	SAN FRANCISCO HCS	96.96	73.509
21	662	SAN FRANCISCO	97.60	73.509
21	662GA	SANTA ROSA	92.29	73.509
21	662GC	EUREKA	96.96	73.509
21	662GD	UKIAH	95.78	73.509
21	662GE	N. SAN BRUNO	99.53	73.509
21	662GF	SAN FRANCISCO CBOC	98.82	73.509
21	662GG	CLEARLAKE	97.75	73.509
22	691	LOS ANGELES HCS	95.00	66.539
22	691GD	BAKERSFIELD	97.24	66.539
22	691GK	SAN LUIS OBISPO	97.77	66.539
22	691GL	SANTA MARIA	95.13	66.539

3.2 Calculating Accessibility

Two models were developed and four separate runs were executed for this analysis. The first used the standard 2SFCA model. The other model used a modified E2SFCA model to weight accessibility based on the acceptability indices. These results were mapped separately and then mapped to show the change between the 2SFCA and modified E2SFCA models.

3.2.1. Two-Step Floating Catchment Area

The two-step floating catchment area (2SFCA) is a methodology for combining related information into an index for comparison across differing locations. It is useful in a GIS to measure spatial accessibility as a ratio between availability (supply) and a population (demand). The two steps, in general, assess availability at the supply locations as a ratio to their surrounding population within a threshold travel time or distance and sum the ratios derived in the first step around each demand location.

Relationships were calculated based on a catchment centered on administrative boundary centroids; in this study census tract centroids were used. The catchment "floats" from one population center to another based on a distance factor representing the potential willingness for a patient to reach a physician. For this study, the maximum allowable distance of travel was the 60-minute drive-time allowed under the Veterans Access, Choice, and Accountability Act of 2014.

The result of this model creates a regional availability measurement (Luo 2004), providing accessibility scores for geographic areas to particular primary facilities. The accessibility score is an index of spatial accessibility applied to populations residing within the chosen geographic boundary. The model does not provide a benchmark for acceptable accessibility, but provides a comparison of accessibility by areal unit based on spatial relationships of the supply (provider) and demand (population). Scores were affected by the supply, demand, and a distance factor, either distance or travel time between the two. The only absolute score is a score of zero, which represents no accessibility within the determined requirements. Beyond that, the higher the score, the greater access to care for populations within the geographic area. Thus, in the 2SFCA, it would be expected that the accessibility score would be greater closer to providers where the supply was greater and the demand was lower. Conversely, the score would be very low if the demand greatly exceeded supply, even if the distance were small.

The method was mostly straightforward to account for these variables of supply, demand, and distance. The first step of the 2SFCA method is shown below:

For each provider (j):

$$Rj = \frac{Sj}{\sum k \in \{djk \leq dmax\} Pk} \tag{6}$$

This formula determined what populations (k) of size Pk are located within the catchment of each service provider (j) of volume Sj. This defined the physician-to-population ratio Rj within a catchment. This is the potential demand for the healthcare service. The second step allocates physician-to-population ratios to the population as shown below:

For each population (i),

$$Ai = \sum_{j \in \{dij \leq dmax\}} Rj \tag{7}$$

The formula determines which providers (j) are located within the catchment of each population (i), and aggregating the Step 1 (Rj) scores to calculate a location's accessibility score (Ai). The only decision required in applying the method was the catchment size (dmax) which was applied to both steps based on the maximum allowable service area under the federal law (McGrail 2012).

In ArcMap 10.2., the process was executed against the datasets previously discussed. This was accomplished through several sum and join functions to assign physician-to-population ratios to the census tracts centroids. Physician-to-population proximity (d) was measured as travel time by calculating distance separation on roads of varying speeds from point-to-point (i.e., nearest road to census-tract centroid to nearest road to primary care facility). Primary care providers were represented by their geocoded address entered using ArcGIS Online. A similar process was used for the second step which applies the accessibility score to the census tract centroid. Those were then applied to the census tract as a whole.

3.2.1.1. Step 1 - Primary Care Catchment Calculation

A new ID field was created for the Facility Table as well as the census tract table. This allowed reference of the catchment between the two features. These two tables were the input for execution of an OD Cost Matrix. The ID field for the census tract and facility represented an Origin ID and Destination ID. The result was a matrix of 140,600 pairs of tracts and facilities. Through selection by attribute, only the instances where the travel time was equal or less than 60-minutes travel time were selected and exported; reducing the matrix to 18,892 pairs. This represented the catchment areas of the facilities.

The tables were then joined by the census tract ID field. The population field in the joined table was next summarized (sum) by the facility ID in a new table in which the population was within a distance of 60 minutes from each facility. Using the sum calculation output, a new field was created in which the physician-to-population (PtP) ratio was calculated in the new field using the formula:

$$PtP_{Ratio} = \frac{Pri\_Care}{Vet\_Pop} \tag{8}$$

3.2.1.2. Step 2 - Census Tract Accessibility Calculation

Once the first step was completed, the table was joined to the OD Cost Matrix table by the Origin ID field to create a new table which contains the census tracts centroid's relationships to each facility and the time between each. The physician-to-population ratio was then summarized by Destination ID field to create the accessibility score for each primary care facility. The table was then joined to the census tract table by the Tract ID field to create a table of accessibility score by tract. A tract with a score of zero had no accessibility within the distance factor. A true null value indicated the census tract has zero veteran population. As these relationships were calculated on census tract centroids, they were then joined to the census tract polygons for mapping purposes.

3.2.2. Modified Enhanced Two-Step Floating Catchment Area

The basic 2SFCA method used a dichotomous distance function where the patient and provider were either within the 60-minute travel allowance (1) or outside the allowable travel distance (0). The result was all census tracts within the catchment areas were given equal weights before the physician-to-population ratio was calculated. The enhanced two-step floating catchment area (E2SFCA) built on the model by weighting the effects within the allowed distance for accessibility within a single catchment. Traditionally, distance decay functions to enhance this method are either discrete or continuous to add impedance to accessibility calculations. In this study, a modified E2SFCA model was developed as was hypothesized by Wang and Luo (2005).

Veterans healthcare does not necessarily hold true to a traditional notion for distance decay. Veterans prefer VA healthcare despite access problems based on the perceived high quality of care, the concept that it is an earned benefit, and the idea that the VA treats service-related conditions better than the private sector (VFW 2015). Therefore, distance decay impedance alone is not necessarily applicable in assessing accessibility for veterans. The greater problem is consistency of care, which is indicated in wait-times for appointments and satisfaction of care. Therefore, the E2SFCA model was modified by weighting impedance factors added to the table based on the appointment completion performance (wait-time) and primary care satisfaction as facility attributes.

In this study, weights were applied to the initial scores from the 2SFCA based on the VA reported wait-time (completed appointments within 30 days in accordance with the Veterans Access, Choice, and Accountability Act of 2014), patient satisfaction scores for primary care, and a composite of these two measures. The three modifications provide a method to incorporate aspatial measures of availability and acceptability into the 2SFCA in place of standard distance decays. All weighting was based on legal requirements, reporting, and standardized healthcare survey measurements. The application of weights generally causes a decline in accessibility scores based on the applied weight in a similar fashion as a distance decay (e.g., a patient satisfaction score of 82% would apply a weight of .82 over the 2SFCA which initially scored a 1). If a facility has a 100% compliance with the law on wait-time or 100% patient satisfaction score, the original accessibility score for a census tract would remain unchanged from the 2SFCA results.

The different weights were indicators of the availability and acceptability of primary care for each provider location. If primary care was less available or acceptable, than the accessibility score applied to the census tract was reduced from the 2SFCA result. Lower satisfaction scores or increased wait times means access declines, whereas otherwise the access scores would be treated equally for all facilities. The differences could be interpreted as stressor on the facility and/or a likelihood of a desire to visit a specific facility. Therefore, more choices or facilities with better satisfaction scores or lower wait times would be considered more available and acceptable to the population within the catchment. To incorporate weighting into the process, the 2SFCA was computed with an additional step.

As the weighting is facility-centric, in the first step of the 2SFCA method, a new population field was added to the result of the 2SFCA to join the census tract and OD Cost Matrix data. This field was populated by multiplying the satisfaction or wait time weight by the population to create a modified population field. For the second step, a new ratio field was added to the 2SFCA table of joins from physician-to-population ratios for origins and destinations. The resulting formula was:

For each provider (j),

$$Rj = \left(\frac{Sj}{\sum k \in \{djk \leq dmax\} Pk}\right) Ix \tag{9}$$

This formula determines what populations (k) of size Pk were located within the catchment of each service provider (j) of volume Sj. This defined the physician-to-population ratio Rj within a catchment. This was the potential demand for the healthcare service and weights that facilities service by the acceptability index (Ix). The second step allocates physician-to-population ratios to the population as executed in the 2SFCA model and shown below:

For each population (i),

$$Ai = \sum_{j \in \{dij \leq dmax\}} Rj \tag{10}$$

The formula determined which providers (j) are located within the catchment of each population (i), and aggregated the Step 1 (Rj) scores to calculate a location's accessibility score (Ai). The results were joined to the census tracts polygons in the same way as with the 2SFCA model and mapped as classified by score and percent change, demonstrating the difference between the 2SFCA and modified E2SFCA results. This was repeated for each index: wait-time, patient satisfaction, and their composite.

Chapter 4 Results

In the examination of veteran healthcare accessibility within the VISN 21 administrative area, it was readily apparent that accessibility is not geographically homogeneous. For the most part, the majority of the veteran population within the study area had some access to Veterans Health Administration care; however, there were indeed areas where care was more accessible. These variations across the landscape were direct functions of the relationships of physical distance and physical access (supply and demand) relationships. When availability and acceptability were taken into account, the variation in accessibility across population areas was greatly affected.

Overall, within the study area, there were a total of 3,559 census tracts with a total veteran population of 955,002. Of those totals, 889,396 veterans living in 3,362 tracts have some level of access to VA health within the constraints of the Veterans Access, Choice, and Accountability Act of 2014. This means that an estimated 65,606 veterans within 197 census tracts have no access within regulatory requirements. Although this number is not small, it represents only 5.54% of the total census tracts and only 6.87% of the total veteran population within the study area. Therefore, 93.13% have some access to care, however, levels of accessibility vary greatly across this group.

This chapter presents the results and key findings of the model execution and modified runs. Specifically, the accessibility scores for the administrative area are explored and put into context from the results of the 2SFCA analysis. This analysis provides context as to where within VISN 21 veterans have varying levels of healthcare access and where access may be stressed or lacking. Additionally, each modified E2SFCA method is then addressed to examine the difference between the standard analysis and the enhanced methods. For each of the weighted factors, wait-times, patient satisfaction, and a composite of the two, the effect on accessibility is presented. Each is discussed as a function of the spatial relationship between the population and Veterans Heath Administration primary care options.

4.1 Spatial Distribution of Demand and Supply

The demand for VA healthcare was determined by the veteran population within each census tract. Included census tracts where either contained within VISN 21 or had a centroid within a 60-minute drive of a VA healthcare facility within VISN 21. The total number of veterans was not evenly distributed across the study area. As demonstrated in Figure 11, some of the concentrations of veterans were in more rural areas, such as the eastern edge of the Central Valley in California and northern Nevada. This was expected since current VA studies show that the rural areas of Nevada are growing in veteran populations while the number of veterans settling in California is decreasing (VA 2015b). According to the VA, about 24% of veterans live in rural areas and 57% of rural veterans receive healthcare through the VA. Additionally, between 2006 and 2014, VA-enrolled rural veterans increased 7% (VA 2015a). Therefore, the result of mapping the demand for this study reflects the general idea that veterans make up a larger percentage of the population in many rural census tracts.

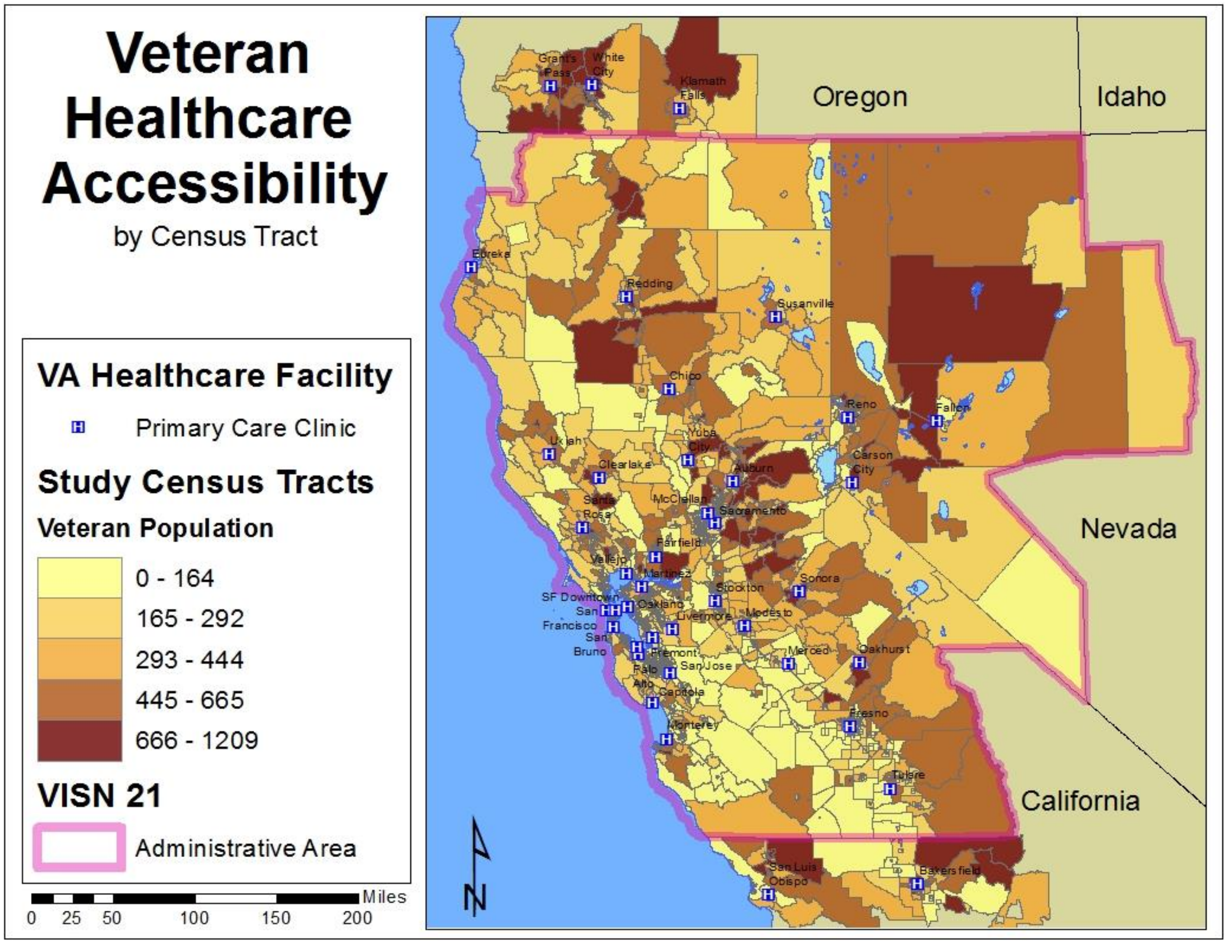

Figure 11 Veteran Population by Census Tract

To understand this population distribution better, the population of census tracts was normalized against the size of the census tract to create a population density map (Figure 12). This map shows that despite the large number of veterans residing in rural census tracts, the population is still concentrated around the San Francisco Bay area, Sacramento, Reno, and along the Interstate 5 corridor. Although there were rural census tracts with larger per capita veteran population, the size of these tracts means that although they may make up a greater percent of the total population in those tracts, the actual residences of the veterans likely were spread out over a larger area. The limitations of using census tract data are addressed in the next chapter.

