SPATIAL ANALYSIS OF VETERAN ACCESS TO HEALTHCARE IN LOS ANGELES COUNTY

by

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To a special person, you know who you are.

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List of Abbreviations

2SFCA	Two-Step Floating Catchment Area
ACS	American Community Survey
CV	Coefficient of Variation
E2SFCA	Enhanced Two-Step Floating Catchment Area
FCA	Floating Catchment Area
FC	Feature Class
GIS	Geographical Information Systems
MOE	Margin of Error
MUAP	Modifiable Areal Unit Problem
OD	Origins and Destinations
USWFCA2	University Southern Wales Floating Catchment Area 2
UCLA	University of California Los Angeles
VA	Veterans Administration

Abstract

This study was undertaken to determine if gaps in health care accessibility existed in Los Angeles County. A primary consideration of this study was the veteran population in Los Angeles County and their accessibility to healthcare. Accessibility is defined by the Veteran Administration (VA) as the acceptable travel time to the nearest VA healthcare center for a veteran to receive desired care. As part of the MISSION (Maintaining Internal Systems and Strengthening Integrated Outside Networks) Act of 2018, veterans may receive primary care outside the VA system if the average drive time to a VA facility is thirty minutes or more. This thesis examines the spatial accessibility for veterans to travel to VA facilities instead of accessing care outside of the VA system. At this time, there are three VA medical centers and seven primary care facilities located throughout Los Angeles County. This study analyzed the areas around the three medical centers and seven primary care facilities and identified gaps in accessing health care based on drive time using the enhanced two-step floating catchment area (E2SFCA) method. It identified where gaps in spatial accessibility exist using veteran estimations at the census tract level extent. The study found that gaps in coverage exist in the eastern area of Los Angeles County. The methodology and detailed analysis can serve to determine differences in drive time distance decay for veterans to access primary medical care in other locations throughout the country.

Chapter 1 Introduction

Many veterans in Los Angeles County, California, have complex health care needs as a result of their service while engaged in conflicts around the world. In exchange for veterans' active duty in any of the armed forces, each veteran may be eligible to receive health care through the Veterans Administration (VA). Veterans who desire to have their health care needs met through the VA must meet eligibility requirements that include active duty service with an honorable discharge (VA Benefits and Healthcare 2019).

Veterans who are eligible and wish to have their healthcare needs provided by the VA include those from World War II, Korea, Vietnam, the Cold War, and more recent wars in Afghanistan and Iraq. The health care needs include those related to the conflict when the veteran served, and many are combat-related traumatic injuries with extensive rehabilitation requirements. There are also illnesses and conditions related to the era served that include environmental exposure associated with the service location, combat-related chemical exposures, intense noise exposure, infectious disease exposure, substance abuse issues, and mental health concerns. Some of the diseases and health conditions that occurred during a veteran's military service may lead to chronic diseases including respiratory, heart, kidney diseases, mental health illnesses, sensory problems, and development of various cancers (VA Benefits and Healthcare 2019). Primary care is the entry point for many veterans to access their VA healthcare benefits.

Primary care is patient-centered, comprehensive, and continuous since it intends to coordinate various types of specialized care and reduce fragmented care delivery (Lin et al. 2018). Primary care is usually provided by physician generalists alone or in combination with nurse practitioners and at designated primary care facilities sites. The focus of care is long-term with a holistic approach. The purpose of primary care is to assist the veteran patient with greater access to available services that leads to better management of health care problems. It also includes modalities for disease prevention and health management education to create less need for specialty care and hospitalization (Lin et al. 2018). The provision of primary care is a critical component for each veteran's overall health management within the VA system.

1.1. Motivation for Study

This study analyzes health care coverage gaps for veterans living in Los Angeles County. Coverage gaps exist if maximum drive times exceed VA mandates or areas in Los Angeles County where no health care facilities exist. This writer became aware of this issue because of family and friends who wanted their care provided by the VA. However, they needed to drive more than 30 minutes to obtain primary care services. Veterans, many of whom have complex health care treatment and care needs, have chosen to have their care provided by VA health care practitioners who have expertise providing care to injured and ill veterans. Many veterans who live in Los Angeles County can be ill-equipped to re-enter non-veteran communities after being discharged from the military. Physical and psychological needs after military discharge may not have been addressed while in the service. This can exacerbate the reasons for their difficulty in transitioning to civilian life. The ease of access to obtain care and services is paramount in both the urban and rural areas of Los Angeles County for veterans. Accessibility, ambiance, and convenience of the distance to travel to receive care is also an incentive for veterans to obtain and follow up with primary care needs (Chatterjee and Mukherjee 2013).

The Veterans Access, Choice, and Accountability Act of 2014 and its amendments mandated specific maximum drive times to access facilities for primary care (Becker 2016). The Maintaining Internal Systems and Strengthening Integrated Outside Networks Act (MISSION) Act of 2018 included the drive time of not more than thirty minutes to access primary care. The issue of VA healthcare access prompted the exploration of research methods that used spatial accessibility in healthcare to understand this potential problem's complexity better. As discussed in more detail in Chapter 2, the past research findings motivated the author of this thesis to study if the current distribution of VA healthcare locations in Los Angeles County ensures veterans can easily access health care after serving their country. The VA states its concern on veterans' physical access to primary care. The Veterans Access, Choice, and Accountability Act of 2014 and its amendments mandated specific maximum drive times to access facilities for primary care (Becker 2016). The MISSION Act of 2018 included the drive time of not more than 30 minutes to access primary care.

This research aimed to assess if gaps in coverage exist from veteran demand locations to VA hospitals and primary care facilities. Adhering to the guidelines provided by the VA in the mandate, MISSION Act of 2018. s stated, veteran healthcare provided by VA healthcare practitioners may provide a better experience for veterans as opposed to healthcare provided by non-VA practitioners. VA leaders and other stakeholders will have a greater understanding of where drive time thresholds exceed mandated requirements. This study's results and suggestions can enhance the body of knowledge to assist planners in the decision process of relocating, opening, closing, or modifying existing primary care facilities.

1.2. Study Area

As discussed above, this study's focus was accessibility for veterans to seek primary medical care in a location not more than 30-minute travel time from their location within Los Angeles County. The county of Los Angeles is the eleventh largest in California with more than 4,000 square miles (County of Los Angeles n.d.) and is the most populous county in the United

States (DPH 2015). The large, broad geographic area and the often congested freeway network of Los Angeles County may cause impedance in accessing health care.

The Los Angeles County network of veteran care (Figure 1) includes three comprehensive medical centers in West Los Angeles, North Hills, and Long Beach. All three medical centers provide primary and specialty care such as mental health, women's health, audiology, cardiology, ophthalmology, optometry, orthopedics, urology, and dental services (US Department of Veteran Affairs 2019). Also, there are seven community-based outpatient care centers within the county. They are in Arcadia, Santa Fe Springs, Commerce, Long Beach, Lancaster, Gardena, and the Ambulatory Care Center in North Hills. The staffing in these PCF centers ranges from one physician as a solo practitioner to additional NPs, and physician's assistants.

The driving distance from the Greater Los Angeles County VA facility to the Long Beach VA facility is 33 miles, which takes approximately 1.5 hours to drive and 2.5 hours via mass transit (Los Angeles Public Transit 2015). The drive distance to North Hills from the Greater LA VA facility is approximately 1 hour and 1.5 hours. This thesis examines the spatial relationship of the PCFs and the veteran estimations per census tracts with access to care within a 15-minute drive catchment.

Meeting the primary health care needs of Los Angeles County veterans requires the geospatial analysis of the maximum drive time standard from a veteran's home to the nearest VA health care facility providing primary care services. This analysis raises the question if the current PCF locations are serving the needs of the veterans or if there are gaps in coverage due to driving time delays to access primary health care. It also adds information and analysis of the presence of locations that are closer than 30 minutes from a veteran's home. Figure 1 below shows the study area with each supply having a unique color symbolized with a square. The major freeways shown were to provide a reference for the reader and their proximity to the hospital and PCF locations. The large, broad geographic area and the often congested freeway network of LAC may cause travel impedance in accessing health care.

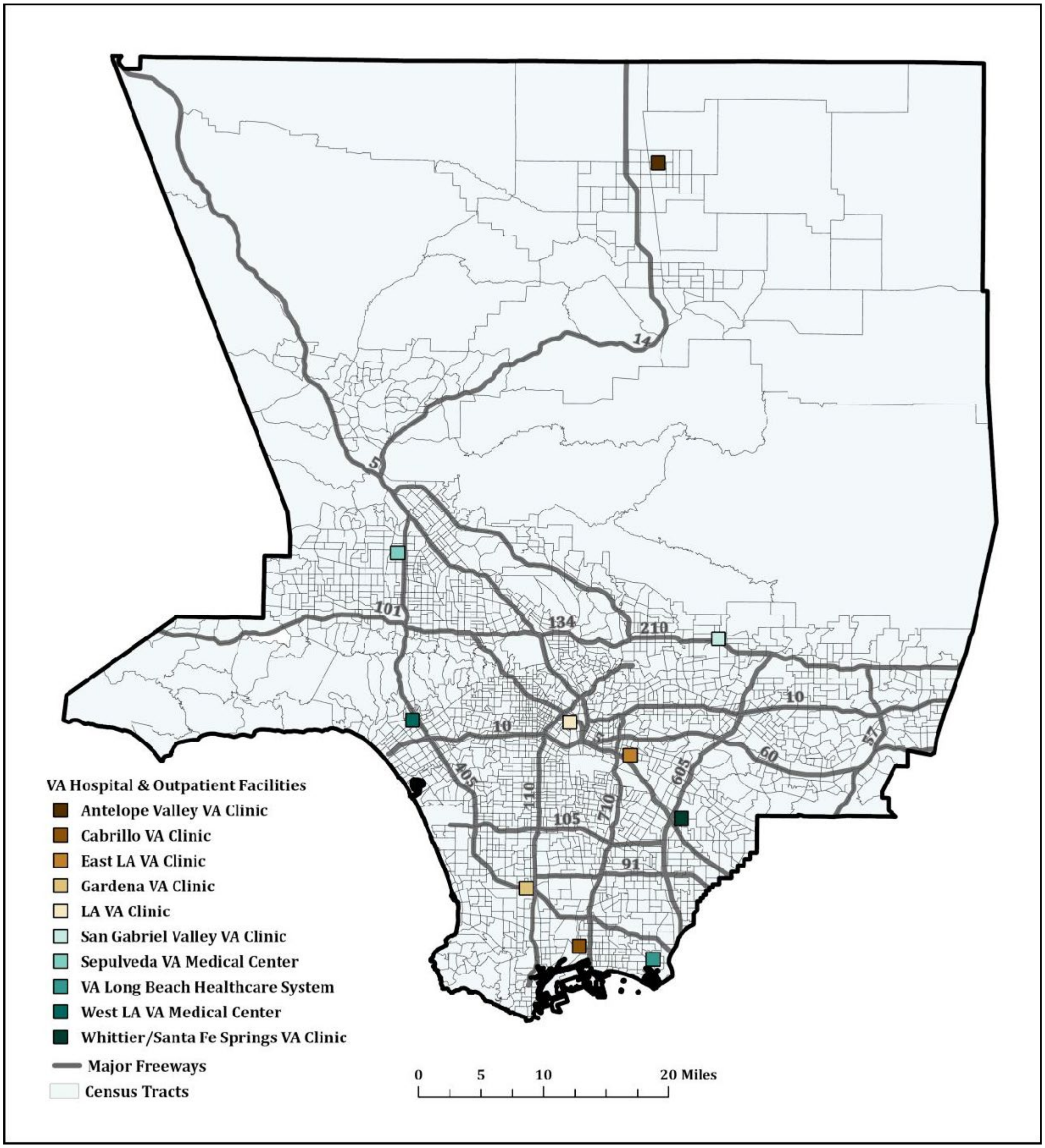

Figure 1. Study Area

1.3. Sociodemographic Data

Los Angeles County has the largest number of veterans in California (LAO Report 2017). There are approximately 264,635 veterans (Los Angeles Almanac 2017) living in Los Angeles County and about 12,000 veterans moving to the county each year (Castro, Kintzle, and Hassan 2014). The most significant percentage of veterans is 65 years old and above, representing 53.2% of the veterans (Los Angeles Almanac n.d.). The second-largest age group is 35-54 years old, which represents 21.8% of the veterans. The third-largest is 55-64 years old, which represents 15.3%. The smallest group comprises veterans 18-34 years old that represent 9.7% of the total veterans (Los Angeles Almanac n.d.).