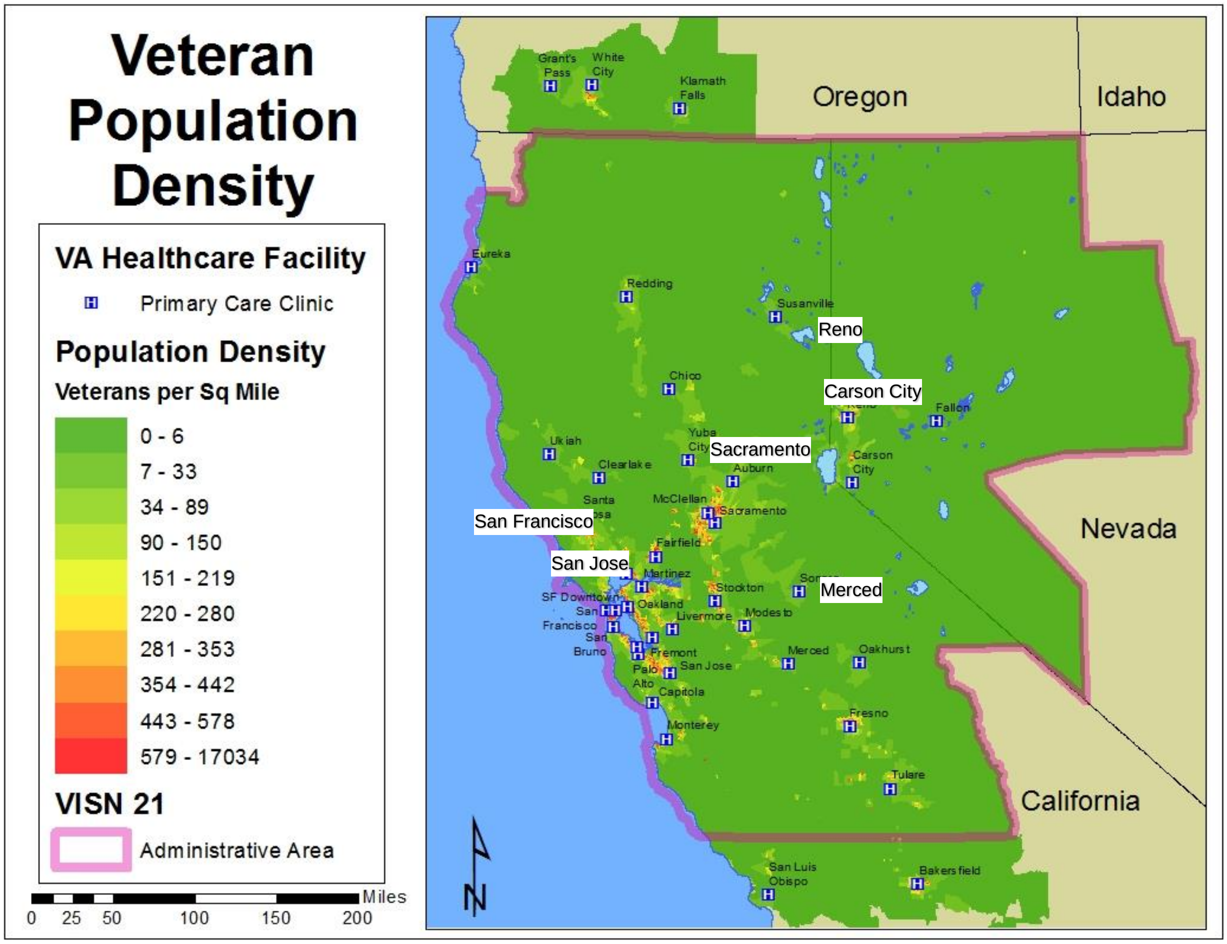

Figure 12 Veteran Population Density by Census Tract

Supply was represented by VA healthcare facilities located within VISN 21 or on the edges of the study area and having a 60-minute maximum driving distance to the census tract centroids within the VISN 21 boundaries. This, combined with the results of the population mapping, ensured accessibility calculations along the edges of the VISN accounted for the effects of other populations or facilities within the constraints of the law. Once this mapping was complete, there were 40 VHA facilities offering primary care services which could be accessible by populations from within VISN 21: 35 within the VISN, three within VISN 20 on the northern edge, and two in VISN 22 on the southern edge of the study area. The facilities and attribute variables used for 2SFCA and modified E2SFCA models are found in Table 4. Figure 13 shows the 60-minute driving distance from facilities as a result of network processing. It also shows some of the major network roads, but does not include rural and residential streets.

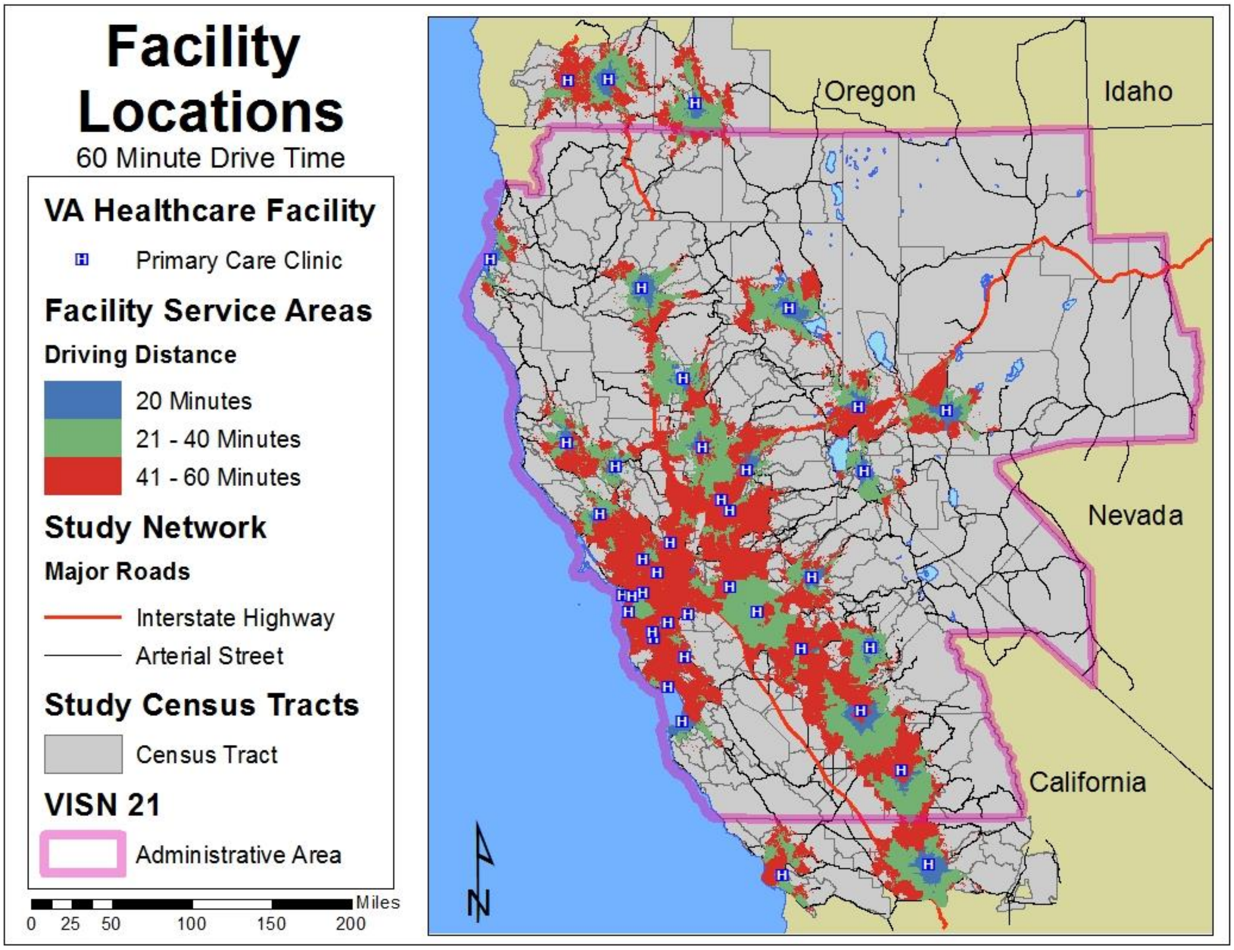

Figure 13 Facilities Meeting 60-minute Drive Time Requirement affecting VISN 21

The execution of these two processes provided an initial analysis of these spatial relationships between demand and primary care supply. The result when mapped is a bit misleading, because it indicates large portions of the study area have no access within the 60-minute requirement. Figure 14 shows the census tract with its centroid within the 60-minute drive time along the network. As the process can only assess drive time from point to point, many of the larger, more sparsely populated census tracts were excluded from the catchment of any particular clinic. Included census tracts were clustered around major population centers such as San Francisco, Oakland, Sacramento, as well as along the Interstate 5 and 80 corridors. Some of the census tracts with higher veteran numbers in the rural areas were excluded because drive times along rural roads prevented reaching the facility from the census tract centroid within the 60-minute cutoff. However, this is only an estimate. In the census tract where the centroid falls outside of the catchment area, it may not mean the entire or even the majority of the population has no 60-minute access because of uncertainty has to how the population is distributed within the census tract. This limitation is discussed further in Chapter 5.

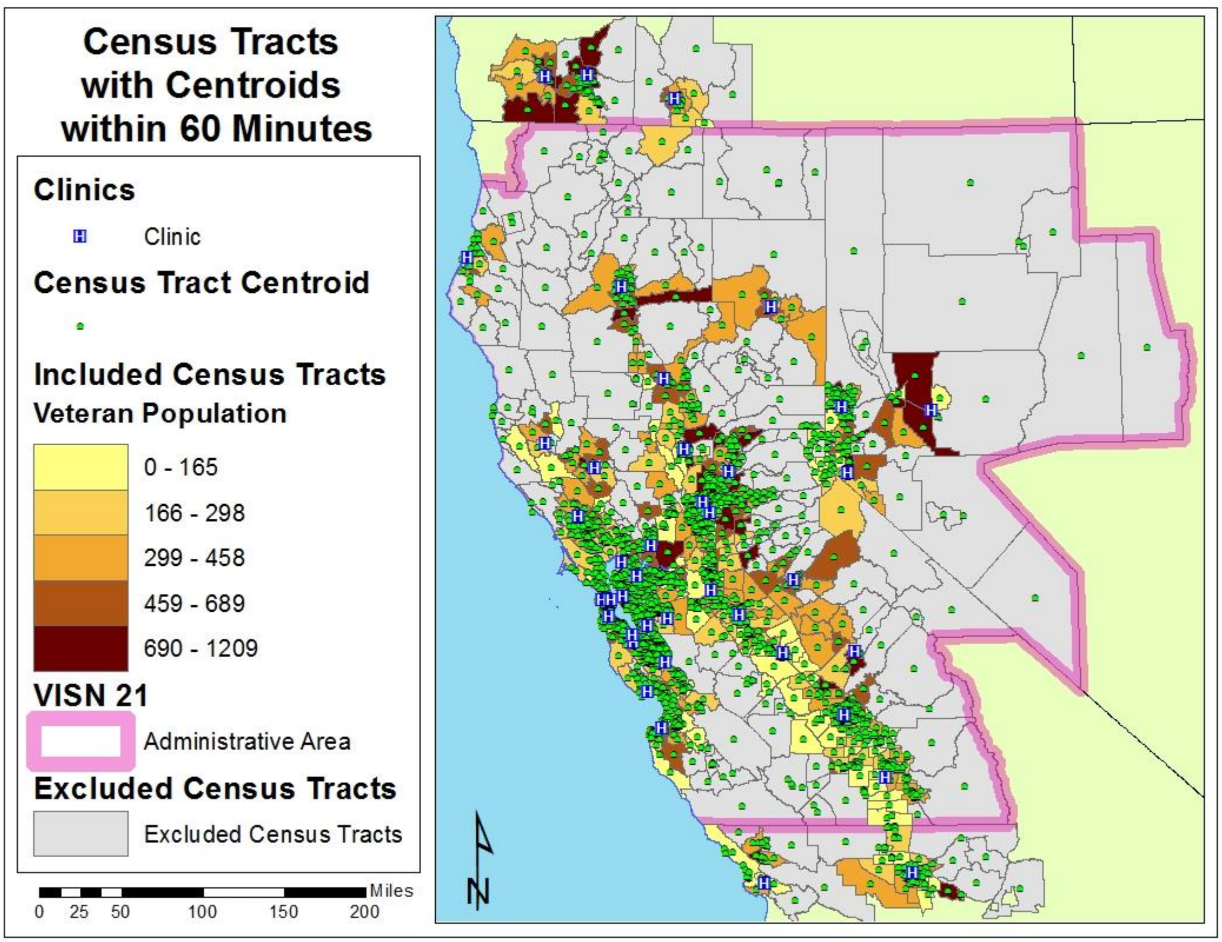

Figure 14 Census Tracts and Centroids within 60-minute Drive-Time

Overall, after processing the spatial data within the constraints of the Veterans Access, Choice, and Accountability Act of 2014, the initial results indicate that most of the veteran population is within the 60-minute driving distance for primary care as required under the law. The census tracts that do not fall within the regulatory requirements represent a large area, but not a large percentage of the population. Overall, when only looking at the geographic relationships between the demand and supply, a vast majority of the veteran population in the study area has at least some access to VA healthcare. This step in the process only shows the physical distance between the two groups, but does not measure the level of access these included populations experience. This was a result of the next steps using the 2SFCA methodology. The results of this part of the processing are summarized in Table 5.

Table 5 Census Tracts and Population with Access to VA Healthcare in accordance with the Veterans Access, Choice, and Accountability Act of 2014

Criteria	Total by Criteria	Percent of Total
Census Tracts with Accessibility	3,362	94.46%
Census Tracts without Accessibility	197	5.54%
Population with Accessibility	889,396	93.13%
Population without Accessibility	65,606	6.87%
Physical Area with Accessibility (sq. miles)	40,859.48	26.72%
Physical Area without Accessibility (sq. miles)	112,053.18	73.28%

4.2 Assessment of Standard 2SFCA Analysis

The 2SFCA results show the level of access for populations within a catchment. As discussed in Chapter 2, the methodology was chosen as it accounts for a population's ability to travel across boundaries and accounts for the impact of possible multiple populations on supply. The floating catchment areas provide a result that enabled more realistic modeling with unrestricted utilization of all locations within the 60-minute driving distance, and provides for overlapping catchments. The results show variation in the amount of services within the catchment area that were considered accessible to the population. All services outside the catchment area were not accessible. The results presented here thereby represent a population-based indexed accessibility score (Ai) for each possible census tract. The results of the formula are absolutes as they are a ratio of ratios between the population and physician-to-population ratio for each facility; however, the results are relative, comparing these relationships across space. Therefore, scores provide a measure of accessibility within the study area, but does not definitively state accessibility as “good or bad” without additional analysis or applied constraints. What this does provide is a comparison of spatial relationships. Since it is built from physician-to-population ratios, as the number increases, the level of accessibility for that population increases as there is more opportunity for care.

The basic 2SFCA model shows the accessibility scores based on the spatial relationships of census tracts and VA facilities offering primary care. The results of this model were influenced by only two factors: the relationship between the population within the determined distance of facilities and the total number of primary care providers at those facilities. The initial results of this model show a wide variance in accessibility scores classified using natural breaks across the study area shown in Figure 15. The large red areas with a score of “zero” demonstrate areas of “no accessibility.” This was a direct result of the census tracts not meeting 60-minute driving distance thresholds and thereby failing to meet that part of the geographic access requirement of healthcare accessibility. Darker green areas represent areas of increased access.

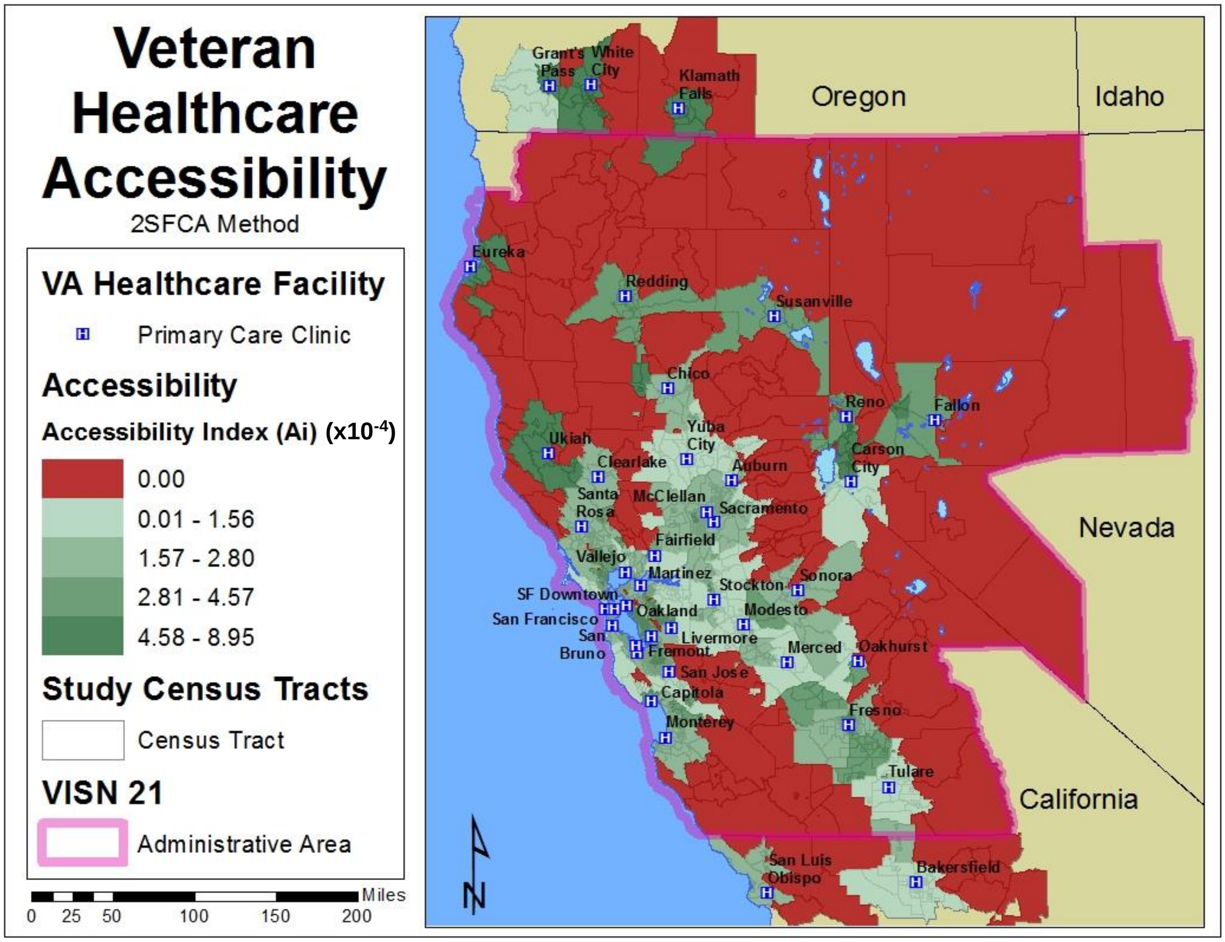

Figure 15 2SFCA Accessibility Score Results

Several of the populations with the greatest access were located in the more rural areas. This was not totally unexpected using this method, as travel speeds are higher and populations fall into multiple facility catchments in several cases. Also, despite some of the census tracts in the rural areas having larger veteran populations, the tracts were larger in area, so there were fewer census tracts within a facility catchment. The bulk of tracts fall into the second lowest classification reflecting the higher physician-to-population ratios due to the large concentration of smaller census tracts in the more densely populated areas.