1.4. Future Research Applicability

This thesis examined spatial access to primary care for veterans in Los Angeles County. A core model was used as a baseline for further analysis. The core model was developed from a third party add-in tool called the USWFCA2, which stands of the University of South Wales Floating Catchment Area 2. The add-in tool accelerated the laborious process when manually applying the E2SFCA statistical equation in a GIS. The 30-minute mandate enacted by VA was considered for a catchment boundary in this analysis. However, due to traffic congestion, urban sprawl, and street network data attributes a 15-minute drive time, catchment provided a more realistic threshold boundary. The applicability of the core model provided results that can be used in future research.

This study indicated if travel time gaps in coverage exist and provided data to assess spatial accessibility regarding veteran healthcare. The thesis examined existing locations and spatially exhibited which veteran census tracts meet the drive time threshold to access care. It also spatially displayed veterans who are inside of drive time distances to access multiple primary care facility locations. The examination of supply and demand volume and the application of the E2SFCA method may assist VA planners, veteran stakeholders, and county administrators in more accurately understanding if gaps in spatial accessibility exist. Other scientists have not conducted such research to this author's knowledge, particularly in the context of Los Angeles County.

1.5. Structure of this Thesis

There are five chapters in this thesis. Chapter 2 provides a review of past spatial studies related to healthcare access, consisting of simple gravity models to advanced spatial analysis using the E2SFCA method. An in-depth analysis of the methodology was highlighted throughout Chapter 3 using an open-source addin tool to expedite the lengthy procedural application of the E2SFCA method in a GIS. Chapter 4 reports the results of the spatial analysis. From the results of the spatial analysis, Chapter 4 also includes a general discussion of potential site parameters to review and one additional location within Los Angeles County is identified. In Chapter 5, there is a discussion about the analysis of the methods and final results. There is also a limitation section in Chapter 5 that provides the reader with insight into how improvements could be made. Also, this chapter offers implications for further research on accessibility to healthcare facilities.

Chapter 2 Related Works

This chapter provides the reader with the background knowledge that qualifies the methods described in Chapter 3. Moreover, this chapter discusses past research in spatial accessibility and a comprehensive assessment of why the E2SFCA method was chosen.

Spatial accessibility models depend on three components: population data in census tracts, the method to aggregate the data, and the defined measure of accessibility (Apparicio et al. 2017). Research on spatial accessibility is essential to promote veteran equitable access to health care facilities. Equity through accessibility leads to patient satisfaction, improved health outcomes, decreased hospitalizations, and reduced cost. These indicators of effectiveness in healthcare are associated with travel time to access care (Saxon and Snow 2016).

2.1. American Community Survey

The American Community Survey (ACS) is sent out by the United States Census Bureau monthly and aggregated yearly, which collects socio-demographics on US residents. The ongoing survey is sent out to more than three million residents and is considered a sample of the population (Berkeley 2017). Moreover, different samples are taken and yield different estimates of the actual population value. The ACS offers one-year, three-year, and five-year estimates where five-year estimates are based on five-times as many samples and provide increased statistical reliability. Depending on the analysis undertaken, the US Census Bureau has general guidelines to best estimate the most warranted dataset. Also, when analyzing a small subset of a population such as veterans, five-year estimates are preferred.

2.1.1. American Community Survey Data: Uncertainty

Uncertainty in the ACS data is the result of the process of how the survey data is collected. Since the ACS conducts sample surveys of a segment of the population, as discussed in Section 2.1 at one year, three-year, and five-year intervals. The data does not reflect the exact characteristics of the entire population. The word uncertainty in this instance can also be considered a sampling error. The sampling error described by the ACS is the difference between a sample survey and if the entire population was surveyed. The sampling error size is expressed as the margin of error (MOE) and is published with each ACS report (US Census Bureau n.d.).

2.1.2. American Community Survey: Margin of Error (MOE)

When using ACS data, there is a need to assess the MOE, which is present in sample size estimates. Three factors contribute to the MOE, and these are the confidence level of the sample size, the sample size itself, and the amount of variability in the population (Bell and Cai 2015). The confidence level that corresponds to the MOE suggests the ACS sample estimate is within the realm of the population estimate. The ACS estimates with corresponding MOEs have a 90% confidence level attributed to them. From these published MOEs, 90% confidence intervals that define a range calculated. This is the range that holds the real value of a population 90% of the time.

One example of a calculated 90% confidence interval for an estimate was taken from the data used in this thesis. One census tract that held a veteran estimation of 438 and had an MOE of 103. Taking the MOE value of 103, then adding and subtracting from the veteran estimate of 438, resulted in a 90% confidence interval for that estimate (US Census Bureau n.d.). When researchers look at ACS estimates and MOE, they must consider that smaller sample sizes will have greater MOE, and some MOE will be larger than the estimate itself. Using larger geography can reduce the MOE, and the smaller the MOE, the more accurate the data is to use (Berkley 2017).

2.1.3. Coefficient of Variation (CV)

The coefficients of variation (CV) calculated within the ACS veteran data are statistical measures that show the amount of sampling error for each census tract. This calculation is used to assess data reliability. The following indicates the reliability of the sampling data: CV < 15 indicates the data is reliable, CV >=15 and < 30 the data is moderately reliable, and CV>= 30 is not reliable, and a coefficient of variation of 0 indicates no data (Census Data, Montgomery, MD n.d.). According to Rural Data Portal (n.d.), and ArcGIS (2012), the measures of reliability are not standardized and vary slightly by researchers to estimate reliability based on established CV formulas. ArcGIS (2012) indicates that the following reliability: CV = < 12 indicates high reliability, CV >12 to not more than 40 is medium reliability, and CV > 40 is low reliability.

2.2. Spatial Accessibility

The assessment of adequate health care accessibility for veterans in Los Angeles County for this research is based on travel time to access a VA healthcare facility. Spatial accessibility is measured in many different ways, such as distances to a health care facility or practitioner, distance to travel in time estimates, and distance decay calculations (Ludivine et al. 2019).

Distance decay, in essence, is how far someone is willing to travel. If a supply location is far away from a demand origin, the less inclined someone would be to use that location for services (GISGeography 2020). The closer the demand is to the supply, the lower the time distance and the lower the decay. As the supply gets further from the demand, the time increases or decays to the point that it is too far in time to travel to access the supply point.

In one study, physicians were used as a supply-side, and population demographics were designated as demand. Using physician as supply to population demand was considered an essential criterion in assessing spatial accessibility in healthcare (Luo 2004). Spatial accessibility in healthcare has been widely studied in the past. One study used four separate categories to define the methods most used: provider-to-population ratios, distance to nearest provider, the average distance to a set of providers, and gravitational models of provider influence. Each spatial accessibility method produced its capabilities and shortfalls (Guagliardo 2004).

2.2.1. Provider-to-Population Ratio

The provider-to-population ratio is a measurement that is used the most. The reason for its popularity is that data sets are easy to obtain and use and do not require advanced expertise in GIS. The provider-to-population ratio is an indicator of supply availability and is calculated inside a geographic area of extent. The extent of these areas can be as small as health service areas or as large as counties and states. Doctors and nurse practitioners, location of primary care clinics, or wait time are all considered health service capacity indicators and are used as the numerator in the equation. Demographic data such as population size within a specified geographical extent is assigned as the denominator. Contiguous areas or regions are evaluated for similarities between provider-to-population ratio values concerning some form of healthcare indicator (Guagliardo 2004). Using physician to the population as supply and demand are considered an essential criterion in the assessment of spatial accessibly in healthcare (Luo 2004). The provider-to-population ratio does have limitations. One of the provider-to-population limitations is that it does not measure distance or travel time.

2.3. Gravity Model Assessment

Gravity models in simplistic terms measure the attraction between two points, a supply origin and a demand destination (Esri n.d.). Gravity models are thought to be reliable in measuring spatial access since the model addresses the decreasing attraction of demand as it moves further away from the supply sites (Crookes and Schuurman 2012). Gravity models, also known as cumulative opportunity measures, are evaluation for accessibly. The cumulative opportunity measures calculate how many opportunities (demand) that are within a specific travel time or distance threshold. If more opportunities exist within a given travel time or distance, accessibility increases (Higgs 2004). Gravity models are mathematical equations that measure spatial accessibility concurrently, including the supply, the demand, and the ranges in time or miles between the two (Pan et al. 2015). The basic gravity model formula is as follows:

$$A_i = \sum_j \frac{S_j}{d_{ij}^{\beta}}$$

The equation of the basic gravity model is A_i becomes spatial accessibility from point *i*, which is considered population. This population point can be a census tract centroid or any area of interest such as a residence. The service capacity is considered S_j at *j,* which is the provider location This measurement usually takes on a numerical capacity range. Travel impedance (distance or travel time) is *d* between points *i* and *j.* The gravity decay coefficient is β (Beta). To interpret the results, the summed supply capacity increases when the total travel impedance declines. (Guagliardo 2004).

2.3.1. Gravity Model Limitations

Some basic limitations with the gravity model are that it only measures supply. Moreover, it uses a statistical equation that nonprofessionals may have a hard time interpreting (Guagliardo 2004). La Mondia, Blackmar, and Bhat (2010) completed a comparison study of transit accessibility models, one of which was a gravity model. They identified three limitations of the gravity model but also indicated the popularity of the model of gravity models to measure accessibility. The first limitation they cited was the gravity model assumes the attractiveness of each destination is equally attractive to all individuals. The second limitation they cited was the model did not consider individual travel patterns, travel behavior, and did not include time constraints to a destination. The third limitation which the authors considered to be a significant limitation was the lack of defining the impedance or friction factor of locations at further distances.

2.4. Two-Step Floating Catchment Area Method

In examining spatial accessibility for health care, the two-step floating catchment area (2SFCA) method was reviewed. In healthcare, supply and demand variables vary; hospital locations, number of doctors at a provider site, road network datasets, and travel to provider locations are all dynamically connected (Luo et al. 2018). The 2SFCA is a unique gravity model (Lou and Qi 2009). The 2SFCA uses spatial and non-spatial factors to measure spatial accessibility based on travel impedance between demand and supply. Wang and Luo (2005) researched to examine consumer access to primary healthcare using spatial and non-spatial factors in Illinois. The spatial component illustrated how geographic locations could be impediments between the provider and the consumer to access healthcare. The non-spatial factors included demographic information obtained from census data. The physician data were obtained from the American Medical Association. They utilized a 2SFCA method to measure spatial accessibility based on travel time from the consumer to the healthcare location. They then grouped the consumers into sociodemographic groups. The study's outcome was combining the spatial and non-spatial results to identify areas of poor access to healthcare. The challenge indicated by Wang and Luo (2005) was integrating the spatial and non-spatial indicators into one spatial analysis, which was accomplished using the 2SFCA method. Their research concluded that integrating spatial and non-spatial factors in one system is essential when designing a method to assess healthcare access. This study showed that GIS was useful to analyze spatial relationships and complete computations related to spatial data.

The 2SFCA method building on the provider-to-patient relationship uses floating catchment areas. They are a determination of travel impedance from supply to demand. Typical travel impedances used in analyzing health care related to spatial accessibility are maximum travel time or distance. Most healthcare studies using the 2SFCA regard a 30-minute drive-time as maximum travel time for people to spend traveling to a primary care clinic (Luo and Qi 2009). The 2SFCA measures the accessibility values from the demand point, which is the sum of the provider-to-population ratio that falls within a catchment area (Shin and Lee 2018). Step one in the 2SFCA method calculates a population that is within the catchment at each provider. In step two, services are allocated to potential populations in the catchments (McGrail and Humphreys 2009). All populations (demand) within a specific floating catchment are considered equal and share the same accessibility to that specific supply location. (McGrail 2012). Results from these steps become the spatial accessibility index score for each demand point. The formulas and procedures are shown below with an explanation of the equation.

The first step begins with using a physician location j, and searches locations k for all populations that fall within a travel time threshold d_o from location j, to compute the physician-to-population ratio R_j that fall in each catchment area. P_k represents the population of k and is in the boundary catchment j ($d_{kj} \leq d_0$). Sj represents the number of physicians at location j; d_{kj} is the travel time between k and j.

$$R_j = \frac{S_j}{\sum_{k e \{d_{kj \leq d_0}\}} P_k}$$

In step two, the population location i, then search every physician location j, that is in the threshold travel time d_0 from location i (catchment area i), then sums up of the physician-to-population ratio (originated from step 1), R_{j} at those locations. A_i^f is the accessibility of the population at location i to physician. R_j is the physician-to-population ratio originating at physician location j who center falls within the catchment centroid at population location i. The d_{ij} is the travel time between i and j.

$$\sum_{j \epsilon \{d_{ij} \leq d_0\}} R_j = \sum_{j \epsilon \{d_{ij} \leq d_0\}} \frac{S_j}{\sum_{k \epsilon \{d_{ij} \leq d_0\}} P_k}$$

When interpreting the results, larger values of A_i^f represent better access to supply at the demand location. Ratios are assigned in the first step, and in the second step, the initial ratios are summed up from overlapping service areas, where potential demand has access to multiple supplies.