Figure 16 is a histogram of the 2SFCA results with the census tracts with a score of 0 removed. The red lines indicate the classification breaks (excluding the 0 class) from the Jenks classification in ArcMap. Analysis of the histogram indicates the results depart from the normal distribution. The data is greatly skewed positively with a very high kurtosis. This kurtosis is a strong indication of multivariate data producing significant outliers in large datasets (DeCarlo 1997). The result is a quite long right tail containing clusters of incidences away from the mean. Although there is a high frequency of incidences around the mean, the kurtosis suggests that the distribution is more peaked than expected and the actual distribution crosses the normal at least twice on either side of the mean. Furthermore, as the kurtosis is positive, the data distribution is identified as multimodal with several peaks, another indication that the result does not follow a normal distribution. Overall, the histogram suggests that the distribution of scores was not random and a result of the interaction of the variables.

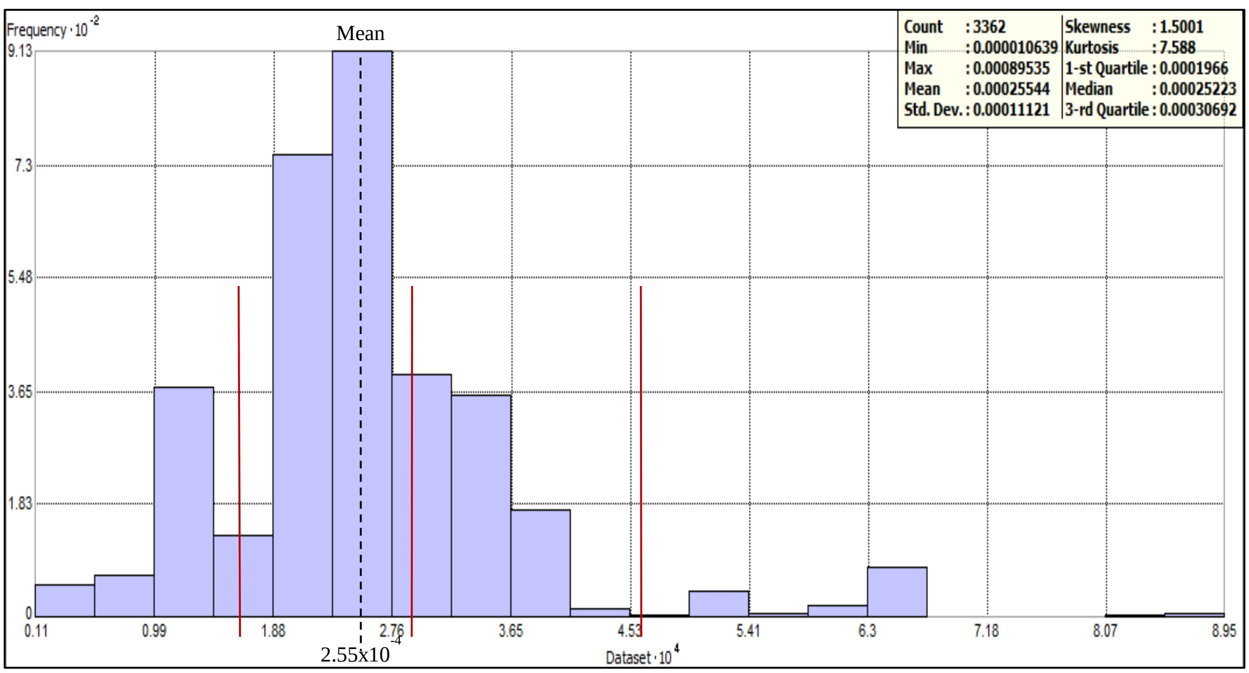

Figure 16 2SFCA Results Histogram

The impact of a population having access to multiple facilities also increases access for many of the census tracts as it improves the physician-to-population ratio allocated to a census tract. Figure 17 focuses on the San Francisco Bay area. Here, despite the large number of census tracts and larger concentration of veteran population, accessibility scores remain relatively positive. For example, the census tracts located between Oakland and Livermore have higher scores, as there are multiple facilities within the 60-minute drive time requirement. Conversely, some of the more urban tracts, such as those around the Palo Alto and Menlo Park facilities, have decreased accessibility despite the facilities being in close proximity. This results from having higher veteran numbers relative to the number of primary care physicians in these catchment areas. In other words, the population in the census tracts around these facilities, despite having more facility possibilities, have to compete more for primary care.

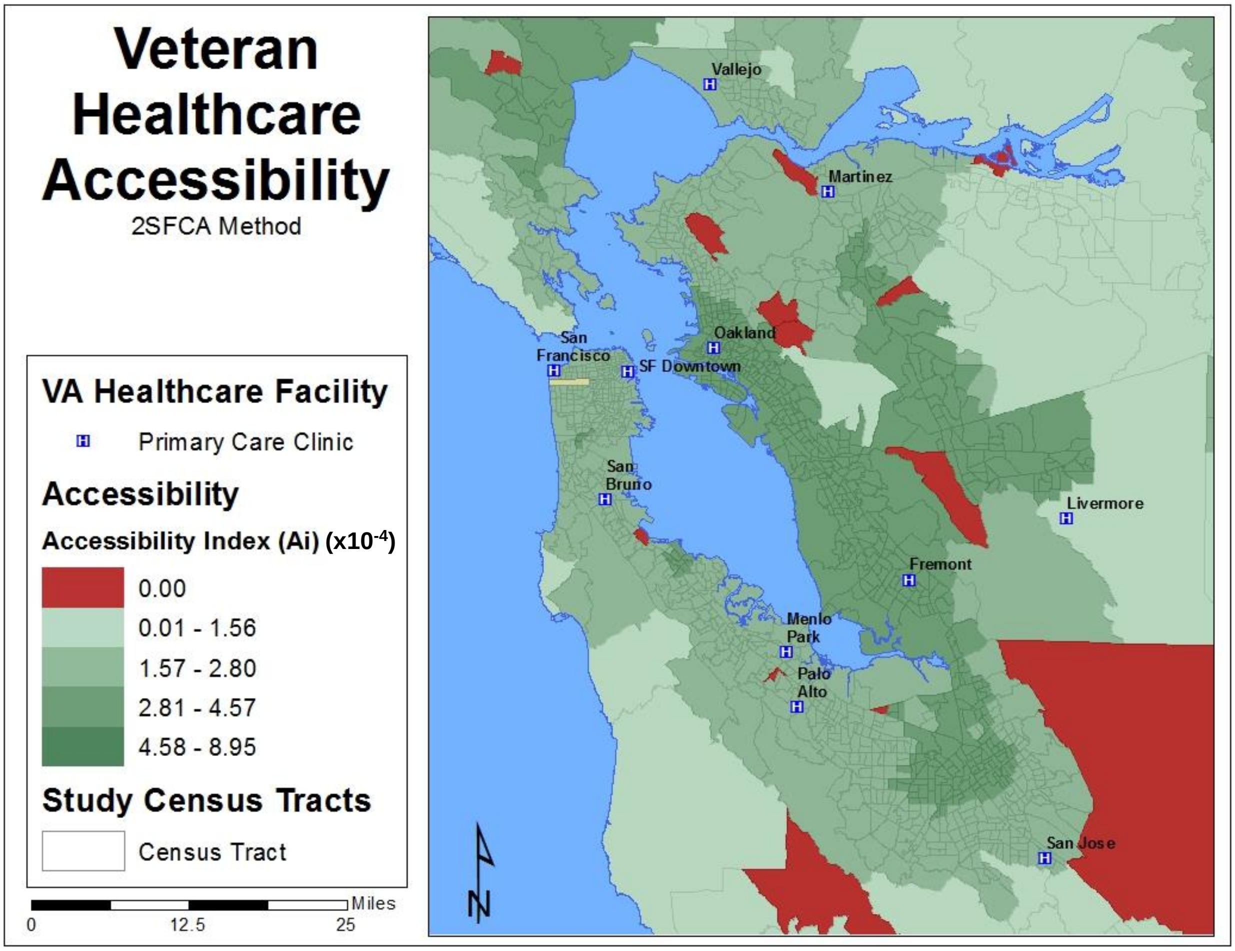

Figure 17 Accessibility in the San Francisco Bay Area

The relationships demonstrate where facilities may be more stressed and populations may have more difficulty readily receiving care. Accessibility for populations in these areas would increase by increasing the physician-to-population ratios either through adding additional providers at existing facilities or opening additional facilities. The uncolored area in downtown San Francisco was a “true null” with no veteran population as the tract incorporates only Golden Gate Park. There were some limitations receiving an accurate measurement for some census tracts due to the resolution of the data used for the analysis. This was more common on the edges of rural areas where the census tract centroid may be located some distance from actual population centers. Limitations are discussed in greater detail in Chapter 5.

4.3 Assessment of Modified E2SFCA Analysis

The Enhanced 2SFCA area analysis weights the standard 2SFCA relationships by various factors exploring the impact of non-spatial attributes of availability and acceptability on healthcare accessibility. Traditionally, this enhancement shows the impact of various distance decay models that result in a decrease in accessibility as the populations are located farther from care. As the Veterans Access, Choice, and Accountability Act of 2014 only specifies a 60-minute driving threshold for primary care, the results of the modified E2SFCA account for weighting based on non-distance factors associated with veteran healthcare: wait-time (the ability to complete primary care appointments within the regulated time frame (availability)), patient satisfaction of primary care (acceptability of care), and a composite of these two factors.

The process was a simple multiplication of the desired weighting factor during the first step of the two-step process against the physician-to-population calculation for each OD Cost Matrix pairing of census tract and facility. It was simplified from distance-based weighting of Lou and Wang’s (2009) method, which used steps of weights to simulate distance decay. Each weight was included in the facility attribute table and an extra step was done using the field calculator. The result was a reduction in accessibility scoring for a census tract as the variables create impedance to care within a catchment.

4.3.1. Wait-Time (Availability) Weighted

The first of the three modifications addressed the Veterans Access, Choice, and Accountability Act of 2014 requirement state an appointment must be completed within 30 days. The Modified E2SFCA results, weighted by the percent of appointments meeting this regulatory requirement, are shown in Figure 18. In most areas, this reduced accessibility scores for veteran populations only slightly, demonstrating that veteran accessibility within VISN 21 is not greatly impacted due to timeliness (availability) of appointments.

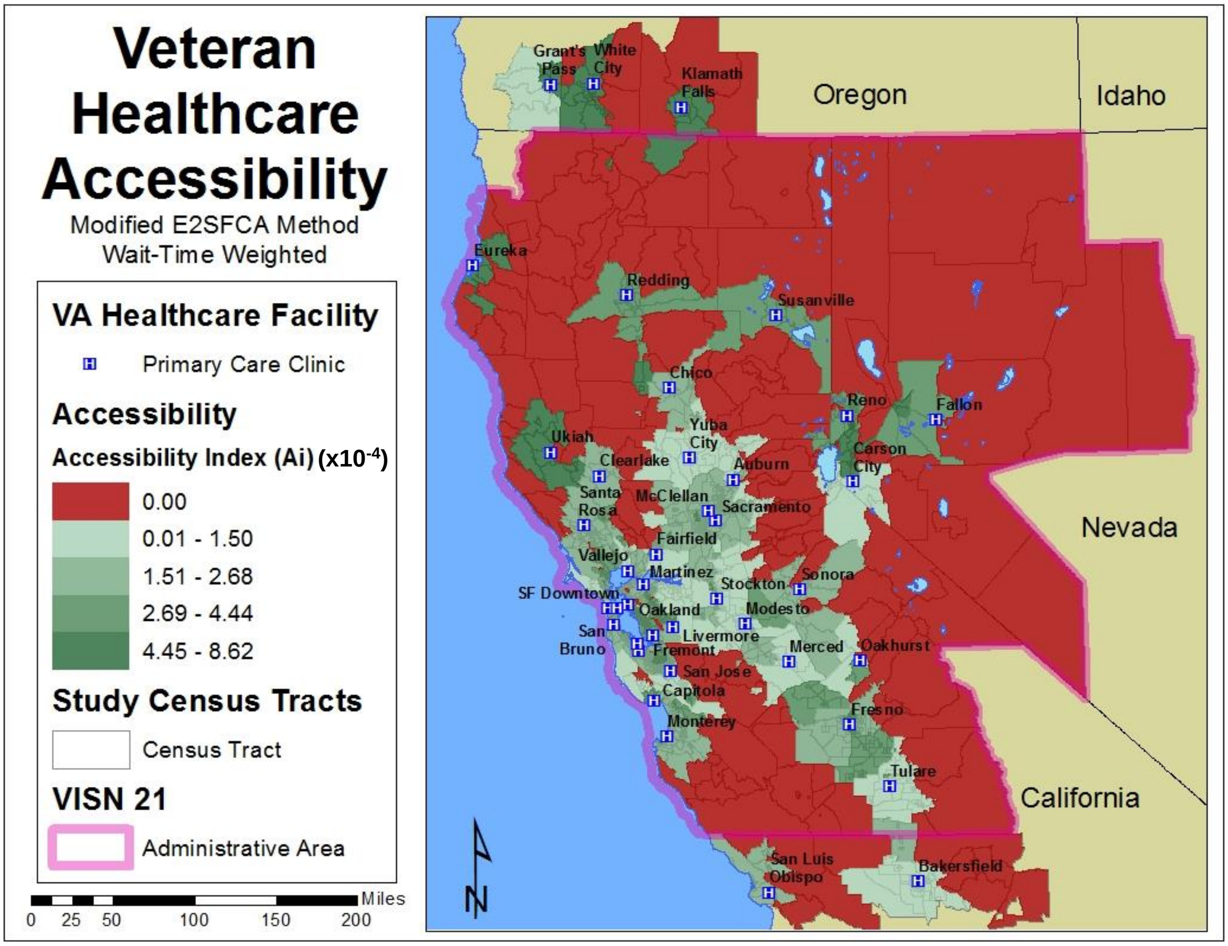

Figure 18 Wait-Time Weighted Modified E2SFCA Results

Additionally, the histogram shown in Figure 19 shows a distribution very similar to that of the standard 2SFCA results. The mean, skewness, and kurtosis were all very close as well. While there is a slight decrease in the mean, the slight increase in skewness and kurtosis is indicative that the right tail was slightly longer than it was from the standard 2SFCA results. Also, the increased kurtosis indicates significant outliers. This reflects the slight increase in variance and clusters of incidences along the tail, notable around the $5.22\text{x}10^{-4}$ and $6.07\text{x}10^{-4}$ accessibility indices. Furthermore, the natural breaks used by ArcMap for classification were very similar as well and the frequency of census tracts within each bin remains nearly the same.

There are a few more instances closer around the mean making distribution even more peaked, which is also indicated by the higher kurtosis value.

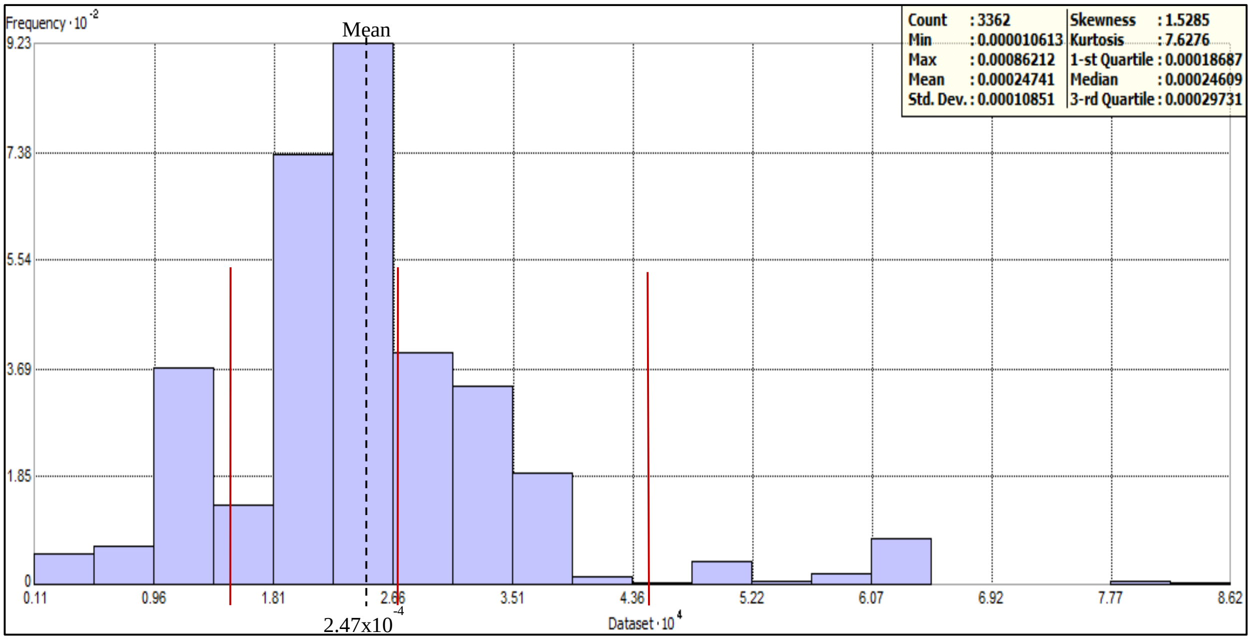

Figure 19 Wait-Time Weighted Modified E2SFCA Histogram

To better show the changes in these relationships, Figure 20 was created by mapping the percent change on accessibility from the 2SFCA results when accounting for wait-times, classified by quartile. The results show where populations are less often completing appointments within 30 days, causing degradation on accessibility.

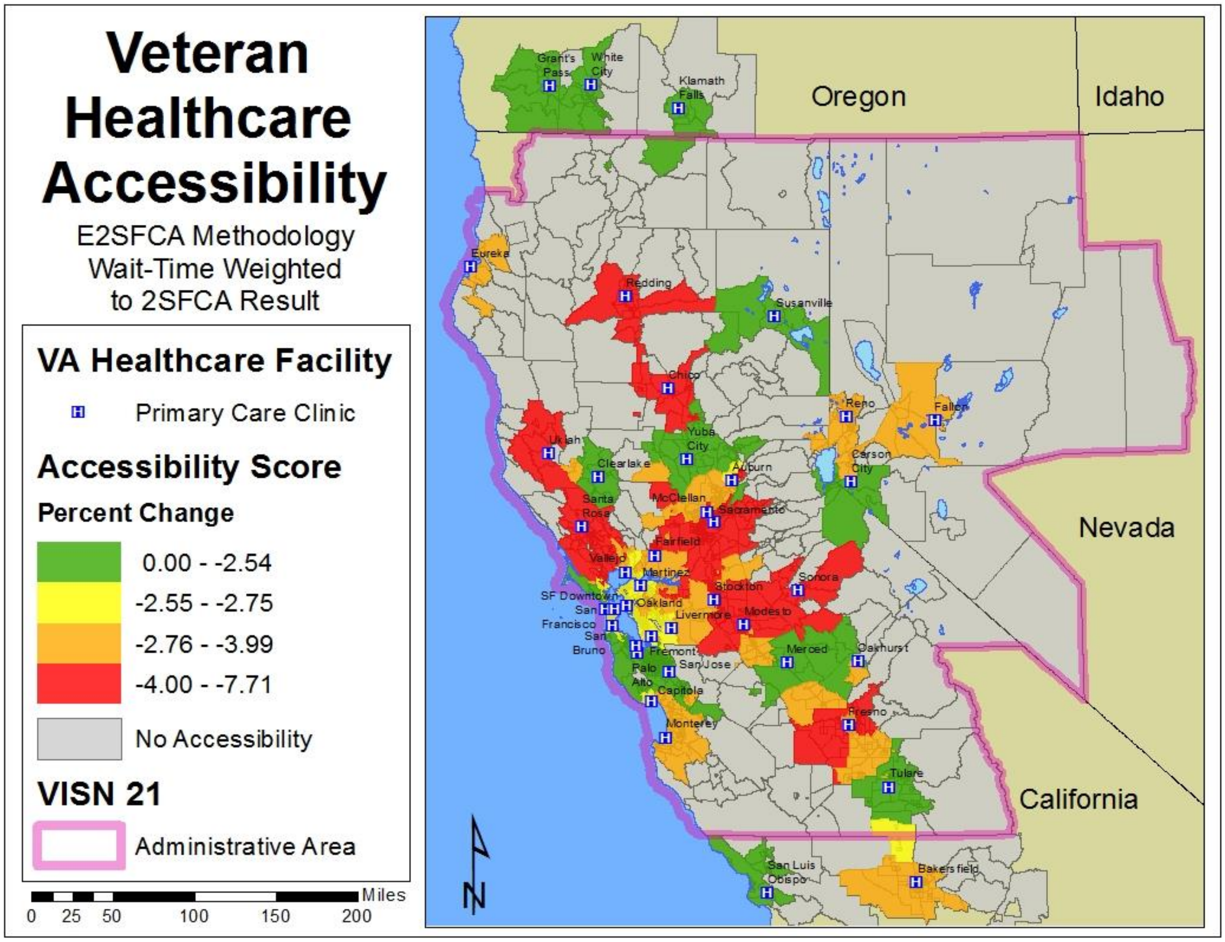

Figure 20 Percent Change in Accessibility Score when Wait-Time Weighted

Although the decreases were relatively small across the study area, the areas in green indicate the least decrease in accessibility as a result of wait-times and the areas in red have the greatest degradation. For example, the Klamath Falls facility had a 30-day completed appointment rate of 100% during the assessed timeframe. Census tracts falling within the catchment of that specific clinic had no change in accessibility score from 2SFCA results. Therefore, wait-times do not have a negative impact on accessibility for veterans residing in those tracts. On the opposite end of the scale, the Sacramento facility had the worst wait-time performance, which caused a greater decrease in accessibility for populations within its catchment. However, reduction in access from the Sacramento facility was moderated by the census tracts northwest of Sacramento which had better wait-time scores. Therefore, the multiple facilities within the catchment reduced the degradation in accessibility scores since the census tracts overlapped the catchments of the Auburn and Yuba City facilities. This is evidenced in the color change moving northward from Sacramento to Yuba City. The yellow census tracts near Auburn and McClellan are degraded due to the performance of Sacramento, but improved by the performance of Yuba City.

Additionally, the results indicate that accessibility was impacted by wait times that exceed the requirements more in rural areas than the urban centers. This was particularly noticeable in the areas around Fresno and Redding. Populations in these areas had relatively high accessibility scores when analyzed using the standard 2SFCA method, but had larger reductions in accessibility once the wait-time weights were applied. This indicates that despite the better relationships of providers available to these populations, they were unable to complete appointments at the same level as some of the densely populated urban areas.

These relationships were also quite evident when focused on the Bay Area. In Figure 21, accessibility in areas around Menlo Park, Palo Alto, and San Jose show only minor decreases in accessibility scores. Furthermore, populations shared between multiple facilities, such as those in census tracts between Modesto and Merced, were impacted less by wait-times than other populations served by only one facility. For example, access between Modesto and Merced was increased since they were served by the catchments of both clinics and Merced had a better rate for completing appointments.

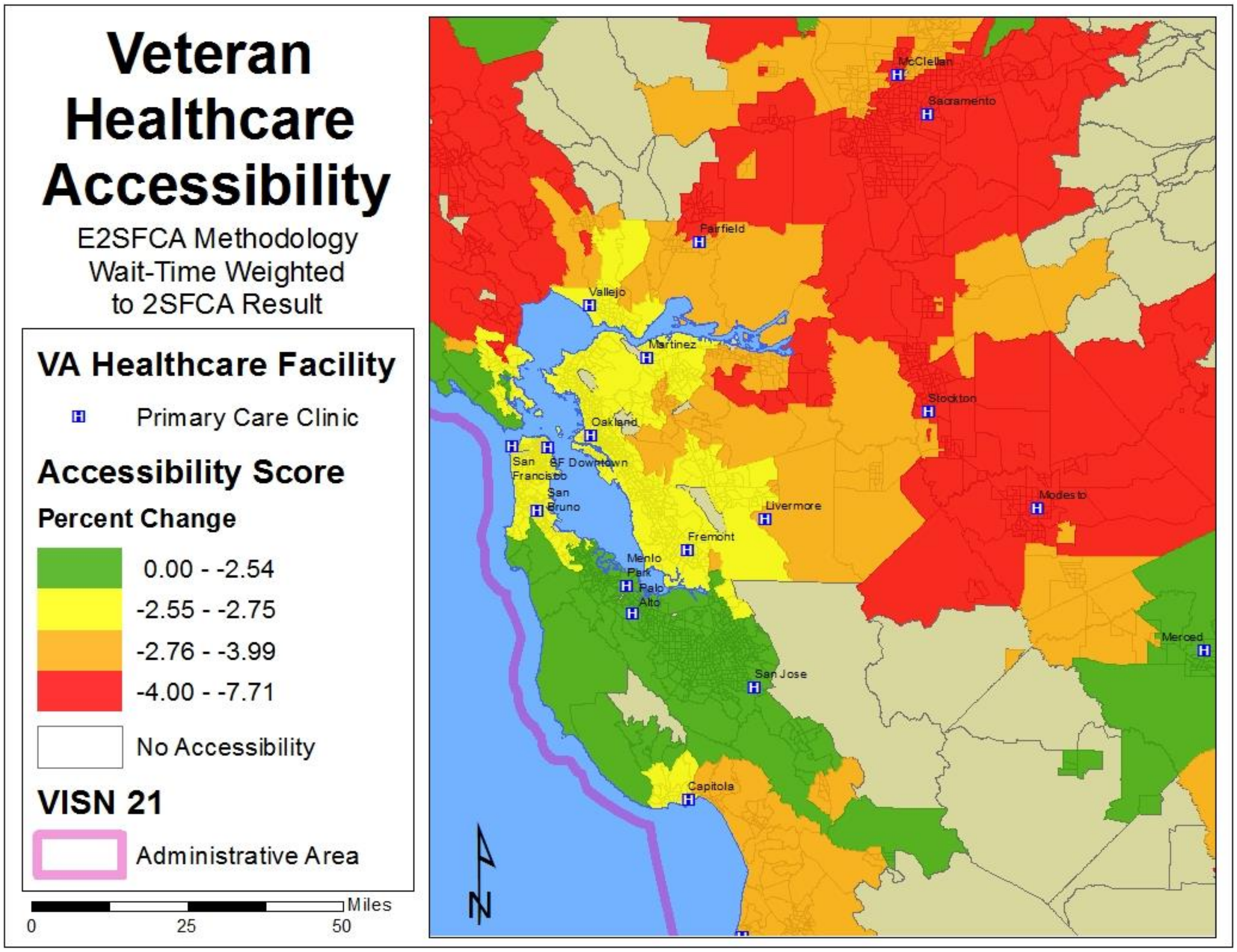

Figure 21 San Francisco Bay Area Change in Accessibility

4.3.2. Patient Satisfaction (Acceptability) Weighted

The second enhanced methodology was weighted primary care patient satisfaction. The result was population accessibility scores that take into account a measure of acceptability of care. Populations likely to be more satisfied with care receive higher accessibility scores than those less satisfied. The highest satisfaction possible was 100%, but no facilities achieved this score. Thus, accessibility scores using this method decreased for all census tracts meeting the 60-minute drive time threshold. The less the decrease in accessibility score, the more accessibility a population has relative to other populations within the study area. The result of this modified E2SFCA method is shown in Figure 22, classified by natural breaks.

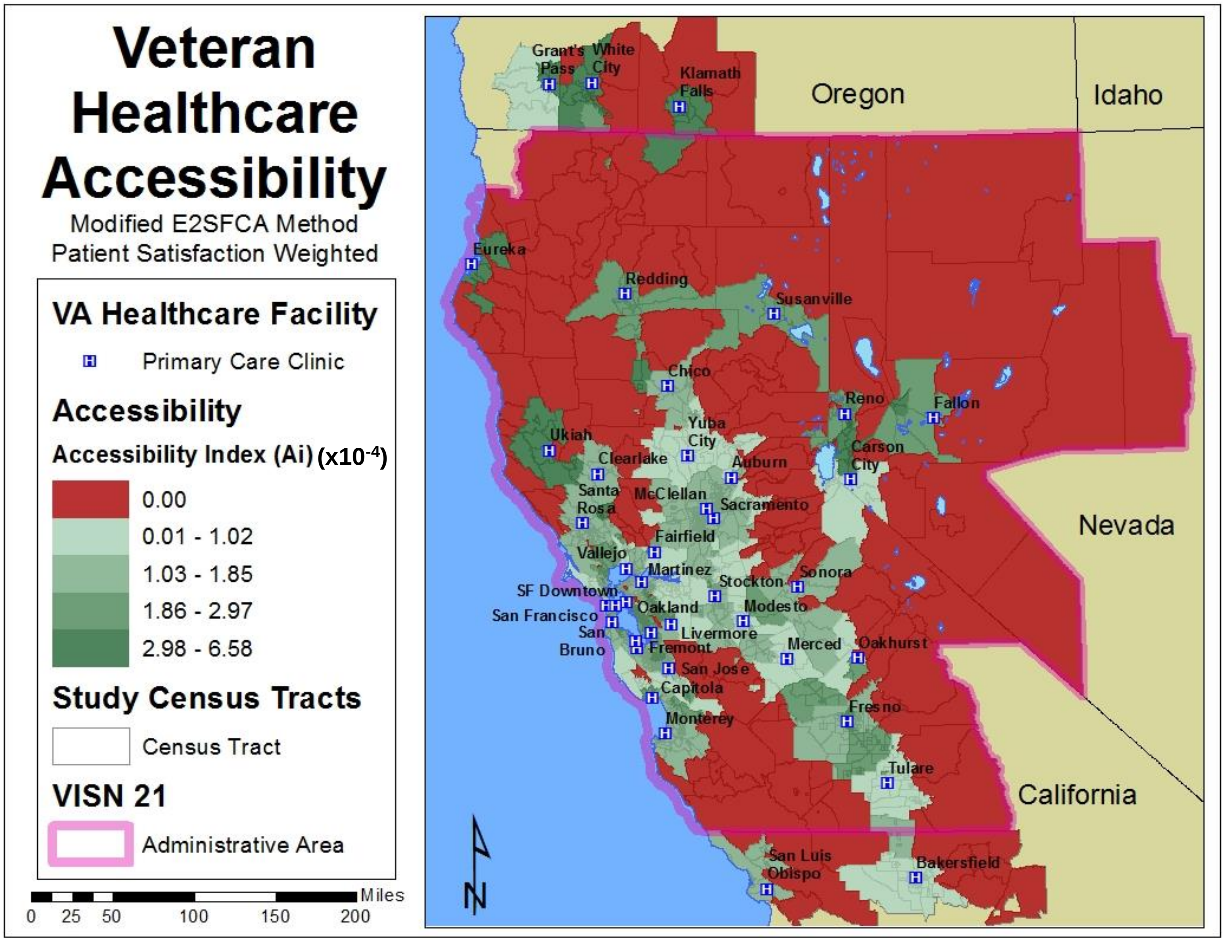

Figure 22 Patient Satisfaction Weighted Modified E2SFCA Results

The resulting histogram in Figure 23 shows the distribution of accessibility scores resulting from patient satisfaction weighting. The result remains positively skewed, but the distribution was quite different than those resulting from the standard 2SFCA and wait-time modified E2SFCA models. The mean accessibility score was reduced and scores were more clustered around the mean creating a much more peaked distribution. The right tail is still long, but outliers were larger with several discrete peaks along the tail. These factors were all reflected in the increased kurtosis when compared to the results of the standard 2SFCA model.

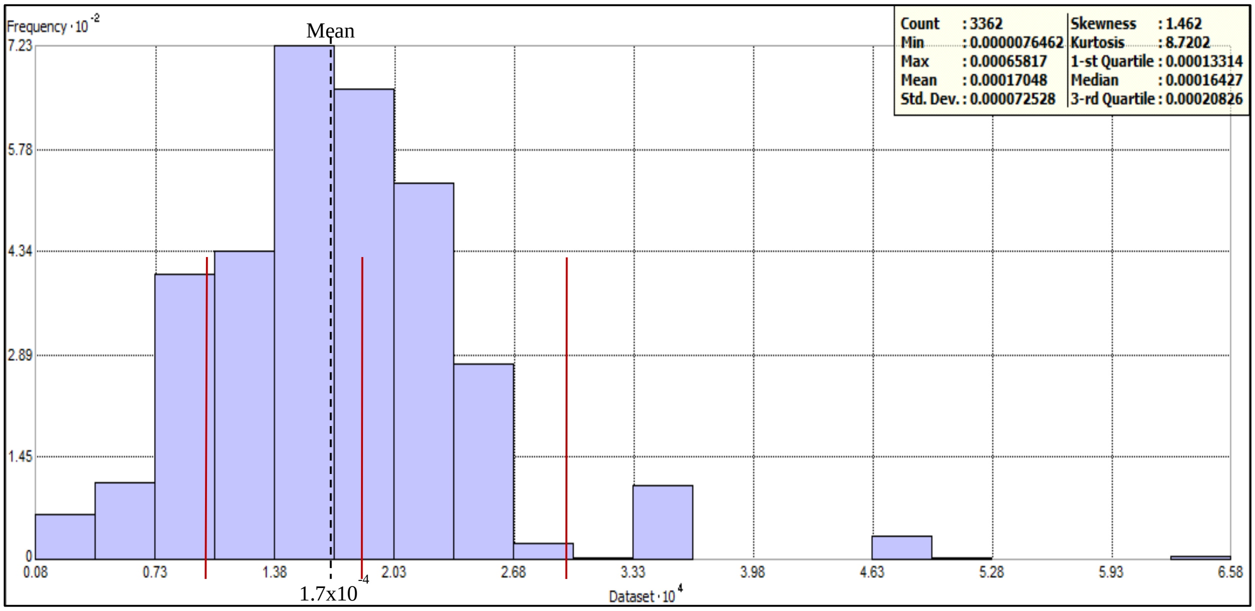

Figure 23 Patient Satisfaction Weighted Modified E2SFCA Histogram

Figure 24 shows the percent change in accessibility scores classified by quartile when compared to the spatial distribution of scores when using the standard 2SFCA model. Only a limited number of the census tracts around Ukiah and Eureka remained in the highest classification, and all populations experienced dramatic decreases when compared to the 2SFCA scores for census tracts. Satisfaction weighting also greatly impacted some areas that had good wait times, particularly around Klamath Falls where completed appointments were 100%, but had the lowest patient satisfaction at only 56.55%.