2.5. Enhanced Two-Step Floating Catchment Area Method (E2SFCA)

The E2SFCA is another type of gravity model that considers distance decay in the modeling process. After careful review of the gravity models described earlier in this study. McGrail (2012) discusses the use of E2SFCA by Luo and Qi (2009) with the addition of three distance decays. The E2SFCA uses different intervals of distance impendence, which provides a more accurate spatial pattern regarding accessibility and shortage areas (Luo and Yi 2009). The E2SFCA distance decay is a factor that can influence care location choices Guagliardo 2004). Luo et al. (2018) used the E2SFCA method to spatially explore the accessibility of medical services for the elderly in Wuhan, China. The E2SFCA, like the 2SFCA, calculates an accessibility index score and requires an additional step using distance decay.

The E2SFCA incorporates a Gaussian distance decay function into its formula, and this thesis used drive time as the distance decay. Conversely, the 2SFCA has fixed distance impedance and does not incorporate multiple distance decays. The use of distance decay provides a more accurate depiction of where coverage gaps exist. The addition of distance decay allows for an in-depth interpretation of the results (Luo and Qi 2009). The statistical equation beginning with step one is shown below.

$$R_j = \frac{S_j}{\sum_{k\epsilon\{d_{kj}\epsilon D_r\}} P_k W_r}$$

$$R_j = \frac{S_j}{\sum_{k\epsilon\{d_{kj}\epsilon D_1\}} P_k W_1 + \sum_{k\epsilon\{d_{kj}\epsilon D_2\}} P_k W_2 + \sum_{k\epsilon\{d_{kj}\epsilon D_3\}} P_k W_3}$$

The first catchment of supply location *j is* represented by thirty-minute drive time. Next, the E2SFCA method calculates three travel time zones from within each catchment. The travel time zones are set up with minute breaks of 0-10, 10-20, and 20-30. Population locations are considered (*k*) in the equation. These population locations denoted by (*k*) are searched within a travel time zone represented as (D_r) from provider location *j*. The following way computes the weighted provider-to-population ratio (R_j) within the catchment area. P_k becomes the population of k that falls within the catchment j**.** Then Sj becomes supply-side count at location j; dkj is the travel time between k an j. In this equation, the D_r is the rth travel zones (i.e. travel time zones1-3) from within each catchment. W_r represents the distance weight with regards to the rth travel time zone. The Wr takes into account the Gaussian function, which captures the distance decay of providers j access (Luo and Qi 2009).

In step two shown below, population location i searches every provider location j. This is done within the 30-minute travel time zone starting at location i. The sum of the ratio, which is the provider-to-population at those locations, is labeled as R_j. At those locations, A_i^f is the accessibility of population at location i with regards to the providers. The travel time between i and j is represented by dij. As with step one, the derived weights using the Gaussian function are applied for representing distance decay in each travel time zone (Luo and Qi 2008). The travel time between i and j is represented by dij.

$$A_i^F = \sum_{j \epsilon \{d_{ij} \epsilon D_1\}} R_j W_r$$

$$= \sum_{j \epsilon \{d_{ij} \epsilon D_1\}} R_j W_1 + \sum_{j \epsilon \{d_{ij} \epsilon D_2\}} R_j W_2 + \sum_{j \epsilon \{d_{ij} \epsilon D_3\}} R_j W_3$$

2.6. Gaussian Function

The Gaussian distribution was chosen as the functional form to consider distance decay in this thesis. Its use was to show supply accessibility based on time limits to access primary care. The Gaussian function used with the E2SFCA identified distance decay through weighted values represented by the normal distribution curve. The literature suggests that the Gaussian curve is an advantageous function to calculate travel impedance through a gravity model. (Luo and Qi 2009, Lin et al. 2018, Chen and Fei 2019). The choice of the impedance coefficient is essential when using the Gaussian distribution since it affects the outcome of accessibility results.

Wang and Tormala (2014) conducted a study to measure access to primary care physicians for an aboriginal people located in Canada. They utilized an E2SFCA method with the Gaussian function to weight distance decay to determine accessibility to a physician. Their weighting method was adopted from research completed by Luo and Qi (2015). Ma et al. (2018) also used an E2SFCA with a Gaussian function to define and assess travel distance weights. Each of these researchers used different beta coefficient weights that were chosen dependent on the study of spatial and non-spatial factors. The populations studied in the research above-identified and tested different travel times as distance decay from the physician location. The weights chosen by researchers depend on the most suitable decay rate applied to the Gaussian curve. The writer of this manuscript tested multiple weights to assess the rate of distance decay for this project. Testing was performed using different coefficients that affected the rate of the curve of the Gaussian model within the computational formulation. The impedance beta coefficient used to show distance weighting was 0.5 with range values of 0-1.0. Testing with other coefficients was also conducted, but the decline was too steep.

Chapter 3 Methodology

Chapter 3 is a description of the data and processes used in this project. The methods utilized were based on the research discussed in Chapter 2. Building on prior work was the basis of this thesis and the methods used to elicit the results presented in Chapter 4.

The first section describes the steps needed to obtain, combine, and calculate all dataset utilized in this project. That data included hospital and primary care facilities with practitioner volume, and veteran estimations per census tract. Subsequent sections within this chapter illustrate the data integration into the methods chosen to achieve the outcome discussed in detail in Chapter 4. The methods utilized within this study were the use of an add-in tool called the Enhanced Two-Step Floating Catchment Areas Accessibility Tool. This was used to ease in the analysis of multiple E2SFCA assessments. This tool also used a Gaussian decay function with decay bandwidth values to mimic different drive times.

3.1. Data Sources

Datasets listed in Table 1 were used to determine if gaps in veteran coverage exist in LAC. Table 1 reports what types of datasets were obtained and what source they came from, including datasets, file type, and source. The demographic dataset used was ACS 5-year estimates of veterans living in Los Angeles County from the years 2012 to 2017.

Table 1. Data Sources

Datasets	File Type	Source
Veteran Demographics	Tabular .CSV	United States Census Bureau American Community Survey
Los Angeles County Census Tracts	Polygon Feature Class	United States Census Bureau TIGER/Line
Los Angeles Network Data	Polyline	UCLA Geo-Portal
VA Locations	Point Feature Class	Veteran Administration

The chosen road network dataset had a drive time attribute. The TIGER/Line street datasets were not used because of connectivity errors in the line segments and no mile per hour or drive attributes in the dataset. The Los Angeles road network provided by the University of California, Los Angeles (UCLA) geoportal had drive-time attributes associated with the dataset and was used for cost impedance in this manuscript. All four of the datasets were obtained online, and the author of this thesis created the VA hospitals and primary care facility layer.

3.2. Demand Volume

The total veteran estimation used in this study was 280,014 dispersed throughout the 2,341 census tracts of Los Angeles County. Each census tract represents an areal unit of a demand-side layer, which was used for further spatial analysis. This thesis used veteran ACS estimates joined with census tracts as the first set of data to be geo-processed. Figure 2 shows the workflow of the data processing to develop demand-side point data, which also records the veteran estimation. The census tract polygons were transformed into points representing their centroids (Figure 3) through the Feature to Point tool of ArcGIS. Of those 2,341 census tracts there were 47 that had no veteran estimates associated with them. These census tracts were occupied by parks, airports, and industrial parcels.

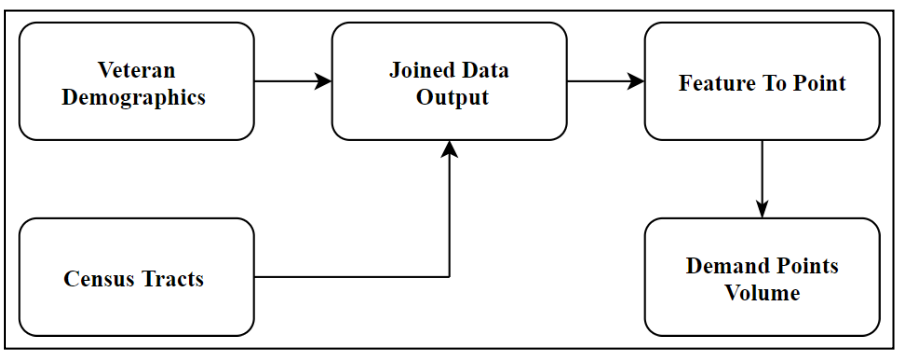

Figure 2. Workflow Diagram Showing
Demand Centroids Creation.

For ease in the visualization of what the feature to point tool did, Figure 3 shows a part of the study area, where polygons were turned into census tract centroids. Graduated symbology with Jenks natural breaks represents veteran estimation. The dark grey census tracks below show which areas have no veterans in the ACS data.

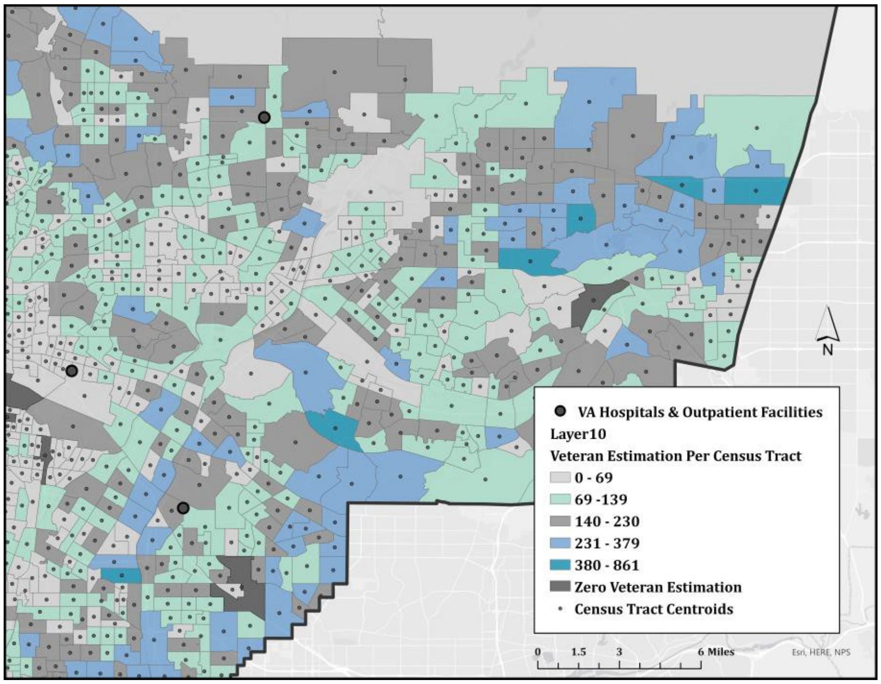

Figure 3. Census Tract Centroid Example.

3.3. VA Hospital and Primary Care Outpatient Facilities

This thesis used VA hospital and primary care facilities as the supply side and volume attribute used in this spatial analysis. To obtain the supply volume attribute, the author of this study called individual VA locations and obtained doctor and nurse practitioner counts. Moreover, the author collected the VA facilities' phones numbers and addresses from their websites**.**

Figure 4 shows the workflow of developing point data representing the locations of the supply locations and the counts. The first step was to obtain VA addresses, these were converted to latitude and longitude. Next, the data was imported to ArcMap and transformed to a point feature class. This was then exported to a new feature class where the supply volume attributes were appended. This data processing resulted in a supply-side input layer usable for further analysis.

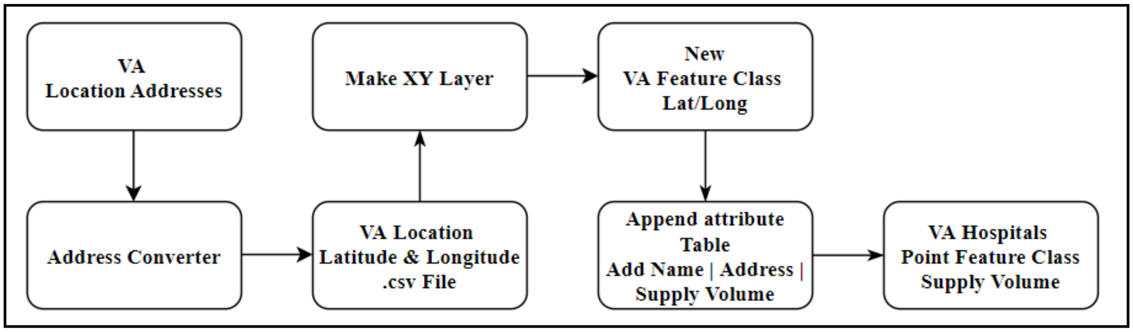

Figure 4. Workflow Diagram Showing Supply Point and Volume Creation.