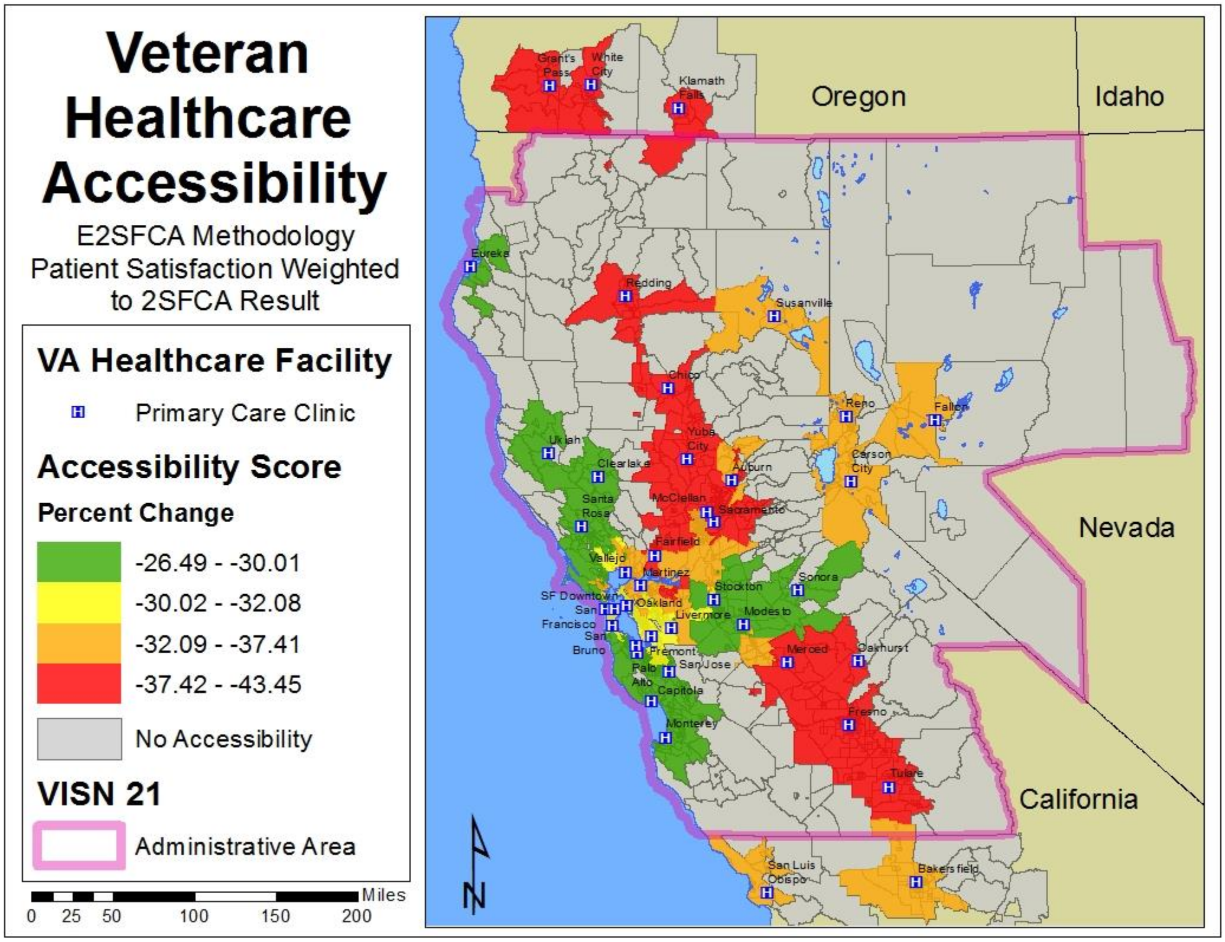

Figure 24 Percent Change in Accessibility, Patient Satisfaction Weighted

The changes demonstrated in Figure 24 appear clustered primarily due to the way the Veterans Administration manages patient satisfaction data. Unlike wait-time data that is regulated by law, patient satisfaction metrics, although standardized using The National Committee on Quality Assurance Healthcare Effectiveness Data and Information Set, are reported at the division level and not the clinic level. Therefore, weighting was applied to all clinics within the division, reducing some resolution where census tracts fall within the catchments of a single division. However, it does account for real spatial clustering where there were differences among tracts within catchments of facilities of multiple administrative divisions. Regardless, the results accurately reflect the impact of patient satisfaction and catchment area analysis methodology, particularly along the borders of divisions where populations have multiple facility options. Figure 25 focuses on one such area with clinics in three different divisions: San Francisco, Palo Alto, and Northern California (Sacramento).

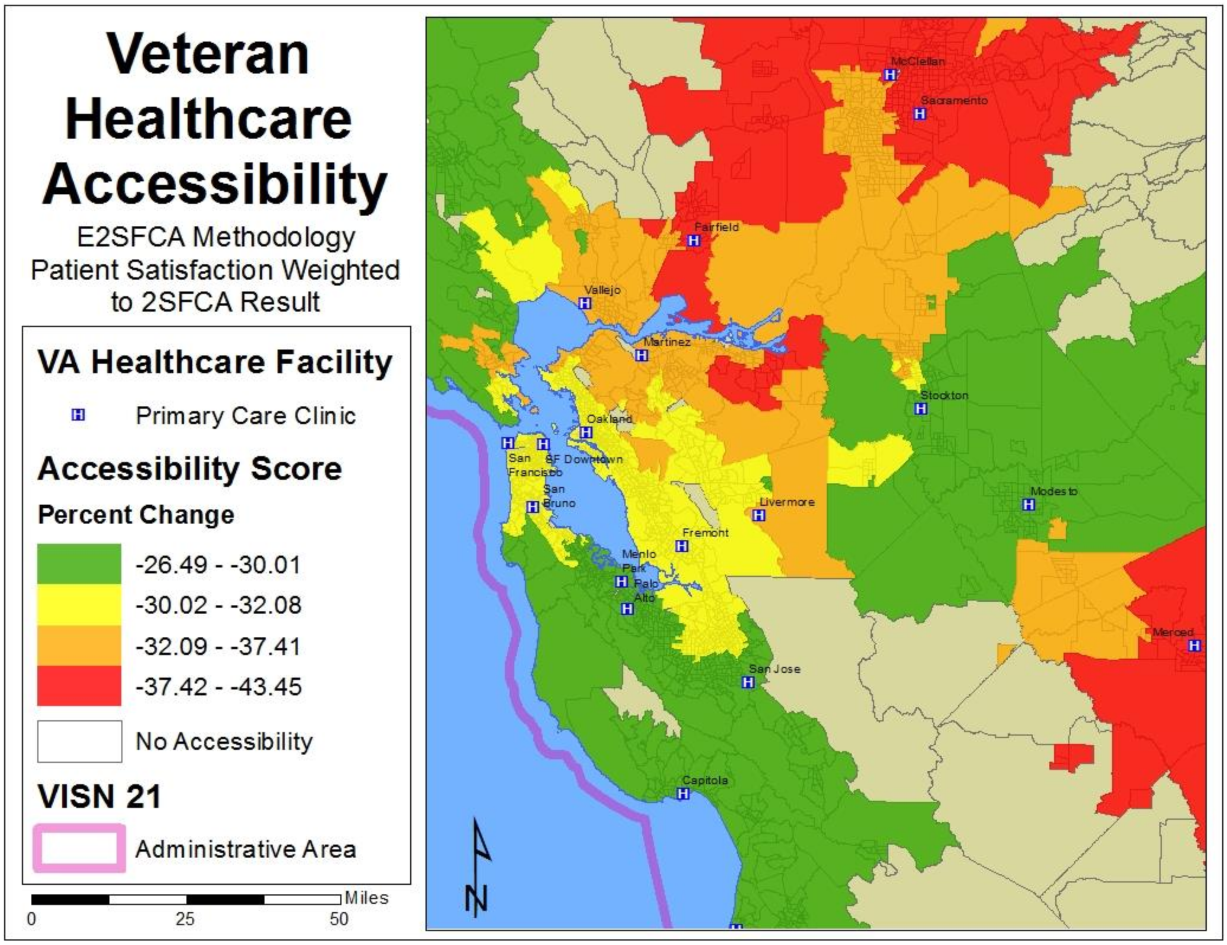

Figure 25 Percent Change in Accessibility Scores, Patient Satisfaction Weighted, San Francisco Bay Area

As a result of census tracts in the Bay Area falling into multiple catchments, lower patient satisfaction experienced at facilities in one division was tempered by the population having access to facilities from another division. For example, the census tracts around Oakland experienced less degradation of accessibility score than those in Sacramento despite the Oakland clinic being in the same division with lower patient satisfaction scores of 61.9%. Several of those tracts were influenced by the higher satisfaction from the catchments of Fremont and Livermore which had satisfaction scores of 71.87% and San Francisco at 73.51%.

Similarly, populations near Stockton have higher accessibility scores relative to some other populations as they have access to the Stockton, Livermore, and Modesto clinics, each of which had satisfaction scores of 71.87%. Conversely, the accessibility of the population in the San Francisco census tracts had a greater reduction in accessibility despite the San Francisco division having the highest satisfaction at 73.51%. This was a result of the high physician-to-population ratios in the original model, compounded here by the low satisfaction scores from the Oakland catchment.

4.3.3. Composite Weighted

The final modified E2SFCA model uses a composite weighting of both wait time and patient satisfaction variables. The results of this composite demonstrate the ability to use multiple variables to assess accessibility. Again, as in the previous results, accessibility scores were reduced to account for failures to meet the Veterans Access, Choice, and Accountability Act of 2014 requirement of completed appointments in less than 30 days and patient satisfaction; however, the composite provided results where acceptability may be higher even if appointments take longer to complete.

Figure 26 provides a map of accessibility scores weighted using this composite and classified using the natural breaks as was done with the 2SFCA result. As seen in the histogram of results, the map shows much less variation as most of the census tracts fall in the middle two classifications. Most notably, the result of this modified E2SFCA model presents a very similar spatial pattern to that of the wait-time weighted methodology results. The greatest exception to this was in the northernmost census tracts that were more influenced by the low satisfaction score of the Klamath facility (only 56.55% of patients' report being satisfied with care overall).

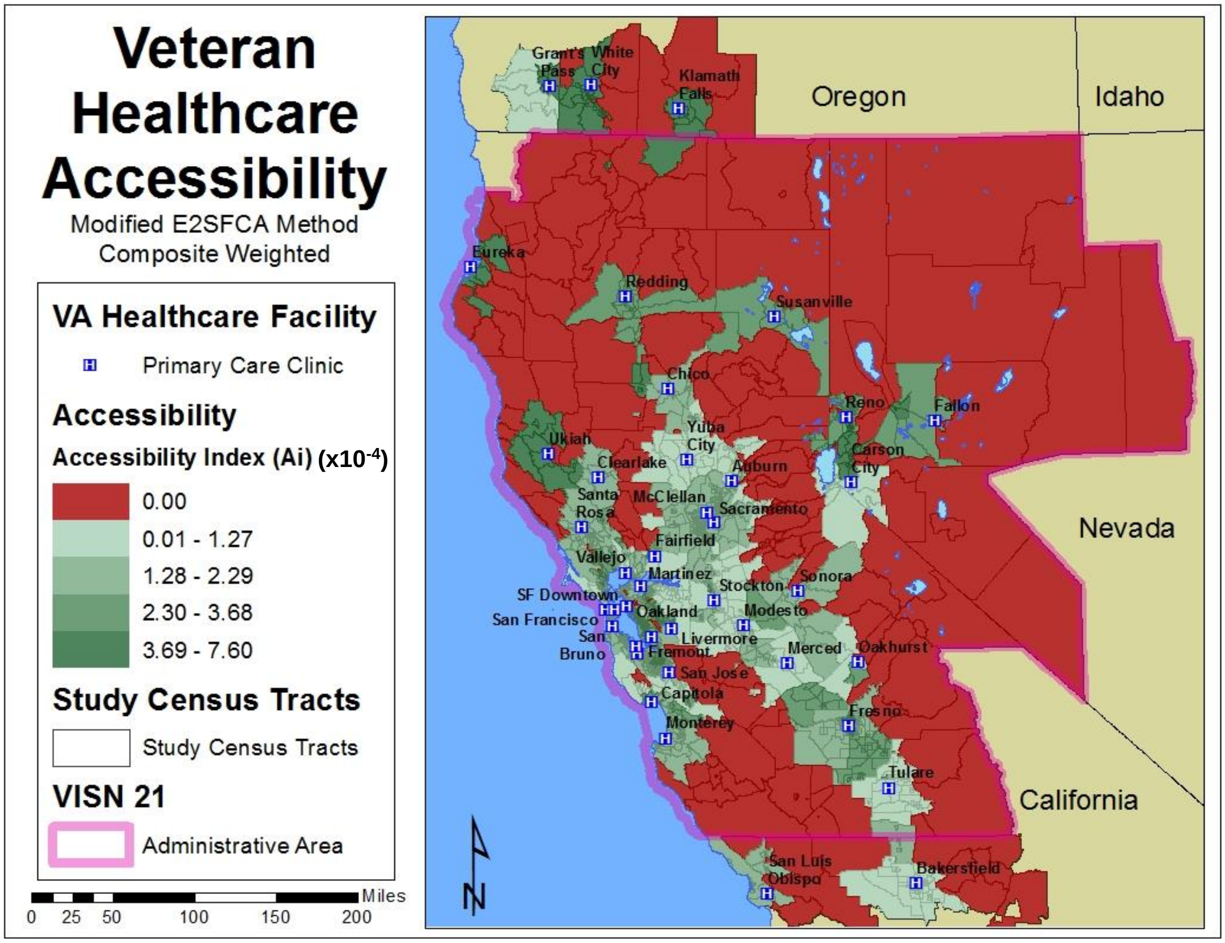

Figure 26 Composite Weighted Modified E2SFCA Results

The histogram in Figure 27 shows the distribution of accessibility scores. This histogram, produced by the modified E2SFCA model, appears more like the original 2SFCA results. The data still shows the same positive skew and high kurtosis as the histograms of the previously discussed results. It is still multimodal with a very long right tail, but the values along the tail are closer to the mean and more spread out than the previous clustered outliers. Additionally, the distribution is less peaked than with the previous two weighted models. Again, the distribution is a departure from the normal distribution, but the variance is not as extreme as with either the wait-time or the patient satisfaction results alone.

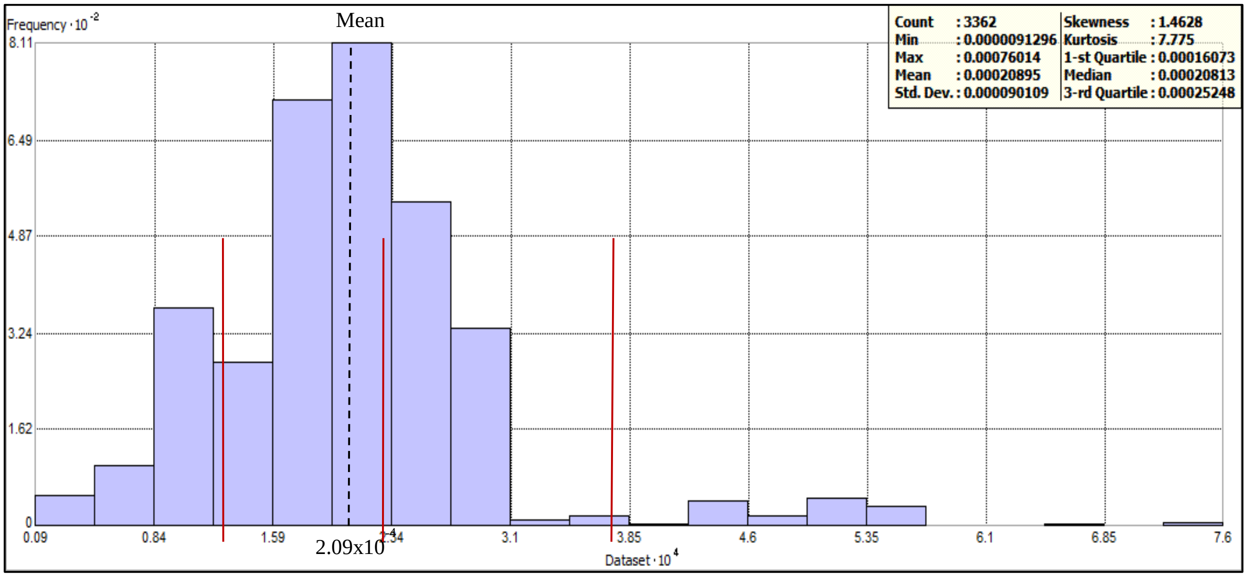

Figure 27 Modified E2SFCA Composite Weighted Results Histogram

This similar pattern was also reflected in maps showing the percent change by census tract (Figure 28). As the reduction in accessibility score was not necessarily coincident with the reduction that resulted from wait-time weighting, the averaging of these two variables into a composite evened the weighting across census tracts. The exception again was along the northern edge of the study area where populations did not experience lower wait-times, but were allocated to facility catchments that experienced the lowest satisfaction rates. As these tracts did not fall into multiple catchments, accessibility scores in the northernmost California census tracts were reduced the most within VISN 21, by as much as -22.47%. The only tracts reduced further were located solely in VISN 20 on the northern edge of the study area. This further demonstrates the effect of having multiple options from overlapping catchments improving accessibility for populations.