3.3.1. Latitude and Longitude

To obtain the latitude and longitude for each VA location, an online address converter was used. The program, which was called LatLong.net, converted street addresses to latitude and longitude based on World Geodetic System 1984. This transformed the addresses to XY coordinates that ArcMap was able to read. A list of all VA hospitals and outpatient facilities by name in alphabetical order (Table 2) was used in this analysis. The three locations with the high supply volume were the VA hospitals in Long Beach, West LA, and the Sepulveda medical center. Phone numbers were added to the table so that any updates in the future with regards to volume could easily be ascertained.

Table 2. Veterans Administration Names and Locations with Supply Volume.

Veterans Administration Facility Name	Latitude	Longitude	Phone Number	Doctor & Nurse Practitioner Count
Antelope Valley VA Clinic	34.703353	-118.124274	661-729-8655	3
Cabrillo VA Clinic	33.79222	-118.22213	562-826-8414	1
East Los Angles VA Clinic	34.014927	-118.154192	323-725-7372	1
Gardena VA Clinic	33.85884	-118.296517	310-851-4705	2
Los Angeles VA Clinic	34.052559	-118.238586	213-253-5000	4
San Gabriel Valley VA Clinic	34.151328	-118.032492	818-672-2800	2
Sepulveda VA Medical Center	34.246545	-118.482171	818-891-7711	23
VA Long Beach Healthcare System	33.778217	-118.119196	562-826-8000	64
West Los Angeles VA Healthcare System	34.05239	-118.4584	310-478-3711	68
Whittier/Santa Fe Springs VA Clinic	33.94238	-118.08182	562-347-2200	4

3.3.2. Supply Volume

Doctor and nurse practitioners’ counts were used as supply volume, which contributed to the accuracy of spatial accessibility scores. Each of the three main hospitals has a higher number of counts than the seven VA clinics. Figure 5 shows the study area of VA locations, names, and supply volume. The total supply volume is 172 doctors and nurse practitioners

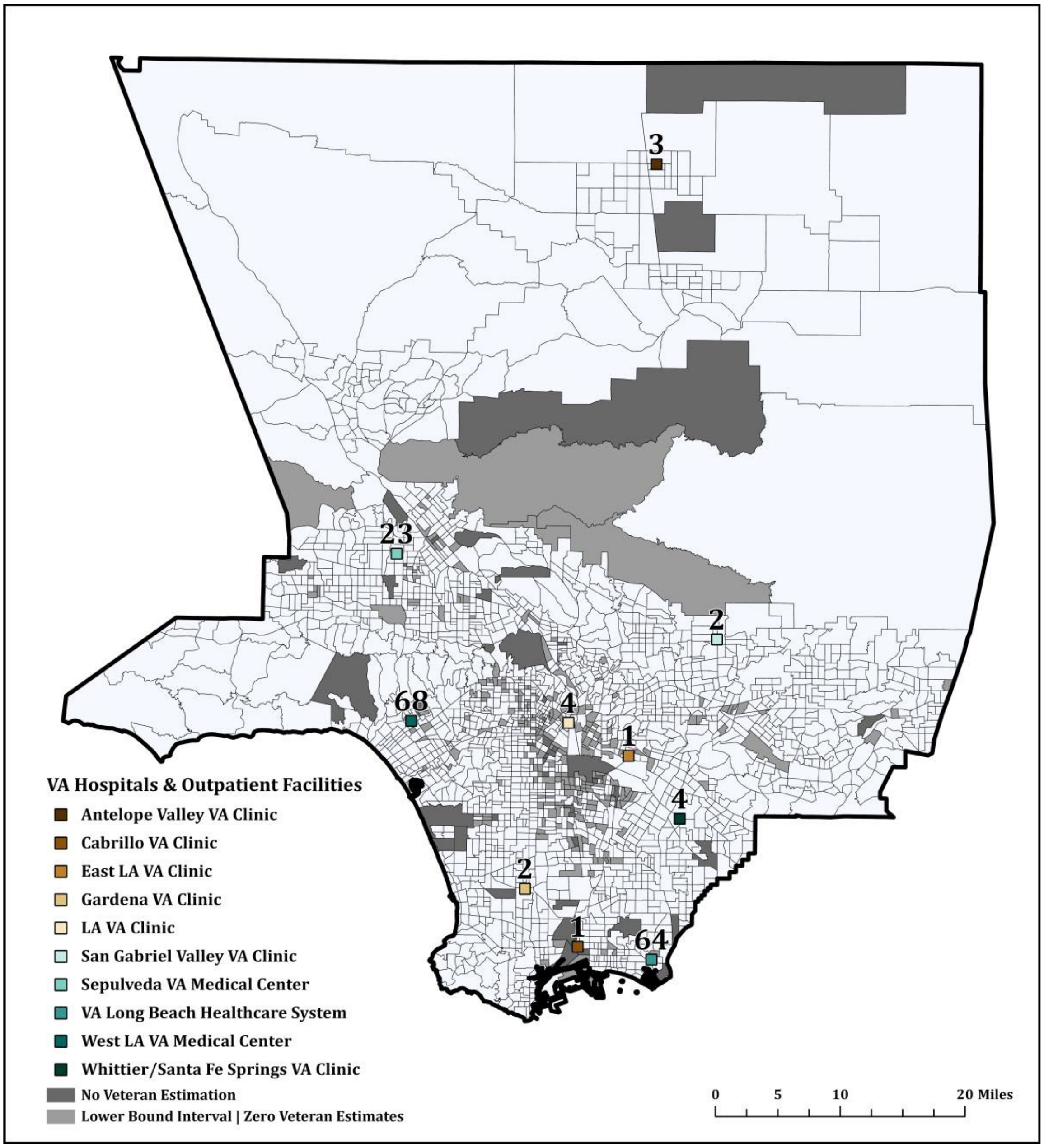

Figure 5. VA Locations and Supply Volume.

3.4. Road Network Creation

The Los Angeles County area is 4,751 square miles, plagued with urban sprawl and traffic congestion, all factors for using drive time as travel impedance in this study. Drive time as impendence provided more accuracy than straight-line Euclidean distance, which is more intuitive to understand since Euclidean distance is a straight line distance between two points and does not follow a road network. Moving around Los Angeles almost always requires the use of a vehicle. The quickest route in conjunction with drive time on road segments provided a more accurate depiction of real-world impendence.

A street dataset was downloaded from the University of California, Los Angeles geoportal. To ensure the dataset was applicable, a new network dataset was created using the road network provided by the source. When the network dataset was created, the travel mode was set with drive time and used as impedance in this study. The resulting network elements after a network dataset was run were road network edges and network dataset junctions used for calculating locations and later used in the E2SFCA analysis tool process. Figure 6 shows a neighborhood where the VA clinic is located in the Antelope Valley area. The green dots represent nodes connecting individual line segments in the network dataset.

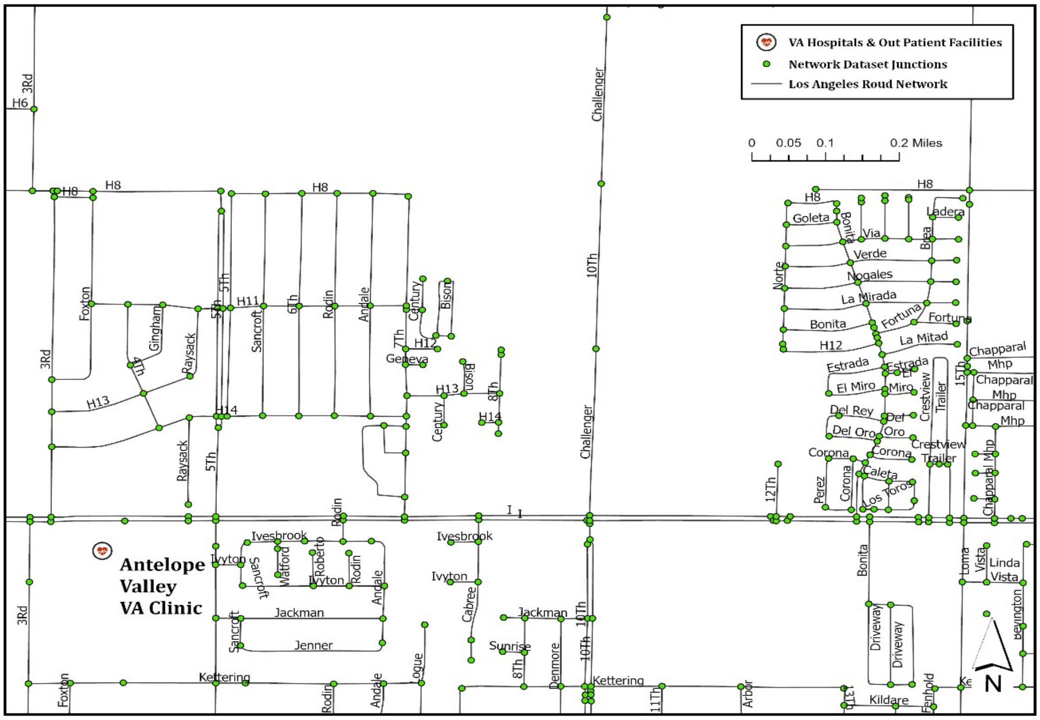

Figure 6. Network Dataset Streets and Network Junctions.

3.5. Origins-Destinations (OD) and Closest Facilities

The USWFCA2 analysis tool produced an origins and destinations (OD) cost matrix layer and closest facility layer. The OD cost matrix and the closest facility solver tools were ancillary outputs produced by the add-in tool. The OD cost matrix detects and measures a least-cost-path from multiple origins along a network and only solves in one direction from origins to destinations. Conversely, the closest facility tool measures the cost between two points called facilities and incidents. It is used to find the path of two points which are closest to each other and it can solve find routes in either direction. The results of those outputs are shown and discussed later in this section. In this analysis, the incidents became demand points, and facilities were the supply points. The cost impendence was drive time in minutes, and all closest incidents to facilities routes that were found had a drive time attribute associated with each route.

Both the OD cost matrix and the closest facility tools found the least cost path and produced six feature layers automatically updated into the table of contents in ArcMap. Within the OD cost matrix output layer, there were six feature layers that represented multiple outputs. The first feature layer was origins, and this represented all of the supply points located during the analysis. The origins layer also had three categorical sublayers consisting of located, unlocated, and if there was an error found. The destinations feature layer found all the census tract centroids that held veteran estimations that were within the 15-minute catchment. Located, unlocated or errors that were found were all subcategories and were inside the destination feature layer. There was a third feature layer called lines representing all of the OD lines found in the analysis.

The study area in Figure 7 shows the output of the OD cost matrix analysis centered around the Antelope Valley VA Clinic. Census tracts (destinations) outside the 15-minute catchment were not found or analyzed during the OD cost matrix analysis. The map shows that all census tracts within 15-minutes of drive time from the supply location to census tract centroids were calculated in the network analysis. The red circle symbol shows the Antelope valley VA clinic's location with black origin-destination lines emanating from that location. The small blue circles represent all thirty-five destinations found during this analysis. All census tracts that fell outside the catchment area were shaded light blue and considered areas lacking accessibility.