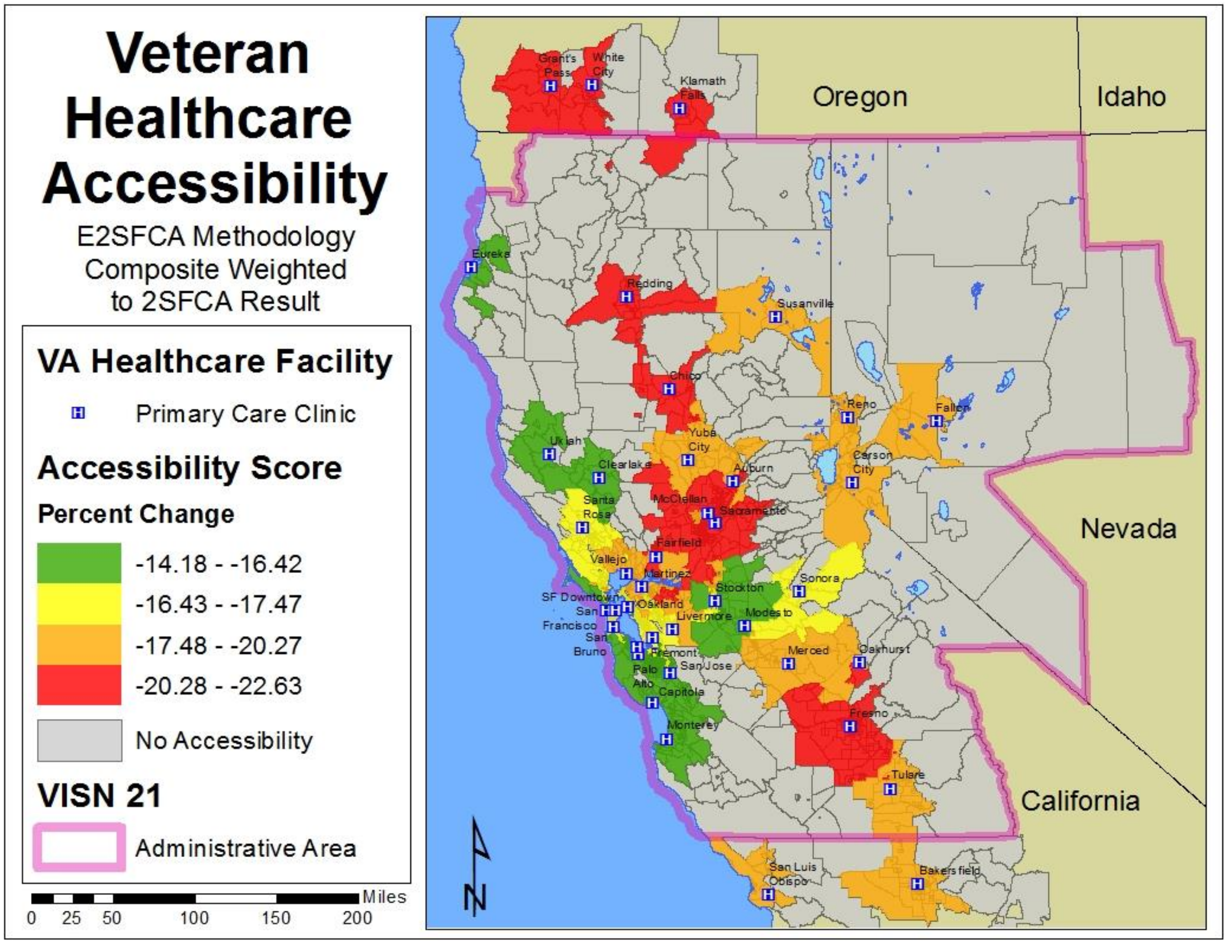

Figure 28 Percent Change in Accessibility Composite Weighted

A similar result was demonstrated in the heavily populated Bay Area. Again, the pattern was similar to that of the wait-time weighted E2SFCA results; however, when census tracts were analyzed more closely, there were small areas of improvement from the wait-time modified E2SFCA results. This is noted in Figure 29 where accessibility scores improved for census tracts south of Capitola. Despite these areas falling into catchments with poorer wait-times, these facilities had higher patient satisfaction scores, thus improving the result when compared to results using the weighting of a single variable. The results demonstrate the interaction of these multiple variables and the histograms of the three modified E2SFCA results suggest that the composite-weighted results also depart from the normal distribution.

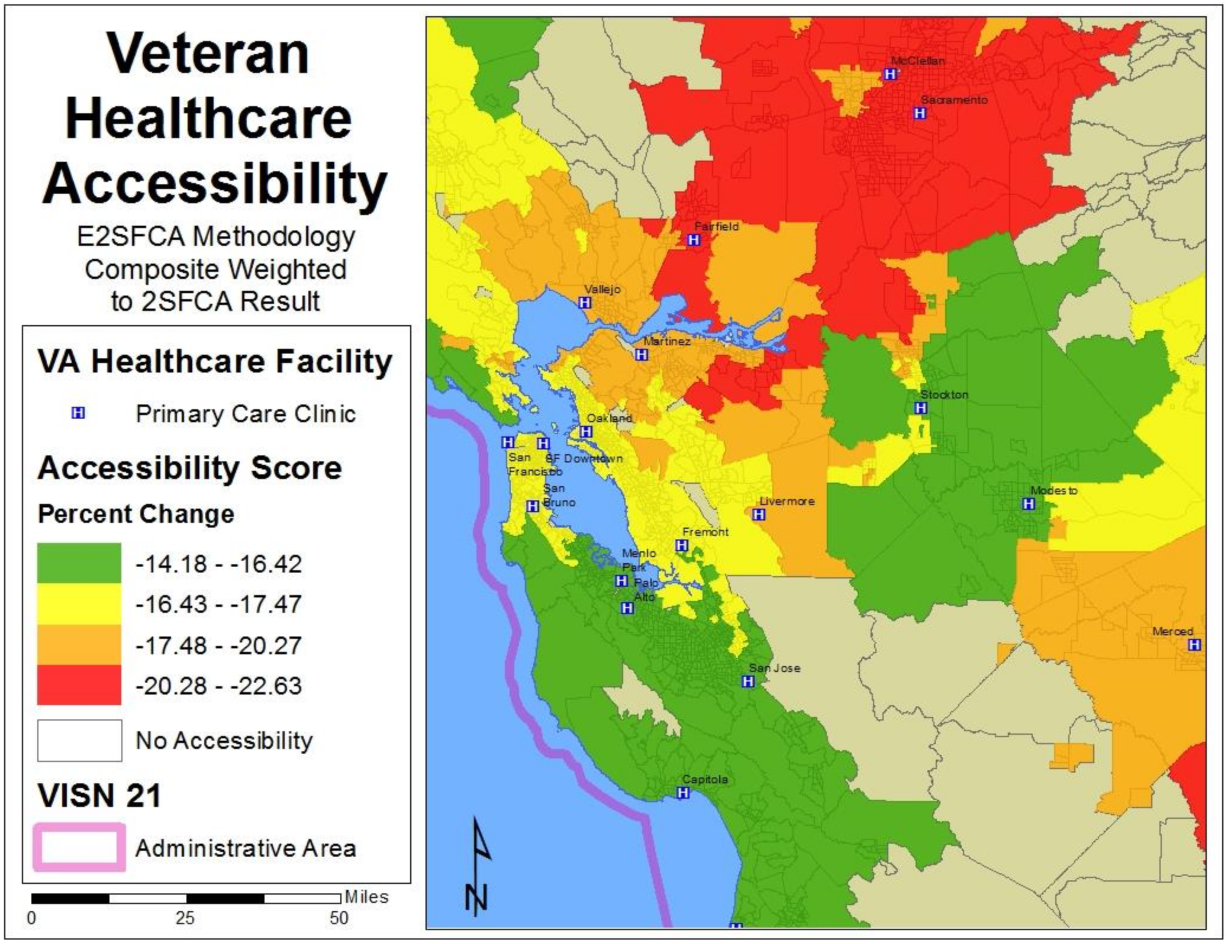

Figure 29 Percent Change in Accessibility Scores, Composite Weighted, San Francisco Bay Area

4.4 Overall Summary of Results

In summary, the results of the 2SFCA analysis showed that a vast majority of veterans had accessibility to Veterans Health Administration primary care. Accessibility scores appeared generally higher for veteran populations in many of the more rural areas within the VISN. Based on the 2SFCA methodology, this was a result of few factors. First, the number of census tracts in these areas was smaller, reducing the total populations within facility catchments. Also, several of these census tracts fell within the catchments of multiple facilities. These factors meant several rural populations had better physician-to-population ratios within the 60-minute driving distance increasing their relative accessibility. Furthermore, the modification of the standard

E2SFCA area provided results that adjusted accessibility based on availability indicated by wait-times regulated under the Veterans Access, Choice, and Accountability Act of 2014 and acceptability of care through patient satisfaction.

Chapter 5 Discussion and Conclusions

The contribution of this study is two-fold. First, it analyzes the spatial relationships of veterans and Veterans Administration healthcare access within one Veterans Integrated Service Network (VISN 21). Second, it offers some reflection and information on approaches to spatial modeling for health care access, in particular, the 2SFCA model and potential modifications to analyze non-spatial attributes of healthcare.

The analysis of VISN 21 was accomplished using a two-step floating catchment area (2SFCA) method that combined different related types of data into a useful index which allows comparison across varying locations. This method provided an assessment of relationships, where consideration of each part of the information individually without a model to show spatial interaction would not provide an adequate understanding of access. The 2SFCA method was developed specifically to address this spatial interaction to measure accessibility to primary care physicians. Previous work on spatial modeling of healthcare accessibility, which has developed significantly in the last decade, along with the high-visibility of veterans' healthcare issues was the inspiration for this project.

The standard 2SFCA method measures spatial accessibility of a population as a ratio of physicians to the population in two steps. The resulting process creates an assessment of primary care catchments, defined by the area from which an institution or service draws a population who use its services. The first step assesses physician availability (supply) to surrounding populations within the threshold travel time dictated by the Veterans Access, Choice, and Accountability Act of 2014. The second step sums up the ratios within the same threshold from each population (demand) location; in this study by census tract centroid. The result is an index that is used to compare accessibility of populations across the study area. These results ultimately provide a starting point for decision-makers to identify possible impediments to care and plan or allocate resources to increase access or improve services.

The second contribution of this study is the use of this data to explore and assess possible modifications to the 2SFCA and E2SFCA methods. Luo and Qi (2009) introduced enhancements to this method through the consideration of distance decays within the catchments. Since this development, other researchers such as Kuai (2015) and Li (2015) have demonstrated some possible modifications to this process through the addition of Kernel Density functions (KD2SFCA), Huff-models (H2SFCA), 3SFCA, and other Modified 2SFCA (M2SFCA) methods in an attempt to address competition, attractiveness, and transportation factors in areas of study ranging from food to healthcare accessibility. Although this study does not pursue a gravity model, it does use this idea and concepts from these types of enhancements to incorporate and address the influence of non-spatial variables on measures of accessibility.

This study builds on those concepts, focusing on VA healthcare and the regulatory requirements under the same act to determine distance thresholds. As VA healthcare is considered an entitlement, issues such as affordability and competition do not have the same impact as in the civilian market; however, the U.S. Government is concerned about the timeliness and quality of care, which is the reason the act was passed. Therefore, those variables are integrated into the model to enhance the 2SFCA (E2SFCA) for a spatial analysis accounting for those concerns. This is also a convenient case for this thesis as these modifications of the 2SFCA begins to account for some aspects of healthcare quality. The idea being that availability and acceptability are pillars of healthcare accessibility whose effects can be modeled and is an area that has not been studied in-depth previously.

This chapter discusses the effectiveness of the methods used in this project, implications of the results, and some possibilities for future studies. The first section addresses the results of the various methods used in this study. This is followed by a statement of some of the limitations experienced in developing and executing this study and possible improvements. The next section provides some suggestions for future or follow-on research related to this study of VA healthcare. The final section is an overarching assessment of the study in meeting the objectives and answering the research questions posed in the first chapter of this thesis.

5.1 2SFCA Analysis

The 2SFCA method is a special case gravity model developed for assessing healthcare accessibility. This model is widely accepted for studying the spatial interaction of a population and its care providers and therefore is of great benefit for answering the overarching spatial question posed in this study. It is easily adaptable to explore access by demographic data and therefore applicable for this type of research. Furthermore, the use of this model provides a new area of research, veteran access to VA healthcare, not widely published previously. While the data integration has some complications, the overall successful implementation in a GIS is well-suited to analyzing the type data available on healthcare and veteran demographics.

The difficulty of providing care to veterans continues to be a sensitive subject in the public and political spheres and the use of this model to explore spatial relationships affecting care is useful as a starting point to address this issue. This method also proves useful to integrating the requirements of the Veterans Access, Choice, and Accountability Act of 2014, providing the distance and wait time limitations needed for this analysis. Therefore, the results to some extent, demonstrate areas that do or do not meet the intent of the law. Those living in areas without access are to be provided alternative care, usually private healthcare, paid for by the VA as required by law.

From the resulting maps in Chapter 4, it is evident that a large area of the VISN has no access to VA healthcare under the stipulations of the law. Analyzing this data further, it is clear that the population with no access is actually quite small compared to the total population of the study area. This is an important realization when assessing the problem, identifying solutions to reduce the number of those uncovered, and ensuring resources are used efficiently. Furthermore, this analysis can provide VHA planners and leadership the ability to better understand and provide solutions to ensure all veterans have access to primary care. It is also of benefit in allowing informed decision-making for budgeting and/or requests for funding alternate care.

Separate from identifying the populations without access to primary care in accordance with the Veterans Access, Choice, and Accountability Act of 2014, the 2SFCA model provides a comparison of veterans' accessibility across the VISN. It is important to recognize that the model results are not absolute, but comparative for the population and study extent. What is interesting about this is that the results indicate that accessibility is sometimes better in rural areas when compared to urban areas, despite the clustering of facilities in more populous areas. Veterans in rural locations have more choices in several instances as increased distances within the allowable 60-minute travel time is possible, providing access to more facilities than in some urban areas with reduced travel speeds. Additionally, lower physician-to-population ratios within census tracts occur when a group's primary care options increase. This is significant as veterans classified as "rural" make up about 24% of total veteran population nationally (RHI Hub 2015). Furthermore, this should help drive priorities for hiring, funding, or establishing new facilities across the administrative area.

5.2 Modified E2SFCA Analysis

The second focus of this study is the possibility of modifying the 2SFCA model to explore the integration of additional variables affecting accessibility. This was done by modifying existing Enhanced 2SFCA models to examine spatial interaction in new ways. The results prove the ability to weight accessibility beyond previous distance decay functions developed by Luo and Wang (2009), particularly by incorporating non-spatial attributes of accessibility.

5.2.1. Wait-Time Weighted Analysis

The first modification builds on the 2SFCA study and E2SFCA concepts and applies weighting based on requirements prescribed in the Veterans Access, Choice, and Accountability Act of 2014. Wait-times are included using a similar process as basic distance decay weighting as it represents an impedance to healthcare availability. As the law dictates, appointments must be completed within 30 days which the VHA refers to as "wait-time" metrics and the VA must track and publish this data bi-weekly. Therefore, the result is a modified E2SFCA model in which accessibility is weighted by facility by the percent of appointments completed within 30 days, incorporating the principle of availability.

The result of this analysis is encouraging in the VA's ability to meet this requirement. In nearly the entire VISN 21 administrative region, wait-times did not significantly decrease accessibility. This demonstrates the ability to satisfy appointments in most cases regardless of underlying physician-to-population ratios. Also, this model allows a method to analyze the impact of this metric spatially. Using change maps, regions that have difficulty completing appointments on time are readily apparent through comparison with 2SFCA results.

Furthermore, the modification of the model demonstrates how ability to complete appointments affects accessibility of care.

Probably the most interesting observation using this weighting is that there does not appear to be a correlation between increased wait-times and 2SFCA results. In many areas, wait times have a greater impact on accessibility when options are limited. For example, several areas, such as around Ukiah or Modesto, have more significant reductions when weighted for wait-time despite being in the top-tier for accessibility as a result of the 2SFCA model. In the case of Ukiah, the reason is pretty straightforward, as several census tracts only have catchments for that one clinic.

The Modesto case is more interesting as several of the populations in that area have physical access to three or more facilities. This indicates that many of the clinics in that area have more difficulty completing appointments, indicating a stress on primary care and incidentally higher stress on veterans to receive timely care. An analysis of the data alone, without the use of a GIS, could not have produced as clear a picture of this potential issue; however, this modified spatial model makes the issue apparent and effectively visualizes the result on a map.

5.2.2. Patient Satisfaction Weighted Analysis

The second modification of the model uses weights based on patient satisfaction of primary care. The VHA follows industry-wide standards for primary care satisfaction surveys and reports these results online quarterly. This data is convenient as it uses the same scaling as wait-time reporting: 0% to 100%, where 100% indicates total satisfaction with the primary care experience. This modification is another departure from standard accessibility analysis which only addresses physical access. As previously stated, historically, accessibility analysis using a

GIS focused on modifications using distance weighting. The modifications in this study account for additional pillars of healthcare accessibility: availability and acceptability (using indicators).

The patient satisfaction variable has the greatest impact on accessibility, reducing the index by at least 26% in the study area and up to more than 43% in some census tracts. When this weighting is applied, several areas of higher accessibility are reduced to a much greater extent than some areas with lower indexes using the standard 2SFCA method. This is especially evident in the rural areas. In general, patient satisfaction is higher in urban areas, despite the greater stress on the availability of services and lower physician-to-population ratios in those areas. Furthermore, when looking at changes from wait-time and satisfaction weighting, the reductions are most pronounced in different areas, creating opposite patterns on the maps. Therefore, this analysis indicates that wait-time does not necessarily correlate to patient satisfaction.

This is particularly notable in the Klamath Falls area. The Klamath Falls clinic had a 100% completed appointment metric for the quarter, but the lowest patient satisfaction for the study area. Therefore, when the model is run, this greatly reduces accessibility within the catchment as populations indicate using those services is less acceptable despite the high level of availability. Populations within multiple catchments have less degradation of accessibility as they have more healthcare opportunities that temper lower satisfaction scores from one facility by higher scores from another. This also demonstrates the importance of choice or more options on accessibility.

5.2.3. Composite Weighted Analysis

The result of the third model modification addresses combining multiple variables or indicators for analyzing accessibility. In this case, a composite weighting accounts for both factors: wait-time and satisfaction. As expected, the results of this model produce much less degradation to accessibility than that of satisfaction alone. The relatively high appointment completion rates across the study area alleviate some of the effects of lower satisfaction.