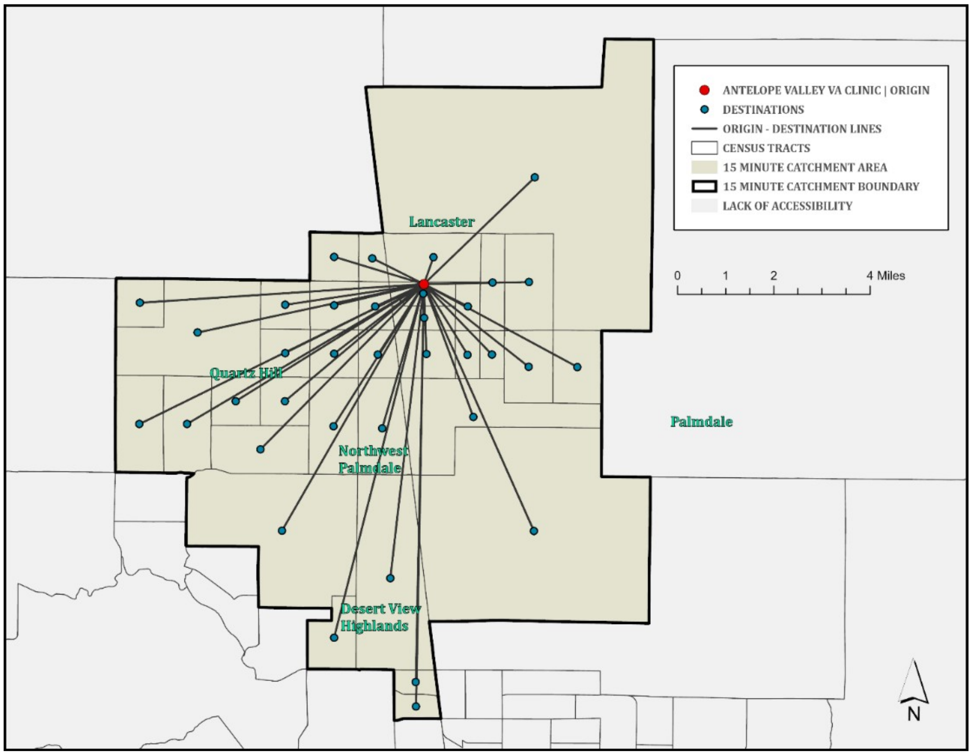

Figure 7. Origins and Destination Map

The areal extent in Figure 8 below is the same as that in Figure 7. The 15-minute catchment boundary represented the spatial extent that was used during the add-in tool processing phase. The fastest routes are on a street network, and no routes extended past 15-minutes. The blue circle symbology is the demand point destinations in which thirty-five points were located. The area outside the catchment boundary shown in light blue were areas that did not receive a score and was considered areas that lack accessibility.

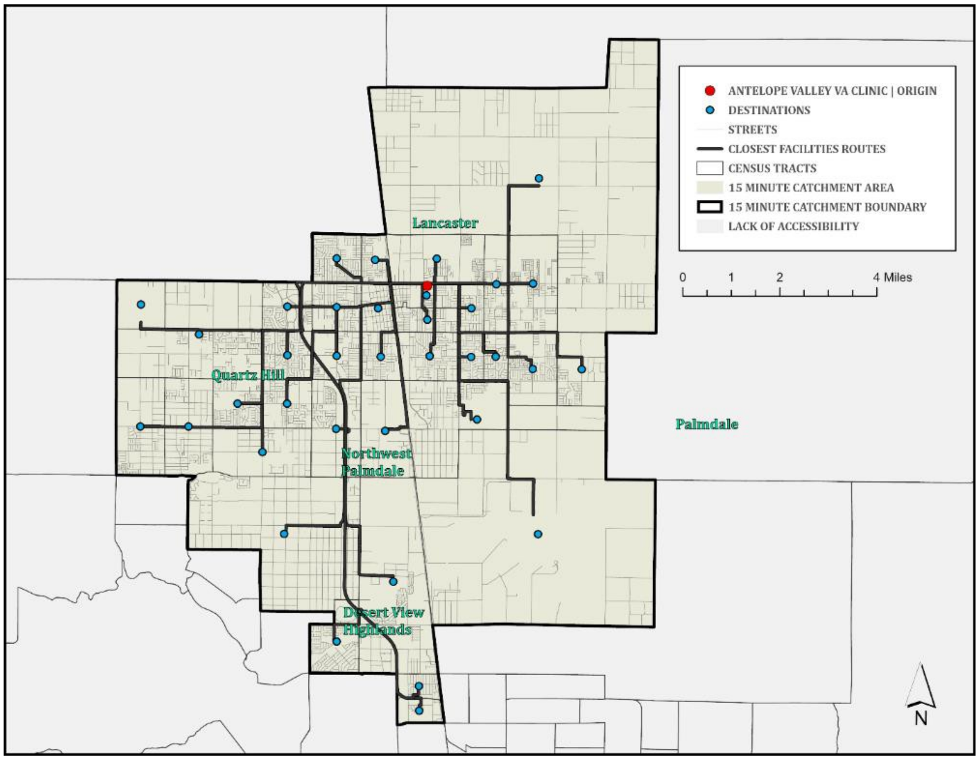

Figure 8. Closest Facilities Results.

An example of the difference between an OD cost matrix line and the fastest facility route can be seen in Figure 9. The study area showed the Antelope Valley VA clinic and the surrounding census tracts. The OD cost matrix line in light blue color is straight and connects an origin to a destination. the fastest route in dark blue follows the local streets and the total drive time in minutes on that route is 14.7 minutes.

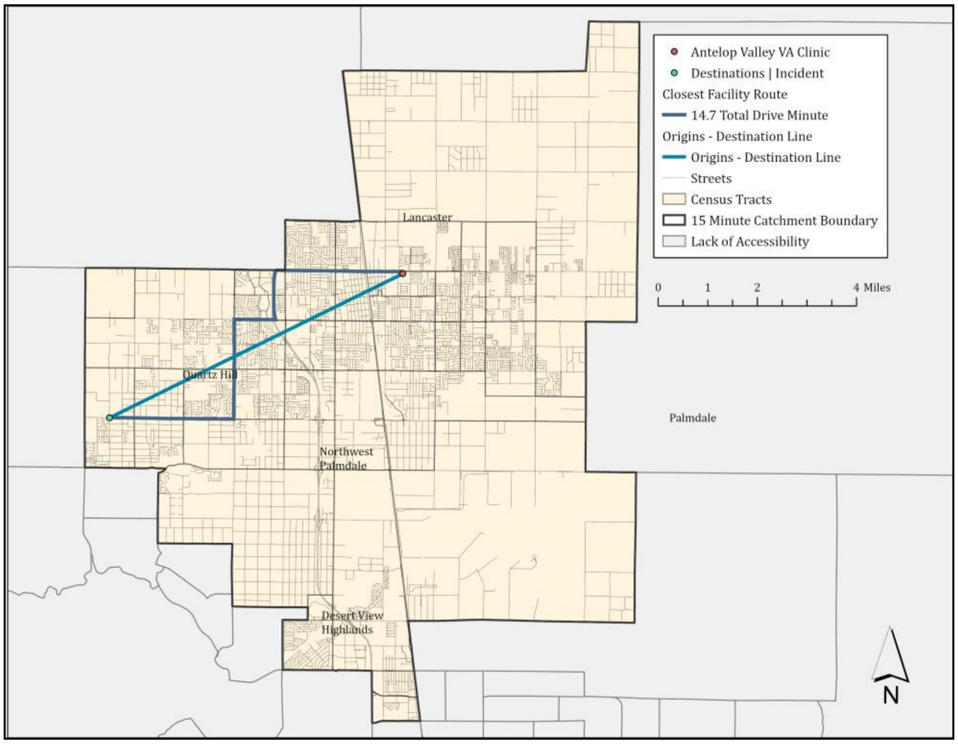

Figure 9. Origins and Destination Line with Closest Facility Route

3.6. Enhanced Two-Step Floating Catchment Area Tool (USWFCA2)

The USWFCA2 analysis tool requires installation on ArcMap10.1 or greater. The analysis also required a supply-side and a demand-side layer as inputs. The supply-side point layer represented the locations of hospitals and outpatient facilities. This layer also held the supply volume of doctors and nurse practitioners at each location. The demand layer was a centroids shapefile that also included veteran estimates per census tract. Figure 10 below shows the inputs in light blue and outputs in light green for the add-in tools operation.

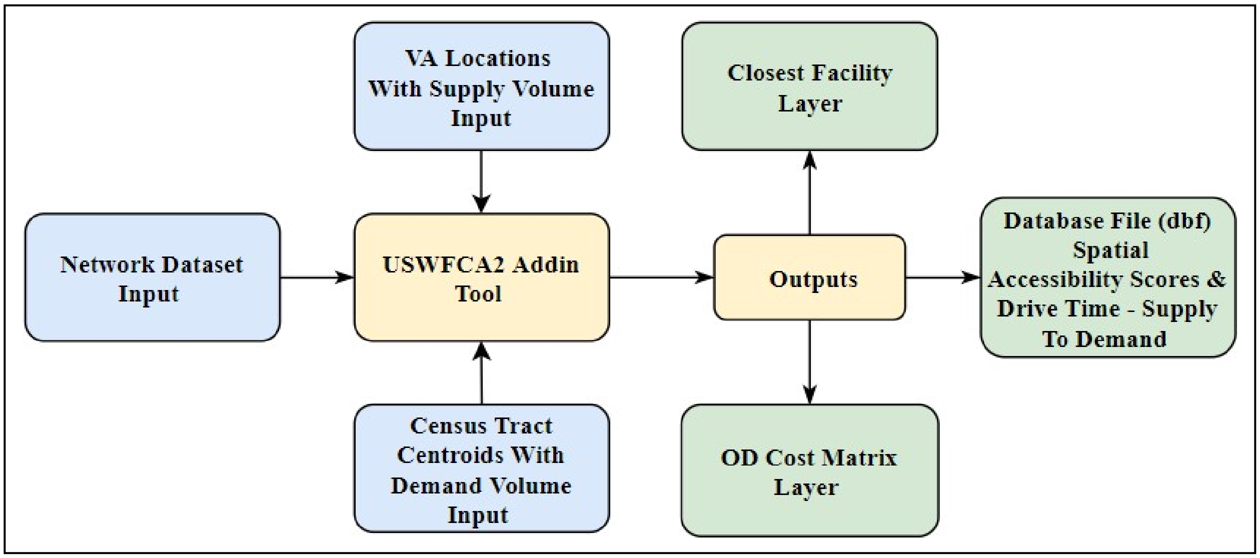

Figure 10. USWFCA2 Addin Tool Workflow Diagram.

The outputs were an origins-destination cost (OD) matrix layer, a closest-facility layer, and a database file, which contained spatial accessibility scores, drive distances from supplies to demands, and the nearest supply points. The analysis tool also required a catchment area to be set, where a 15-minute threshold was used as the spatial extent.

3.6.1. USWFCA2 Addin Tool Settings

The initial setup of the USWFCA2 add-in tool required all processed data to be in a geodatabase. It included a network dataset, which was used to obtain the OD cost matrix and closest facility layer to be discussed later in this chapter. The add-in tool uses a graphic interface where users of the tool input parameters. They are catchment size of the study, a scale multiplier, travel impedance, supply and demand layers, and decay bandwidth values.

The add-in tool produced an output database file, which was joined with the LAC census tracts layer to assess spatial accessibility scores, drive time to visualize the results. Table 3 shows the newly created fields calculated by the add-in tool. The fields that were discussed in the results chapter were m1_SupID, m1_Dist, and m1_fca. The floating catchment area (FCA) accessibility score is what this thesis called spatial accessibility scores. The OID of its nearest supply point was used to assess how many estimated veteran census tracts were closest to which supply location. The FCA accessibility scores were the results used in sensitivity analyses that were described in Chapter 4.

Table 3 Database File Output

LSOAcentro	the field we elect to copy from the demand points layer
DemandID	OID of each demand point in the analysis
m1_SupID	OID of its nearest supply point
m1_Dist	distance/time to the nearest supply point
m1_Choice	number of supply points within the FCA threshold set
m1_ChoiceW	total supply volume within the FCA threshold set
m1_AveD	average distance/time to these supply points
m1_AveDW	weighted average distance/time to these supply points
m1_fca	FCA accessibility score

Source: Mitch Langford, December 2015.

Census tracts were given an identification value (m1_SupID), which represented which specific hospital or outpatient facility they were closest to. Those results were calculated when the closest facility network analysis was run. Figure 11, a catchment area map, shows which census tracts were closet to which individual supply point. A green circle symbol represents each hospital and clinic location.

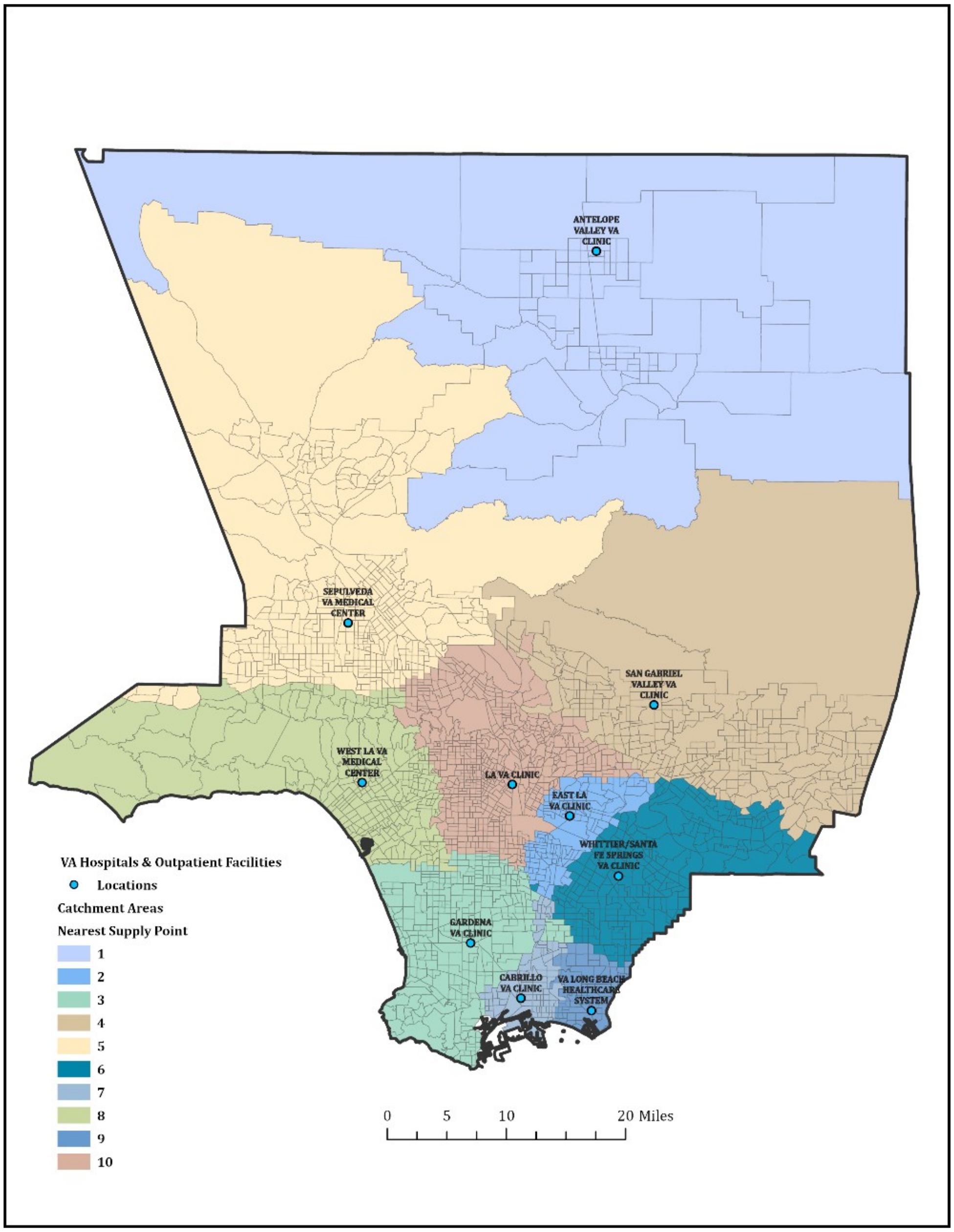

Figure 11. Catchment Areas.

The catchment numbers listed in Table 4 correspond with supply points denoted by numbers shown in Figure 11. There is also a column showing the ratios between veterans' estimations per census tracts and the doctor and nurse practitioner count per catchment area.

Table 4. Nearest Supply Catchment Data.

Catchment Number	Nearest Supply Point	Veteran Estimation Total Closest Facility Catchment	Doctor Nurse Practitioner Count	Ratio Between Veteran Estimates and Doctor & Nurse Practitioner	Census Tracts Total Per Catchment
1	Antelope Valley VA Clinic	19,254	3	1:6418	83
7	Cabrillo VA Clinic	9,960	1	1:9960	87
2	East Los Angles VA Clinic	7,706	1	1:7706	127
3	Gardena VA Clinic	43,668	2	1:21834	299
10	Los Angeles VA Clinic	41,975	4	1:10494	567
4	San Gabriel Valley VA Clinic	38,938	2	1:19469	271
5	Sepulveda VA Medical Center	43,729	23	1:1901	371
9	VA Long Beach Healthcare System	11,125	64	1:174	60
8	West Los Angeles VA Healthcare System	32,882	68	1:484	255
6	Whittier/Santa Fe Springs VA Clinic	30,920	4	1:7730	221

The methods described above were used to identify gaps in spatial accessibility for veterans in Los Angeles County. The implemented methodology can be duplicated or further expanded upon by the readers of this manuscript.

Chapter 4 Results

This chapter examined the gaps in veteran access to VA primary care clinics in Los Angeles County using the E2SFCA method and taking into account uncertainty in the ACS data. It was noted that although veterans had access to facilities situated throughout the county, there were some areas with no access at given drive times and other areas that had more accessibility than others. This variation was produced by drive time distances and by differing ratios of access to healthcare practitioners relative to the number of veterans. The E2SFCA method was used to examine the relationship between the veteran locations and access to primary care clinics and to assess the spatial accessibility score results.

The core model used represented a decay bandwidth of 50. Then sensitivity analyses were performed which produced results from different decay bandwidths values. The highest decay bandwidth is then taken as a core model, which serves as the baseline to test both uncertainty in the ACS counts of veterans and various scenarios that could increase or smooth variations in coverage across Los Angeles County.

One notable finding is that in the eastern portion of Los Angeles County there was a lack access for veterans to VA primary care. Therefore, one scenario tested was to increase the supply volume to a clinic somewhat isolated in the eastern part of the county. This was done by increasing the supply volume at the San Gabriel Valley VA clinic. Analyzing scores from three different supply volumes revealed that there was an increase in spatial accessibility scores that spatially extended further out from the San Gabriel outpatient facility. Related to this, a second sensitivity analysis was performed by suggesting and modeling for a new location for VA primary care, using an existing medical building that could work in partnership or provide options for leasing.

4.1. Analysis Overview

The USWFCA2 addin tool mimicked the E2SFCA statistical equation and produced results which used a Gaussian function and a decay bandwidth option. This author contacted the addin tools creators and it was determined that a decay bandwidth in the ranges from 20 to 50 were generally considered the best values (Langford and Higgs 2019). The addin tool creator suggested that it can be used to control the specific shape or rate of decline of the Gaussian decay style function. It is a number that refers to the actual floating catchment area threshold distance set, which in this analysis is a 15-minute drive time. Then it is applied in the calculation of the rate of decay. This ranges from 1.0 at the supply location point, that is where the first catchment is created to a theoretical minimum of 0.0 at the catchment outer limits. In short, higher decay values produce a slower rate of decay so that large portions of populations at longer distances are included in a catchment than with lower decay values. The addin tool creator also suggested there really is no right answer and decay bandwidth values requires one to assess the best fit for each type of study that is proposed. Analyzing those two values, showed that the value of 50 produced a more gradual rate of decay while the value of 20 had a rate of decay that was sharper and did not spatially extend to the fifteen-minute catchment. In Figure 12 and 13 are histograms showing the distribution of result from the decay bandwidth value 20 and 50. The total census tract count is on the Y-Axis, and the spatial accessibility scores are on the X-axis. There are mean and standard deviation vertical line demarcated in both figures with mean on the left and the standard deviation on the right.

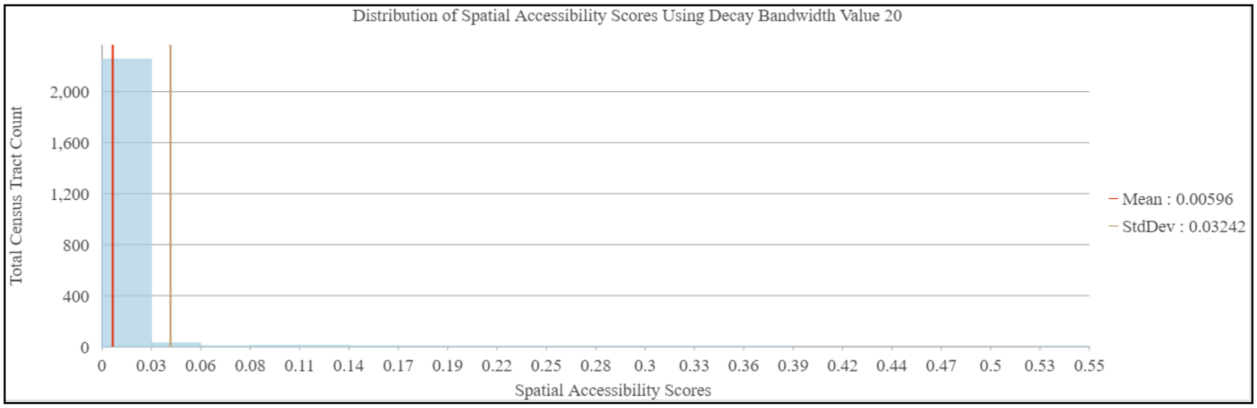

Figure 12. Distribution Using Decay Bandwidth Value 20

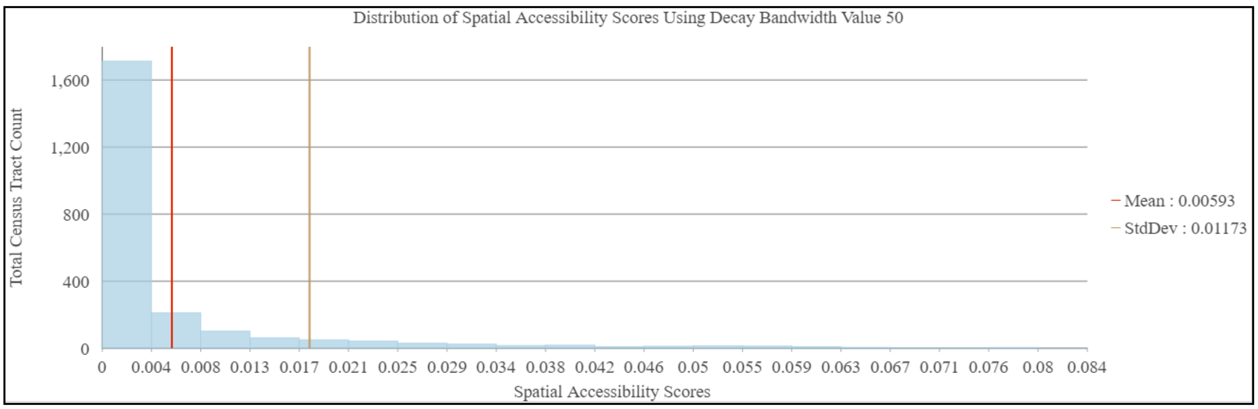

Figure 13. Distribution Using Decay Bandwidth Value 50

Figures 14 below shows the decay bandwidth value of 50 and the amount of coverage area it encompassed. The decay bandwidth value of 50 was chosen over a decay band width value of 20 from results through sensitivity analyses and became the core model. The decay bandwidth value of the 50 map is a visual observation of how much more coverage was utilized using a higher value as opposed lower bandwidth value of 20.

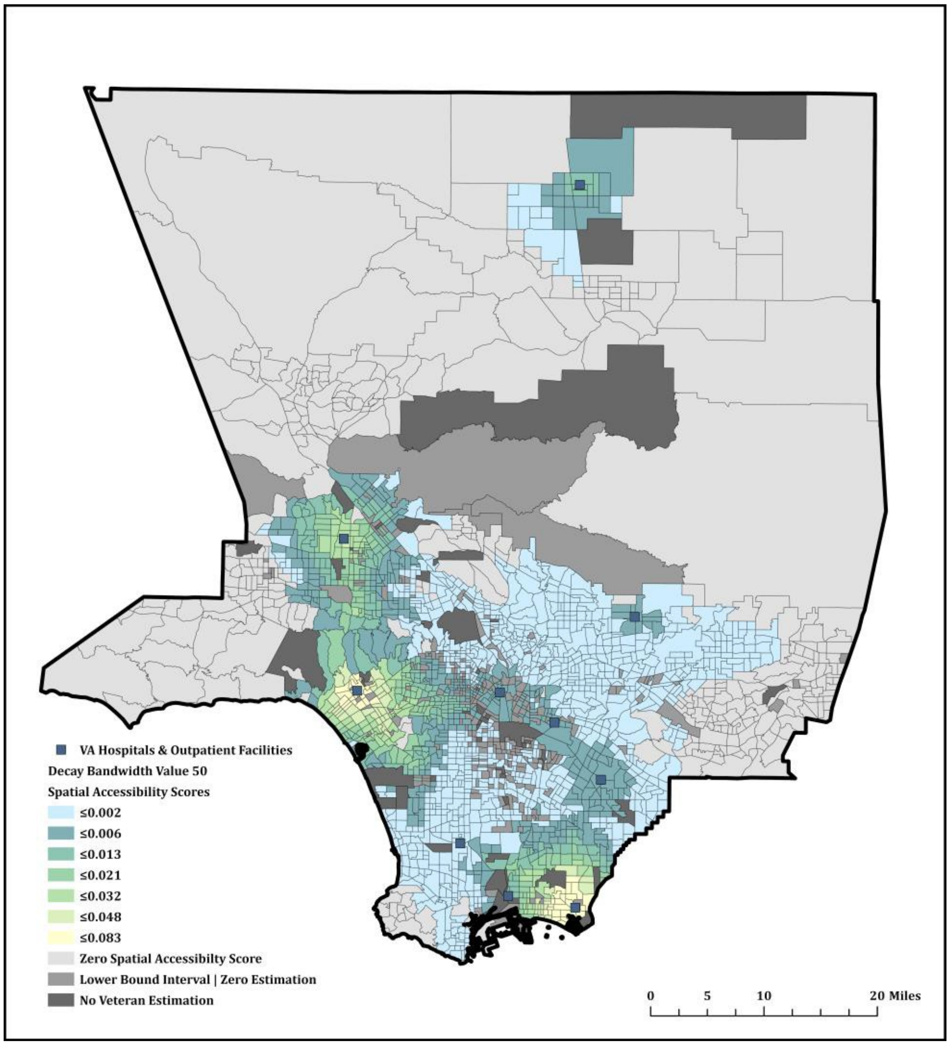

Figure 14. Decay Bandwidth Value 50.