Exploring the maps using the three methods, the composite model produces a map of accessibility scores that appear similar to that of the wait-time model, but when looking at the percent of change, appear closer to the patient satisfaction map. This is a result of balancing the disparities noted in spatial variability between the 2SFCA and each weighted result. As several of the greatest changes occur in different areas without apparent correlation, the use of a composite evens out some of these disparities. However, the wide range in satisfaction scores influences accessibility to a greater extent than the narrow ranges found in wait-time metrics overall.

The use of the composite is helpful as it begins to assess accessibility using a holistic approach accounting for multiple factors impeding care. Also, understanding these relationships provide more nuanced indexing throughout the study area. Notable are the areas around Sacramento and Fresno. Both areas have good 2SFCA results, but poor wait-time and patient satisfaction results. These variables compound impedance to accessibility for many populations within catchments despite a large choice of facilities. This identifies facilities that decision-makers may want to prioritize for more detailed analysis or development of improvement programs in appointment and patient satisfaction, given the cumulative spatial impact of problems at these facilities.

5.3 Limitations and Improvements

The acquisition and quality of data is the greatest limitation experienced in this study. All data in the project reflects the most current and most complete data available. In other words, the study uses the “best-available” data within the scope and budget of this thesis. In many cases, it is impossible to find data collected over precisely the same time period, but instead the latest information or most complete data are used. The most crucial data to proper model execution are all from the same time period to ensure accurate interaction of variables. These include provider information, wait-time, and patient satisfaction. Additionally, a late summer collection period prevents the likelihood of an outbreak such as influenza affecting the weighting (e.g., for wait times).

Also, the large extent of the area used for this study limits the data available for building the road network. The size of the area means purchasing detailed road data is not feasible; the cost is estimated at over $3,700 just for the portion of the study area within California. Therefore, some detail is lost, especially when calculating travel time from speed limits. As speed limits are a function of MTFCC classification, some smaller routes are given longer travel times than are probably true in reality. This is especially prevalent in rural areas where, for example, smaller, two-lane county roads are given the same speed limit as urban surface streets. This in turn reduces the maximum distance along the network, reducing the size of catchments.

A cross-check with analysis from ArcGIS Online however, indicates that these limitations in road network data likely does not affect the study results in a significant way. Figure 30 shows the areas where ArcGIS Online differs from the study network when the Service Area tool is executed. This tests the network as well as refines the study area. The result shows the number of census tracts affected is quite small: 69 of the 3,559 total or less than 2%, and only 57 of those are actually in the VISN. Furthermore, the areas for the most part, are small as well, usually less than a few square miles. The exception is in flatter, rural areas such as parts of the Central Valley and high deserts. Mountainous areas are less affected due to the slower speeds possible on these roads, but shows some impact as well. Despite this, some of these centroids are included in the processing when within the set snapping distance for the network analysis portion of the model run. Thus, this figure represents only a possible worst case.

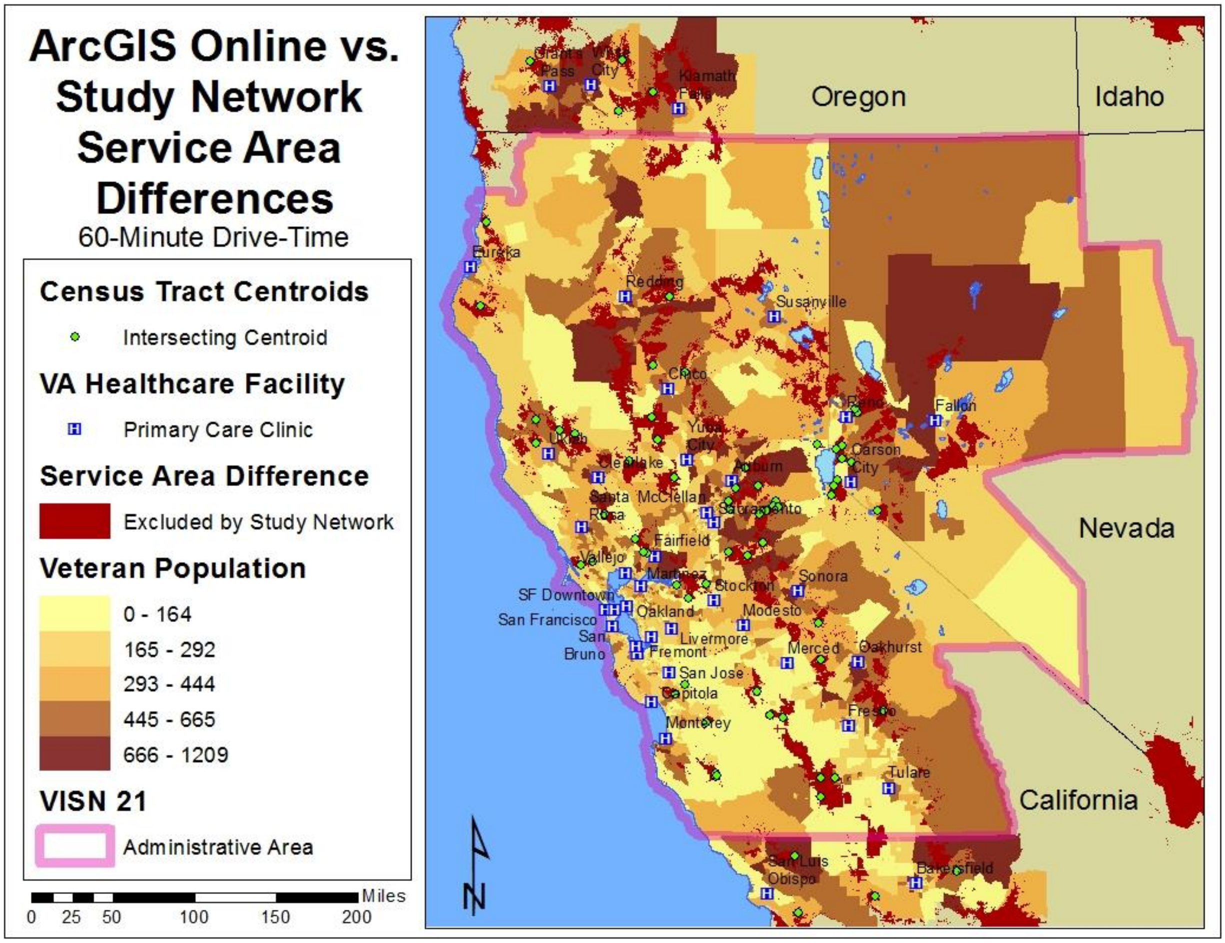

Figure 30 Service Area Comparison: ArcGIS Online and Study Road Network

Additional problems with the data used for development of the road network are apparent when the model results are explored in detail. Once the analysis was completed, each area with an accessibility score of zero was examined closely and it was found that 12 total census tracts, nine in VISN 21, were given accessibility scores of zero when they likely should have received a score above zero. In these areas, it is likely that errors with the MAF/TIGER data prevented the OD Cost Matrix process to establish a pair because the census tract centroid was unreachable along the network. During processing, census tract centroids are snapped to the closest point along the network. In these few areas, the model cannot calculate a solution due to limitations in the MAF/TIGER file completeness.

Figure 31 demonstrates an example where the centroid is closest to a segment not connected to the entire road network. The census tract in this figure is located in San Francisco, but this problem with disconnected segments is more prevalent in remote and mountainous areas. This is probably due to the classification of the segment within the MAF/TIGER files where some segments are classified as four-wheel drive trails, private roads, or parking lot access roads. As these are not included in the network build, they leave some gaps where segments are not connected to other segments classified as a different road types.

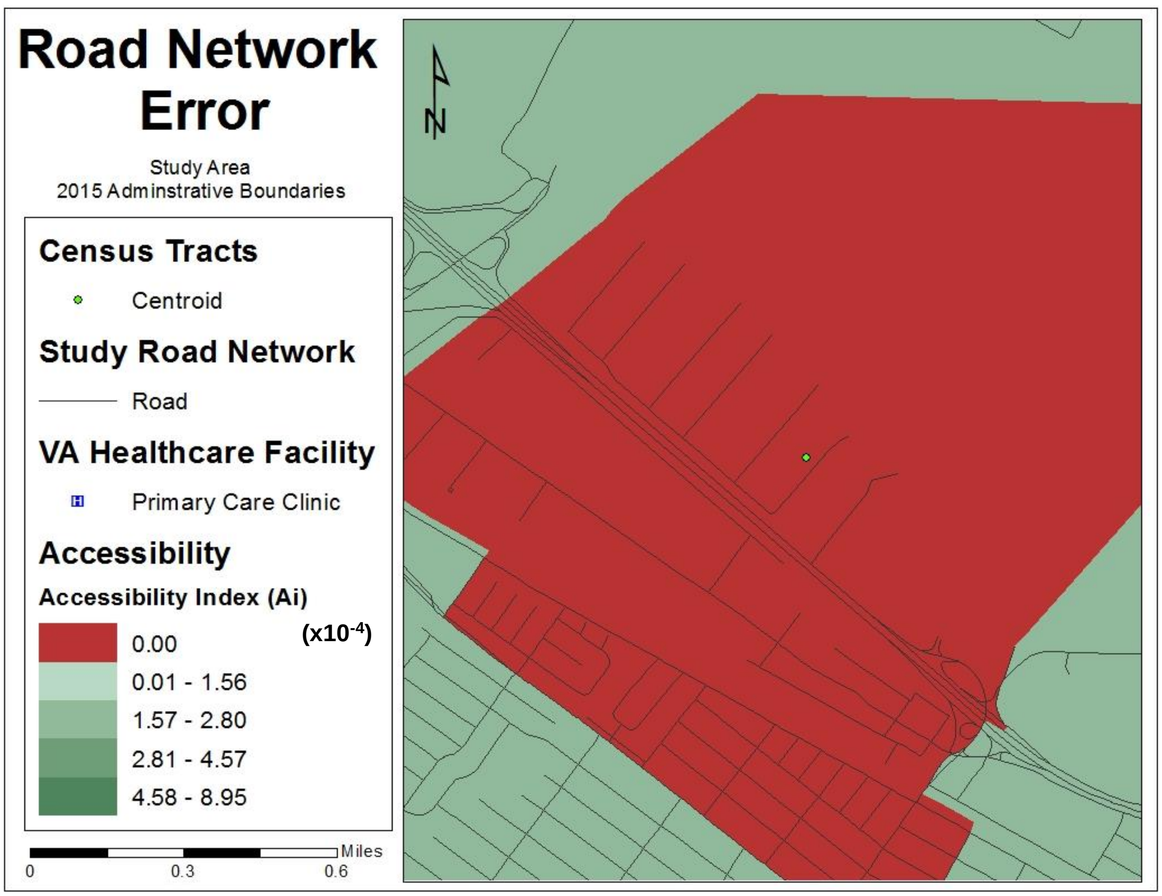

Figure 31 Network Error in San Francisco, California

Furthermore, the network does not account for potential traffic congestion. Although not an issue in most rural areas, traffic congestion in large, urban areas such as around the San Francisco Bay area could potentially reduce accessibility by reducing catchment area size. This may also occur around choke points such as bridges or mountain passes. A more detailed network that includes historical time-of-day congestion trends could account for this, but is unavailable within the scope of this project. Additionally, traffic congestion is not discussed in the Veterans Access, Choice, and Accountability Act of 2014 or Project ARCH guidelines so is not pursued for this thesis. More limiting is the location of census tract centroids when snapped to the network that may not correlate to actual population centers within those census tracts. This limitation is discussed later in this section.

In all these cases, the areas that produce network errors are randomly distributed across the study area and the populations are quite small with an average of only 282 veterans. Overall, the total observed errors for the nine census tracts that probably should have been assigned accessibility scores represent only 0.34% of all tracts and 0.36% of the total population. Therefore, these errors do not significantly change the overall results and probably would not change the classification of the maps. If the data quality is improved or more detailed, these areas should obtain a similar accessibility score as surrounding tracts. This finding is significant however and should be recognized to prevent such a recurrence for future studies.

The final key limitation is in the aggregation of veteran populations at the census tract level. Population data from public sources is only available down to the census tract level. Although this is a common areal unit used for this type of research, it has its limitations, particularly in the larger, rural census tracts with reduced population density. Here, the inability to accurately depict the actual location of population clusters may result in census centroids being a poor representation of where people actually live. In many of these areas, the population is probably clustered on the edges of the large census tracts nearer to cities or highways rather than near the census tract centroid. This is evident in areas along the central valley where tracts have higher veteran populations, but are excluded from the 60-minute drive time even though the census tract edges may be very close to a facility. The tracts to the east of these clinics run up mountains. In these cases, populations are probably located on the lower slopes, and in reality, within the catchment of the facility. Figure 31 shows a depiction of census tract densities within and outside the 60-minute drive-time threshold.

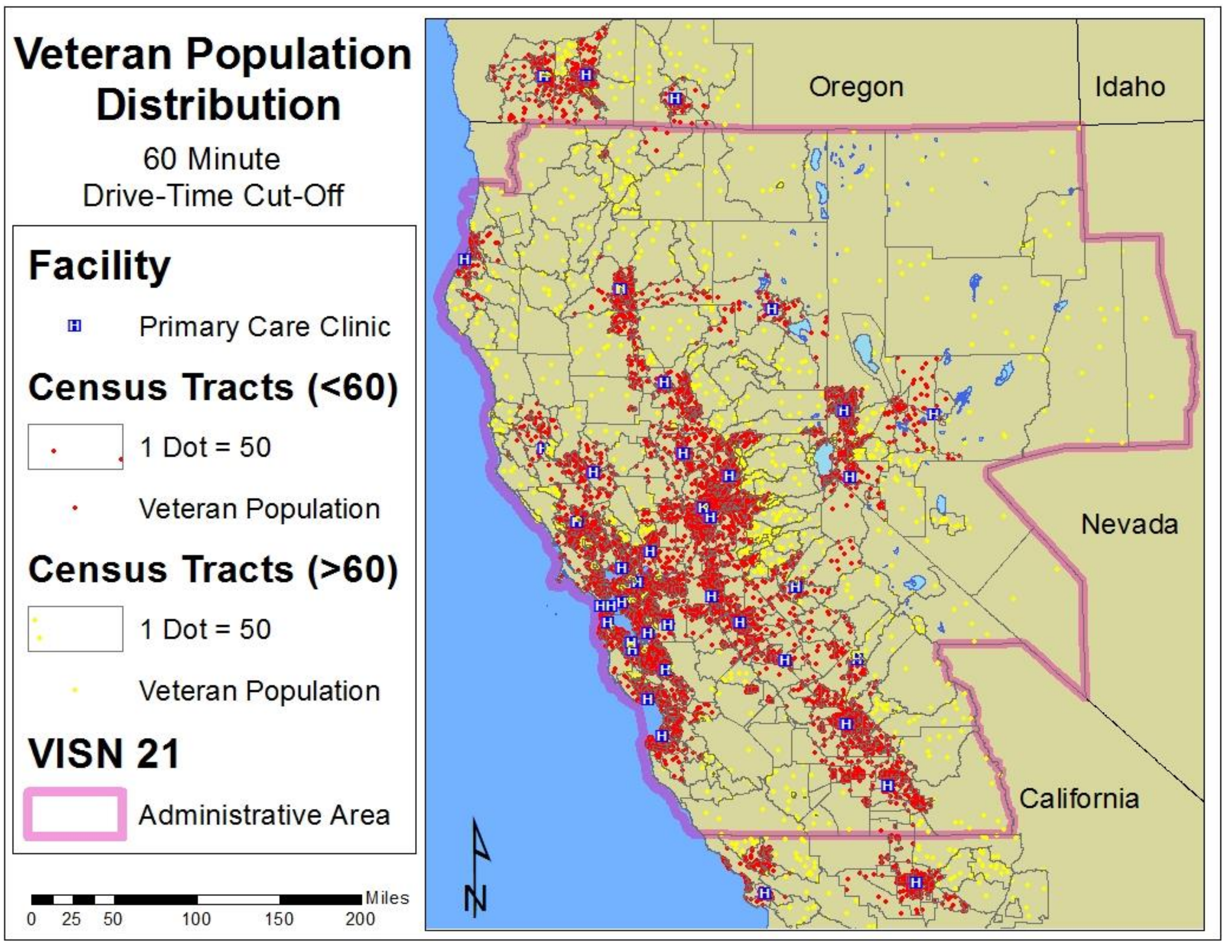

Figure 32 Dot Density Map of Veteran Population by Census Tract

Another opposite situation occurs in Fallon, Nevada; the easternmost clinic. This census tract is excluded despite abutting the facility, but is comprised mostly of desert, so the population is likely widely distributed throughout the tract and possibly outside the driving threshold. In either case, 2SFCA methods calculate distance along the network from point-to-point. Therefore, a census tract is excluded from the calculation if its centroid is outside the 60-minute threshold or not close enough to the network to be “reachable.” In these cases, it is very possible that some populations are identified in areas of “no accessibility” because the areal units do not meet the model requirements or the clustering of populations cannot be identified.

These limitations can be reduced through the acquisition of more detailed population data providing greater resolution on the disposition of populations. Also, it is possible that dasymetric methods can be used to identify areas with a higher probability of population clustering, such as overlaying a land use raster to place points on inhabited areas instead of simply using the census tract centroid. This would also ensure that the points are within range to snap to the network. Furthermore, if money and/or time are not restricted, the network can be more detailed and accurate, improving the assessment of catchment size within the drive-time restriction. This might extend the number of census tracts determined within the catchment and improve accessibility calculations not just in those tracts, but in all the tracts served by a nearby facility.