Figure 15 below, the Decay Bandwidth Value 20 map showed coverage that does not spatially extend past a 10-minute drive time catchment, which suggested a sharp rate of decay at or around 10-minute drive time interval. Both maps use Jenks natural breaks and are shown with no spatial accessibility scores represented by the light grey color. A darker grey showed a lower bound interval with zero and negative veteran estimation, and the darkest grey showed census tracts with no veteran estimation. They are visual representations to assess how much of the 15-minute drive time catchment each decay bandwidth value covered.

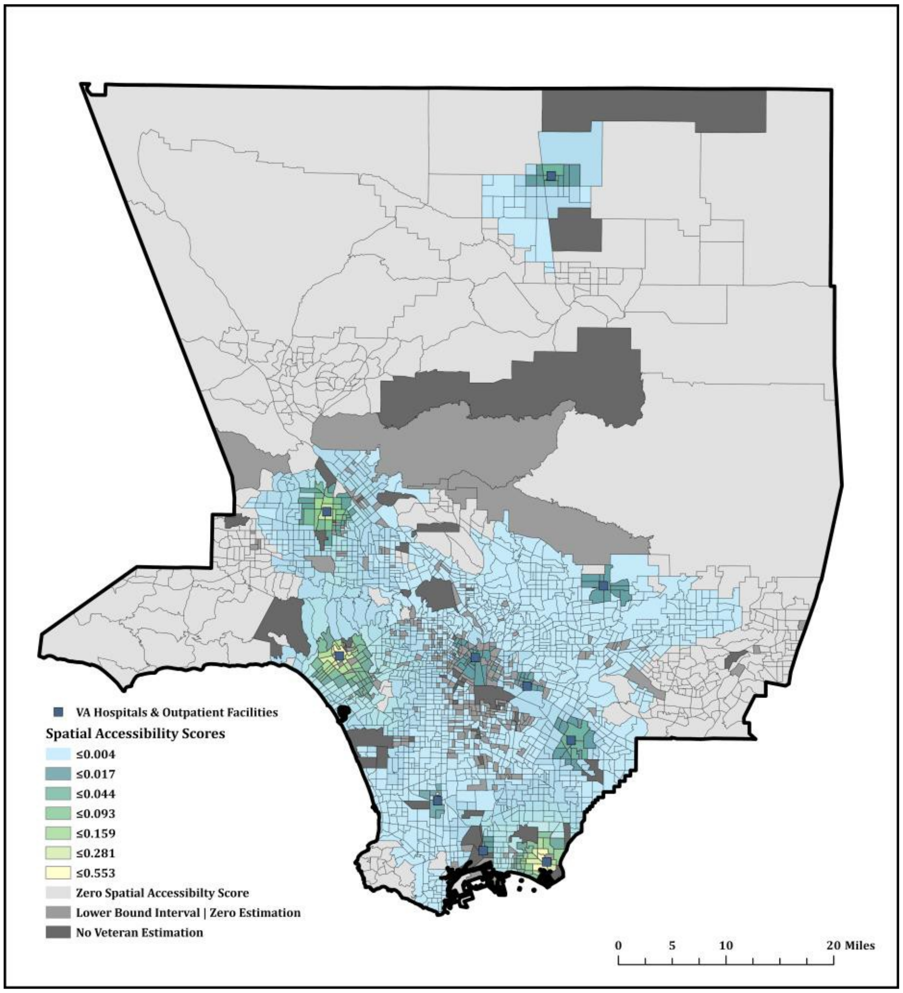

Figure 15 Decay Bandwidth Value 20.

As discussed in Chapter 2, the choice of the decay bandwidth was important when using the Gaussian distribution model as it will affect the outcome of the spatial accessibility results. The Gaussian distribution model, which as the literature suggested and cited within this study, is part of a gravity model used to identify accessibility for healthcare demand and supply in an identified location. Testing was undertaken using a decay bandwidth of 20 and 50. The decay bandwidths and sensitivity analysis results are discussed later in this chapter. Drive time in minutes was used as the travel impedance. The decay bandwidth of 50 produced results that reached a threshold boundary of 15-minutes. The threshold boundary was the spatial extent that was set during the addin tool process and used within the core model.

4.1.1. Decay Bandwidth Symbology Comparison

For purposes of direct comparison, the interval classification from the decay bandwidth 20 was imported into the decay bandwidth 50 map. This is shown in In Figures 16 and 17 when both maps are compared.

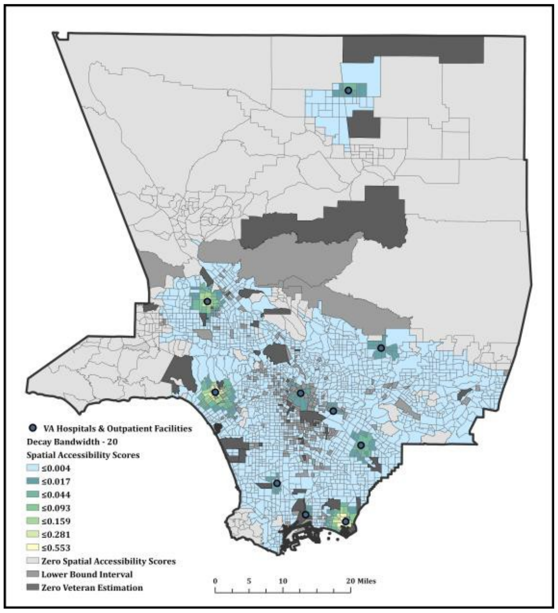

Figure 16. Decay Bandwidth 20

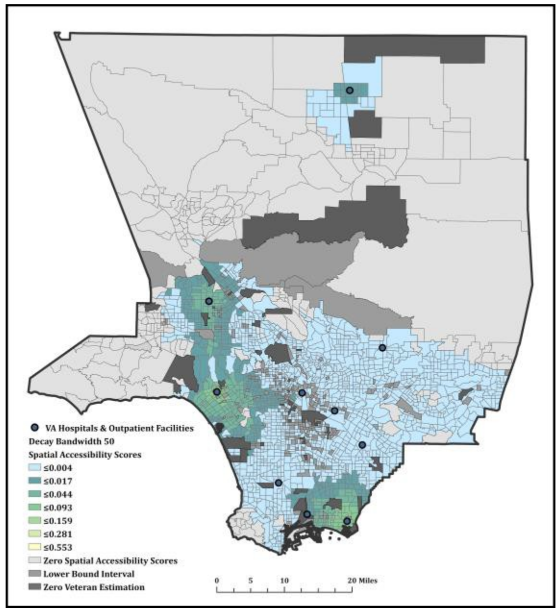

Figure 17. Decay Bandwidth 50 with Same Intervals

4.1.2. Decay Bandwidth 20 Testing

The decay bandwidth value of 20 used the same parameters from decay bandwidth 50 test. The only change that was made was the reduction in decay bandwidth to a value of 20. The value of 20 produced results that did not reach the outer 15-minute catchment. Total census tracts that were given scores in this analysis were 1,412 with a total veteran estimate of 151,356. As discussed earlier in this chapter the decay bandwidth value of 20 produced a sharper rate of decay then that of the decay bandwidth value of 50. The rapid decay in distance created more census tracts with zero SA scores. The rapid decay started at approximately the ten-minute drive time catchment. There were 929 census tracts that did not receive a spatial accessibility score.

From those 929 census tracts there were an estimated 128,656 veterans who lack accessibility. As seen in Table 5 below, the percentage of veterans that received no spatial accessibility scores was 46%. The decay bandwidth value of 20 had 54.1% veteran estimates with spatial accessibility scores.

Table 5. Decay Bandwidth 20 Coverage.

	Decay Bandwidth 20 Census Tract Total	Veteran Estimation Total
Convenient Accessibility	1,412	151,356 (54.1%)
Lack of Accessibility	929	128,656 (46%)
Total	2341	280,012

4.1.3. Decay Bandwidth 50 Core Model

The decay bandwidth value of 50 used a threshold size of 15-minute drive time impedance. This 15-minute floating catchment became the spatial extent for this, and other analyses discussed later in this chapter. Any census tracts that fell outside of the catchment area of fifteen minutes were not assigned a score. Table 6 below, and Figure 15 above showed the results when the decay bandwidth value of 50 was used. The total demand volume inside the 15-minute catchment was 222,370 estimated veterans. The total demand volume for veterans outside a 15-minute catchment was 57,642. This showed that out of the 280,012 estimated veterans inside the county boundary 79.4% were assigned a score and dispersed through 1,969 census tracts. The decay bandwidth value of 50 and its total of 79.4% created a difference in coverage of 25.3%. Meaning, the value of 20 testing resulted in coverage for 25.3% fewer veterans in the county than the decay bandwidth of 50.

Table 6. Decay Bandwidth 50 Coverage.

	Decay Bandwidth 50 Census Tract Total	Veteran Estimation Total
Convenient Accessibility	1969	222,370 79.4%
Lack of Accessibility	372	57,642 20.6%
Total	2341	280,012

4.1.4. Drive Time Analysis and Spatial Accessibility Scores

To better assess differences between a decay bandwidth value of 20 versus 50, a table was created from results of both analyses. The results were partitioned into drive times of 0-5, 5-10, and 10-15- minutes. Each increment of drive time had low and high spatial accessibility scores assigned to a cell. Census tract totals with and without scores were shown to establish where the lack of coverage existed. The decay bandwidth of 20 produced more census tracts with zero SA scores.

In Table 7 below is an evaluation and comparison of drive time the decay bandwidth 50 showed high and low spatial accessibility scores in each drive time catchment window, where high scores represent better spatial accessibility. The 0-5-minute drive time from supply points resulted in a low score of 0.0008 and a high score of 0.083. The total census tracts that were found in a 5-minute catchment was 345. The 5-10 minutes low score was 0.0002 and the high score 0.052 which was made up of 1039 total census tracts. At the drive time of 10-15 minutes the low score was 0.00002 and high Score 0.014, covering a total of 585 census tracts. The best scores were centered around the three main hospitals and were inside a 0-5-minute drive time. The Long Beach VA Medical Center, West Los Angeles VA, and Sepulveda VA medical center.

Table 7. Decay Bandwidth 20 and 50 Spatial Accessibility Scores with Drive Time.

Decay Bandwidth 20					
Drive Time Minutes	Low	High	Total number of census tracts per Drive Time Catchment With SA Scores	Total Veteran Estimation	Census Tract Count with No Accessibility
0 – 5	0.000794	0.553412	345	35,207	0
5 – 10	0 -0.000001	0.030275	1039	112,477	32
10 – 15	0 - 0.000001	0.000006	585	74,686	525
Total			1969	222,370	557
Decay Bandwidth 50					
Drive Time Minutes	Low	High	Total Census Tracts per Drive Time Catchment with SA Score	Total Veteran Estimation	Census Tract Count with No Accessibility
0 – 5	0.000824	0.083927	345	35,207	0
5 – 10	0.000207	0.052985	1039	112,477	0
10 – 15	0.000023	0.014952	585	74,686	0
Total			1969	222,370	0

The decay bandwidth value of 20 had a sharp decline in distance at the ten-minute catchment boundary. Almost all spatial accessibility scores beyond ten-minutes from their respective supply point were given a score of zero. This analysis showed that a decay bandwidth value of 20 would not produce accurate spatial accessibility scores inside a fifteen-minute catchment area. As seen in Table 7 above the census tracts started to receive zero spatial accessibility scores at the 5-10- minute drive time, and of those 32 tracts in that drive time received a zero spatial accessibility score. There was a steep rise in tracts with no scores at the 10-15-minute interval.