Finally, it is important to realize that this study demonstrates “potential” accessibility. It is a “worst case” where all eligible veterans use VHA primary care as their main source of healthcare. Although it is understood that not all veterans choose the VA as their first stop for care, exact usage data is not available for this study. Published reports from the VA state that overall, approximately 25-32% of veterans use the VA as their sole source and use is increasing with younger, post-9/11 veterans (VA 2014b). These reports however, do not indicate the spatial distribution of VA healthcare usage so are not useful to determine actual use in the study area. Therefore, it is not possible to determine exactly how enrolled veterans were distributed across the study area based on VA statistics available publically.

The VA does have a large data collection capability which could improve this study by using the actual number of enrollees and their addresses though privacy stipulations restrict the availability of this data outside the Veterans Administration. The VA keeps detailed databases on eligible veterans, actual enrollees, address information on enrollees, demographic data, and historical medical data. All of these types of data could refine this study or provide additional concrete data for additional model modifications and some of this data is already being used internally by the VHA to analyze, plan, and program future initiatives. This is shown in various press releases, slide presentations, and industry reports online. For example, Willis (2014) provided an article for Esri on work undertaken by the VA Planning Systems Support Group (PSSG) to collect and analyze geographic data for evaluating access and to planning new sites. The PSSG maintains data from the VA Site Tracking System (VAST) and the enrollee travel time file, and can compute drive time for enrollees to the nearest VA facility based on the type of care required.

5.4 Future Directions

One of the greatest benefits of this study is that it demonstrates accessibility using an index that allows comparison across space. Therefore, the use of these methods provide a wide range of possibilities for future research or more detailed study within a smaller area and all provide a starting point for follow-on study. Through the use of the 2SFCA method, the mapped relationships provide quick indicators of where services may be needed.

One of the greatest opportunities for follow-on study using these methods is location-allocation analysis. There are two parts to support decision-making along this path. The first is to fill the gaps in areas where no access is available, locating possible facility sites that increase service to the greatest number of veterans while ensuring cost effectiveness. The second part is to improve accessibility in areas where access is possible, but accessibility scores are lower. In these cases, the system is stressed and changes in the capacity of service or facilities may need increasing.

Optimal location-allocation (LA) locates a set of new facilities such that the cost from facilities to customers is minimized and an optimal number of facilities are placed in an area of interest in order to satisfy the customer demand (Azarmand and Jami 2009). Azarmand and Jami (2009) looked at several possible models to solve this problem with the goal of identifying areas where a new location may be sited to serve an unallocated population. Although this publication described several models, there are two of interest to this thesis: The LA General Model and LA Model Each Customer Covered by Only One Facility.

The Location-Allocation General Model, also known as the multisource Weber problem, contains several assumptions applicable to this study. First, the solution space is continuous in that there are no breaks between the demand and supply. Each customer’s demand can be supplied by several facilities, which is similar to the current location-allocation for VA healthcare. This model however, ignores the opening cost of a new facility as is not considered in this thesis although may be a later decision point. Facilities in this case are uncapacitated in that there is no decision made on how many persons can be allocated to a single facility and parameters are deterministic supplying all the demand. Finally, there is no relationship between new facilities; each is independent. Therefore, this model would ensure every veteran has access to care, but does not account for cost effectiness.

Outputs of this model include the total cost for the transportation of goods and services between facilities and customer, the number of facilities, the coordinates of the new facilities, quantity supplied to customer by facility, and the distance between a customer and new facility. Since this model does not contain capacity constraints, an optimal solution means the facility that is closest meets the demand for each customer. This does not consider accessibility measures, but can be used to identify new locations where accessibility shortages occur.

The second possibility is the use of The Location-Allocation Model Each Customer Covered by Only One Facility. It is similar to the General Model, but each customer can use only one facility (Azarmand and Jami 2009). The strength of this model is it maximizes access while minimizing costs since there are no overlapping catchments. However, as the results of this thesis show, limited healthcare options have an increased effect on accessibility. Also, these limitations make accessibility much more vulnerable to variables in availability and acceptability. Overall, both these models are related, possible follow-ons to this thesis as they represent opportunities for future research.

Another possible future development is the exploration of additional spatial relationships affecting accessibility through the incorporation of new variables. The strength of this study is that any relationship affecting access to care is applicable and the interaction of multiple influences on the population can be addressed. The model provides increased realism as populations are not allocated to just one service. Therefore, it provides insight into relationships that might not be readily evident through traditional statistical, non-spatial analysis. In other words, it addresses the reality of a population within a given catchment's boundary to make choices. The models in this research are easily adjusted to study the effect of other healthcare variables on accessibility and some measurements that might be used include facility metrics such as revisits, appointment delays, immunization, infection, or treatment success.

Additionally, follow-on application and study could be conducted using the wealth of data collected and maintained by the VA. Similarly as discussed as an opportunity for improvement, VA-maintained data provides a wide variety of possible demographic and facility data useful with these models. Some data is unavailable outside the VHA due to the Health Insurance Portability Accountability Act of 1996 Privacy Rule, but the VHA does provide a process for requesting data for research. The VHA Data Portal provides a gateway to four reporting databases not available for open access or public use. An access request is required for either research or operations purposes (Kok 2013). This capability is available for possible opportunities in future research using similar methodology as this thesis.

Finally, accessibility of specific populations can be assessed as well. Similar to follow-on studies based on facility metrics, researchers could focus on certain key demographics. In this study, only total veteran populations are assessed, but future studies could look at properties such as certain age groups or eras. For example, War on Terror veterans may be of specific interest as they use VA healthcare more often than Gulf War veterans. Also, accessibility of populations based on specific medical needs can be assessed using this model, providing insight for the efficient development or allocation of services. It may be of interest as well to apply the same method to secondary or tertiary care to determine how accessible other services are according to rules in the Veterans Access, Choice, and Accountability Act of 2014. Overall, these methods show the potential benefits for assessing a wide-range of spatial relationships.

5.5 Final Conclusions

The results of 2SFCA and modified E2SFCA analysis and mapping demonstrate the challenges faced by the VA in providing timely, quality, primary care accessibility for veterans. Although there are several improvements that can be made to these methods to provide more detailed analysis at a higher resolution, the methods developed and executed in this study exhibit the spatial relationships between veteran populations and VA providers. It also shows, for the most part, veterans do have access to care within the stipulations of the Veterans Access, Choice, and Accountability Act of 2014 for VISN 21. Furthermore, it validates the great variability in these relationships across the landscape and identifies areas where availability and acceptability of care are satisfactory or may need improvement to ensure the VHA mission is achieved.

More interesting, this study shows the ability to modify the standard 2SFCA to assess accessibility using varying weights. This ability allows for a wide-range of measurements to conduct accessibility analysis down to micro levels. Providing a method to begin to measure availability and acceptability as part of accessibility is a starting point in which the process can be weighted using a host of variables such as infection rates, revisits for the same condition, or recovery time. The same concept can address the affordability of care by weighting possible costs, for example, cost for equal services, insurance coverage caps, copayments rates, or service payment completion.

Ultimately, the methods in this study answer the spatial research questions proposed in the introduction. The relationships between populations and primary care providers provide an understanding of veteran accessibility to VA primary care within the study area, identifying areas in which accessibility to care may be stressed. It also expands upon previous research through the exploration of the incorporation on non-spatial factors of availability and acceptability and their impact on accessibility through the use of wait-time and satisfaction indices. Furthermore, the idea of modifying the 2SFCA method to answer additional questions using current GIS technology provides benefit not only to VA decision-makers, but to anyone who desires to understand accessibility and explore other factors which may influence spatial relationships.

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Appendix A: American Community Survey Data

Field	Subject	Measure	Subject	Description	Type
GEO.id	Id	Absolute	Census Tract ID	ID	Integer
GEO.id2	Id2	Absolute	Census Tract ID 2	ID	Integer
GEO.display-label	Geography	Absolute	Tract Name	County, State	Text
HC02_EST_VC01	Veterans	Estimate	Total	18 years and over	Total
HC02_EST_VC03	Veterans	Estimate	Period of Service	Gulf War (9/2001 or later)	Percent of Total
HC02_EST_VC04	Veterans	Estimate	Period of Service	Gulf War (8/1990 to 8/2001)	Percent of Total
HC02_EST_VC05	Veterans	Estimate	Period of Service	Vietnam era veterans	Percent of Total
HC02_EST_VC06	Veterans	Estimate	Period of Service	Korean War veterans	Percent of Total
HC02_EST_VC07	Veterans	Estimate	Period of Service	World War II veterans	Percent of Total
HC02_EST_VC10	Veterans	Estimate	Sex	Male	Percent of Total
HC02_EST_VC11	Veterans	Estimate	Sex	Female	Percent of Total
HC02_EST_VC14	Veterans	Estimate	Age	18 to 34 years	Percent of Total
HC02_EST_VC15	Veterans	Estimate	Age	35 to 54 years	Percent of Total
HC02_EST_VC16	Veterans	Estimate	Age	55 to 64 years	Percent of Total
HC02_EST_VC17	Veterans	Estimate	Age	65 to 74 years	Percent of Total
HC02_EST_VC18	Veterans	Estimate	Age	75 years and over	Percent of Total
HC02_EST_VC21	Veterans	Estimate	Race	One race	Percent of Total
HC02_EST_VC22	Veterans	Estimate	Race	White	Percent of Total
HC02_EST_VC23	Veterans	Estimate	Race	Black or African American	Percent of Total
HC02_EST_VC24	Veterans	Estimate	Race	American Indian and Alaska Native	Percent of Total
HC02_EST_VC25	Veterans	Estimate	Race	Asian	Percent of Total
HC02_EST_VC26	Veterans	Estimate	Race	Native Hawaiian and Other Pacific Islander	Percent of Total
HC02_EST_VC27	Veterans	Estimate	Race	Some other race	Percent of Total
HC02_EST_VC28	Veterans	Estimate	Race	Two or more races	Percent of Total
HC02_EST_VC30	Veterans	Estimate	Race	Hispanic or Latino (of any race)	Percent of Total
HC02_EST_VC31	Veterans	Estimate	Race	Latino	Percent of Total

HC02_EST_VC34	Veterans	Estimate	Median Income in the Past 12 Months	Civilian population 18 years and over with income	2013 Inflation-Adjusted Dollars
HC02_EST_VC35	Veterans	Estimate	Median Income in the Past 12 Months	Male	2013 Inflation-Adjusted Dollars
HC02_EST_VC36	Veterans	Estimate	Median Income in the Past 12 Months	Female	2013 Inflation-Adjusted Dollars
HC02_EST_VC39	Veterans	Estimate	Educational Attainment	Civilian population 25 years and over	Total for Veterans
HC02_EST_VC40	Veterans	Estimate	Educational Attainment	Less than high school graduate	Percent of Total
HC02_EST_VC41	Veterans	Estimate	Educational Attainment	High school graduate (includes equivalency)	Percent of Total
HC02_EST_VC42	Veterans	Estimate	Educational Attainment	Some college or associate's degree	Percent of Total
HC02_EST_VC43	Veterans	Estimate	Educational Attainment	Bachelor's degree or higher	Percent of Total
HC02_EST_VC46	Veterans	Estimate	Employment Status	Civilian population 18 to 64 years	Total for Veterans
HC02_EST_VC47	Veterans	Estimate	Employment Status	Labor force participation rate	Percent of Total
HC02_EST_VC48	Veterans	Estimate	Employment Status	Civilian labor force 18 to 64 years	Total for Veterans
HC02_EST_VC49	Veterans	Estimate	Employment Status	Civilian labor force 18 to 64 years - Unemployment rate	Percent of Total
HC02_EST_VC53	Veterans	Estimate	Poverty	Below poverty in the past 12 months	Percent of Total
HC02_EST_VC57	Veterans	Estimate	Disability	With any disability	Percent of Total

Source: U.S. Census Bureau, 2009-2013 5-Year American Community Survey

Appendix B: Primary Care Facilities

VISN	Division	Station	Name	Address	City	State	Zip	Longitude	Latitude	FTE
21	Fresno	570	Central California HCS	2615 E Clinton Ave	Fresno	CA	93703	-119.780	36.772	15.02
21	Fresno	570GA	Merced CBOC	340 E Yosemite Ave	Merced	CA	95340	-120.464	37.332	2.5
21	Fresno	570GB	Tulare CBOC	1050 N Cherry St	Tulare	CA	93274	-119.337	36.222	4
21	Fresno	570GC	Oakhurst CBOC	40597 Westlake Dr	Oakhurst	CA	93644	-119.669	37.338	1.3
21	Northern California	612A4	Sacramento VAMC	10535 Hospital Way	Mather	CA	95655	-121.297	38.571	20.83
21	Northern California	612B4	Redding Outpatient Clinic	351 Hartnell Ave	Redding	CA	94612	-122.367	40.564	7.3
21	Northern California	612BY	Oakland Outpatient Clinic	2221 MLK Jr Way	Oakland	CA	94612	-122.273	37.811	8.56
21	Northern California	612GD	Fairfield Outpatient Clinic	103 Bodin Cir	Fairfield	CA	94535	-121.958	38.268	3.4
21	Northern California	612GE	Mare Island Outpatient Clinic	201 Walnut Ave	Vallejo	CA	94612	-122.287	38.116	2.2
21	Northern California	612GF	Martinez Outpatient Clinic	150 Muir Rd	Martinez	CA	94553	-122.111	37.994	9.85
21	Northern California	612GG	Chico Outpatient Clinic	280 Cohasset Rd	Chico	CA	95926	-121.851	39.751	3.6
21	Northern California	612GH	McClellan Outpatient Clinic	5342 Dudley Blvd	McClellan	CA	95652	-121.386	38.665	8.13
21	Northern California	612GI	Yuba City Outpatient Clinic	425 Plumas Blvd	Yuba City	CA	95991	-121.614	39.130	2.4
21	Palo Alto	640	Palo Alto HCS	3801 Miranda Ave	Palo Alto	CA	94304	-122.141	37.402	11.6
21	Palo Alto	640A0	Menlo Park	795 Willow Rd	Menlo Park	CA	94025	-122.158	37.463	0.2
21	Palo Alto	640A4	Livermore	4951 Arroyo Rd	Livermore	CA	94550	-121.764	37.638	4.3
21	Palo Alto	640BY	San Jose CBOC	80 Great Oaks Blvd	San Jose	CA	95119	-121.778	37.233	9.6

21	Palo Alto	640GA	Capitola CBOC	1350 41st Ave	Capitola	CA	95010	-121.964	36.975	1
21	Palo Alto	640GB	Sonora CBOC	13663 Mono Way	Sonora	CA	95370	-120.339	37.978	1.8
21	Palo Alto	640GC	Fremont CBOC	39199 Liberty St	Fremont	CA	94538	-121.980	37.550	3.7
21	Palo Alto	640HA	Stockton CBOC	7777 S Freedom Rd	French Camp	CA	95231	-121.282	37.879	5.3
21	Palo Alto	640HB	Modesto CBOC	1225 Oakdale Rd	Modesto	CA	95355	-120.957	37.662	4.8
21	Palo Alto	640HC	Monterey CBOC	3401 Engineer Ln	Seaside	CA	93955	-121.802	36.650	7.95
21	Reno	654	Sierra Nevada HCS	975 Kirman Ave	Reno	NV	89502	-119.798	39.515	18.2
21	Reno	654GA	Sierra Foothills Outpatient Clinic	11985 Heritage Oak Pl	Auburn	CA	95603	-121.099	38.940	4
21	Reno	654GB	Carson Valley Outpatient Clinic	1330 Waterloo Ln	Gardnerville	NV	89410	-119.748	38.925	3
21	Reno	654GC	Lahontan Valley Outpatient Clinic	345 W A St	Fallon	NV	89406	-118.780	39.476	2.7
21	Reno	654GD	Diamond View Outpatient Clinic	110 Bella Way	Susanville	CA	96130	-120.626	40.405	1
21	San Francisco	662	San Francisco HCS	4150 Clement St	San Francisco	CA	94121	-122.504	37.781	13.22
21	San Francisco	662GA	Santa Rosa Clinic	3841 Brickway Blvd	Santa Rosa	CA	95403	-122.793	38.514	7.5
21	San Francisco	662GC	Eureka VA Clinic	930 W Harris St	Eureka	CA	95503	-124.181	40.780	5.7
21	San Francisco	662GD	Ukiah VA Clinic	630 Kings Ct	Ukiah	CA	95482	-123.198	39.148	3.6
21	San Francisco	663GE	San Bruno CBOC	1001 Sneath Ln	San Bruno	CA	94066	-122.424	37.635	2.62
21	San Francisco	662GF	San Francisco Downtown	401 3rd St	San Francisco	CA	94107	-122.397	37.782	2.07
21	San Francisco	662GG	Clearlake CBOC	15145 Lakeshore Dr	Clearlake	CA	95422	-122.630	38.949	1.6

20	White City	692	S. Oregon Rehab Center & Clinics (SORCC)	8495 Crater Lake Hwy	White City	OR	97503	-122.834	42.440	15.02
20	White City	692SS	Grant's Pass CBOC	1877 Williams Hwy	Grants Pass	OR	97527	-123.339	42.417	3.6
20	White City	692GA	Klamath Falls CBOC	2225 N Eldorado Ave	Klamath Falls	OR	97601	-121.784	42.247	3.6
22	Greater LA	691GD	Bakersfield CBOC	1801 Westwind Dr	Bakersfield	CA	93301	-119.042	35.376	3.6
22	Greater LA	691GK	San Luis Obispo CBOC	1288 Morro St	San Luis Obispo	CA	93401	-120.660	35.279	3.6

Note: Latitude and Longitude were derived from U.S. Census Bureau Geocoder.

Sources: Dominy (2015), U.S. Department of Commerce (2016), VA (2010)