4.2. Source of Error

A scale multiplier that was built in the addin tool was used in this thesis to assess the spatial accessibility scores. SA scores are inherently small with many zeros to the right of decimal which can be cumbersome when assessing scores from many iterations. Spatial accessibility scores that the addin tool produced used a scale multiplier of 10. The scale multipliers function was to decrease the number of zeros to the right of decimal to ease in the analysis of different scores, plotting of maps, and to preserve precision.

One example and results from the core model (decay bandwidth 50) with the SA scores and scale multiplier set to ten. The highest spatial accessibility score was a 0.083 and was a census tract that the VA hospital in Long Beach occupies. The Long Beach VA had a supply volume 64, and the census tract centroid had a 0.1755 drive time in minutes from the nearest supply point. That census tract also had a demand volume (veteran estimation) of 56. Conversely, the lowest non-zero spatial accessibility score was a census tract in the San Pedro area at 0.00002 with a drive time distance from supply at 14.956 minutes. The total veteran estimation for that census tract was 239, with the closest supply point at the Gardena VA

Clinic.

In this study the highest (best) scores emanated around the three main hospitals that had high supply volumes. There were census tracts in this study that did not receive spatial accessibility scores, because they were tracts with zero estimations or had lower bound scores that were zero.

4.3. Uncertainty Analysis

The upper and lower boundary maps shown later in this section represented ACS data with upper and lower confidence intervals for each tract. The upper and lower estimates for veteran population at the 90% confidence level, as provided in the ACS data, were tested on the core model to show how much and where results would change if the upper or lower scenarios were true across the study area. The analysis used ACS data with corresponding MOE in each census tract. The MOE value in each tract represented a confidence level of 90% that the MOE was accurate using the standard error calculation of 1.645. This indicated the veteran estimate in the lower intervals was the census tract population minus the MOE. The upper intervals published for each census tract included the census tract population plus the reported MOE for the tract.

The values in the Table 8 below represented a census tract in Los Angeles County within this study with the highest estimation of veterans and the corresponding plus or minus, upper and lower MOE. It represented the equation to find the upper and lower bound intervals.

Table 8 Confidence Interval Equation.

Veteran Estimation		MOE			
861	-	201	=	660	Lower Bound of the Interval
861	+	201	=	1062	Upper Bound of the Interval

The process for finding the coefficient of the variation (CV) started by finding the standard error which was found by dividing the MOE by 1.645. The 1.645 value is what the US Census Bureau referenced as 90% data confidence. The CV was another way to measure uncertainty in the data. The CV is the standard error divided by each veteran estimate. This author calculated the CV values in an excel table from conversion equations provided by the census bureau. The highest scores from CV results were census tracts with low estimates and relatively high MOEs. Most veteran estimations per census tract that received a high CV score and had MOE values that were half of or above the estimate. The highest score was from a census tract with a CV of 182.37 and a veteran estimation value of one and an MOE of three. An example of a census tract that was considered moderately reliable was one which had a CV score of 20.26 with an MOE of 143 and a veteran estimation of 429. The lowest score and most reliable had a CV value of 13.3, with a veteran estimation of 388 and MOE of 85.

One way to visualize the values of the CV was to group them into three classes. As discussed in Chapter 2 and seen in Figure 18, CV values that were 15 or less were considered reliable. Values that were between 15 and 30 were considered moderately reliable and anything above 30 were considered not reliable. There were 11 reliable census tracts, 846 moderately reliable, and 1437 were not reliable.

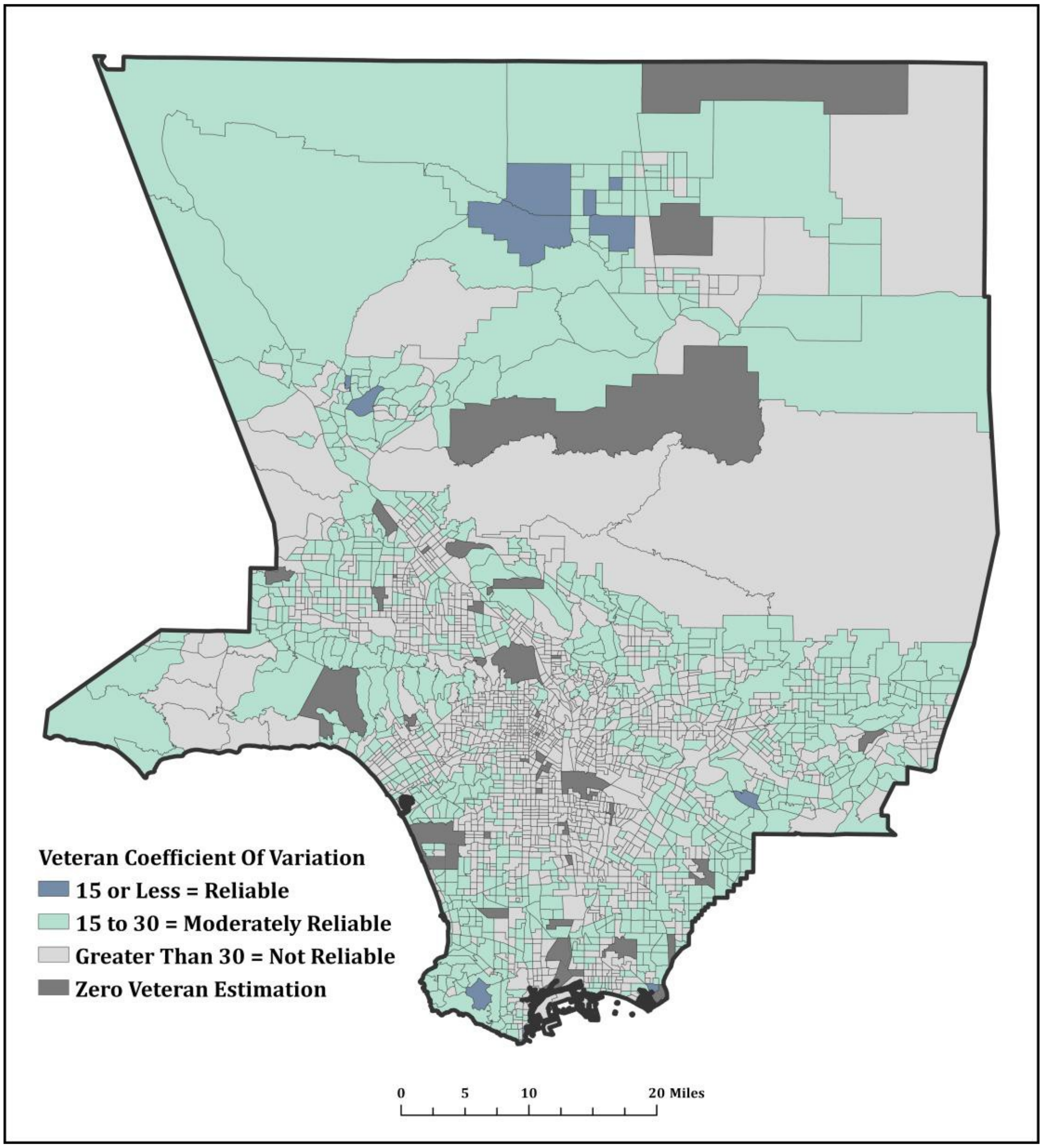

Figure 18. Coefficient of Variation Map.

The upper and lower bound interval maps shown in Figures 19 and Figure 20 below were processed using the core model parameters. The color scheme and graduated symbology was matched, yet the values could not be. This was because the highest spatial accessibility score from the lower bound was larger than the highest score from the upper bound results. This created 265 census tracts with negative veteran estimation and thirty-one census tracts with zero estimates. The census tracts with negative and zero lower bound interval estimates were dispersed throughout the county. There is also symbology using shades of grey to represent census tracts with no veterans, tracts with no veterans due to the lower bound assessment, and tracts that received no spatial accessibility scores. The confidence interval equation using the lower boundary resulted in census tracts with negative values. Because the E2SFCA statistical equation is complex, the author of this thesis manually converted all census tracts with negative values to test if results from zeros or negatives would alter results. The results of converting census tracts with negative values to zeros did not produce different results.

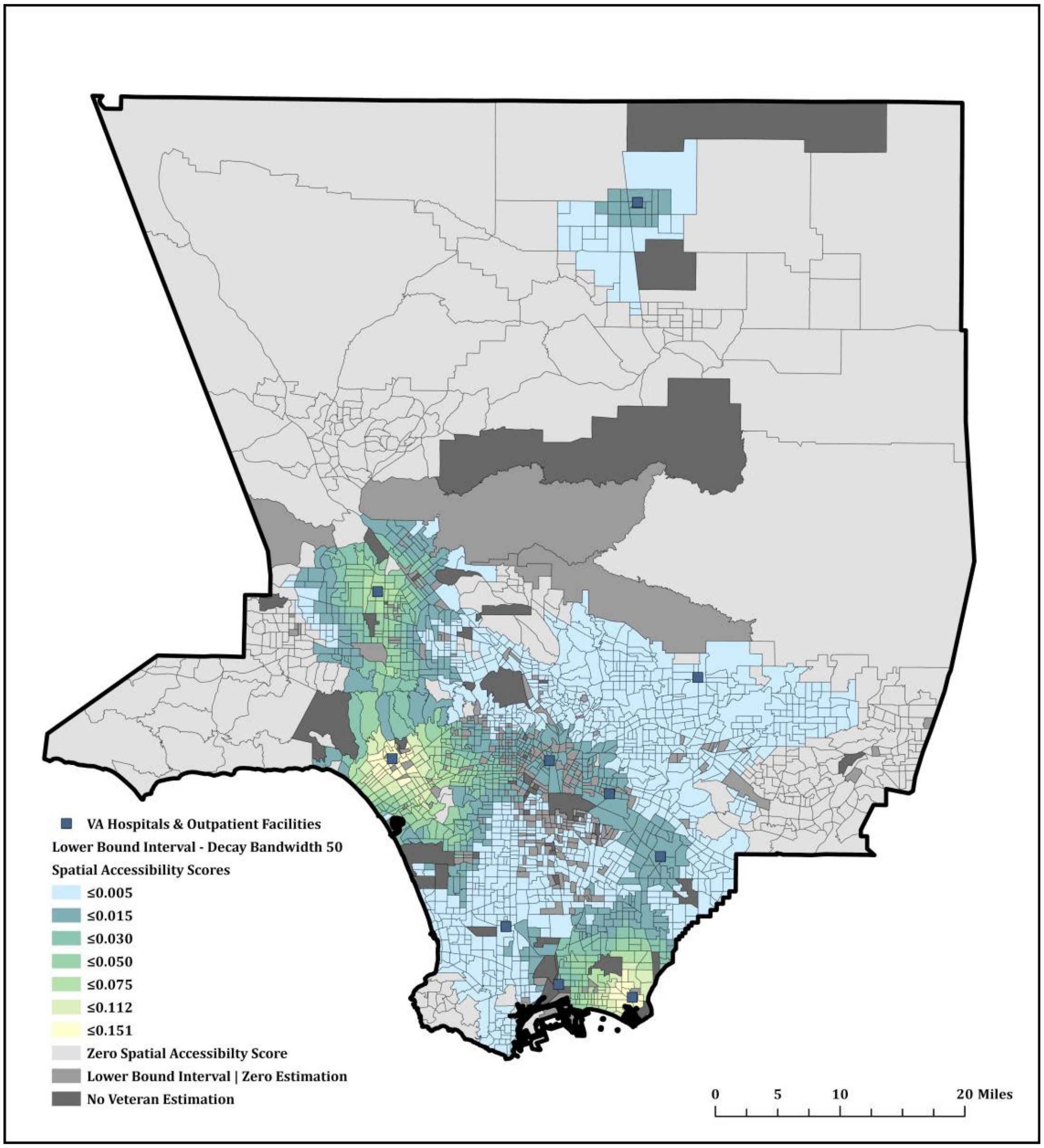

Figure 19. Lower Boundary Interval Map.

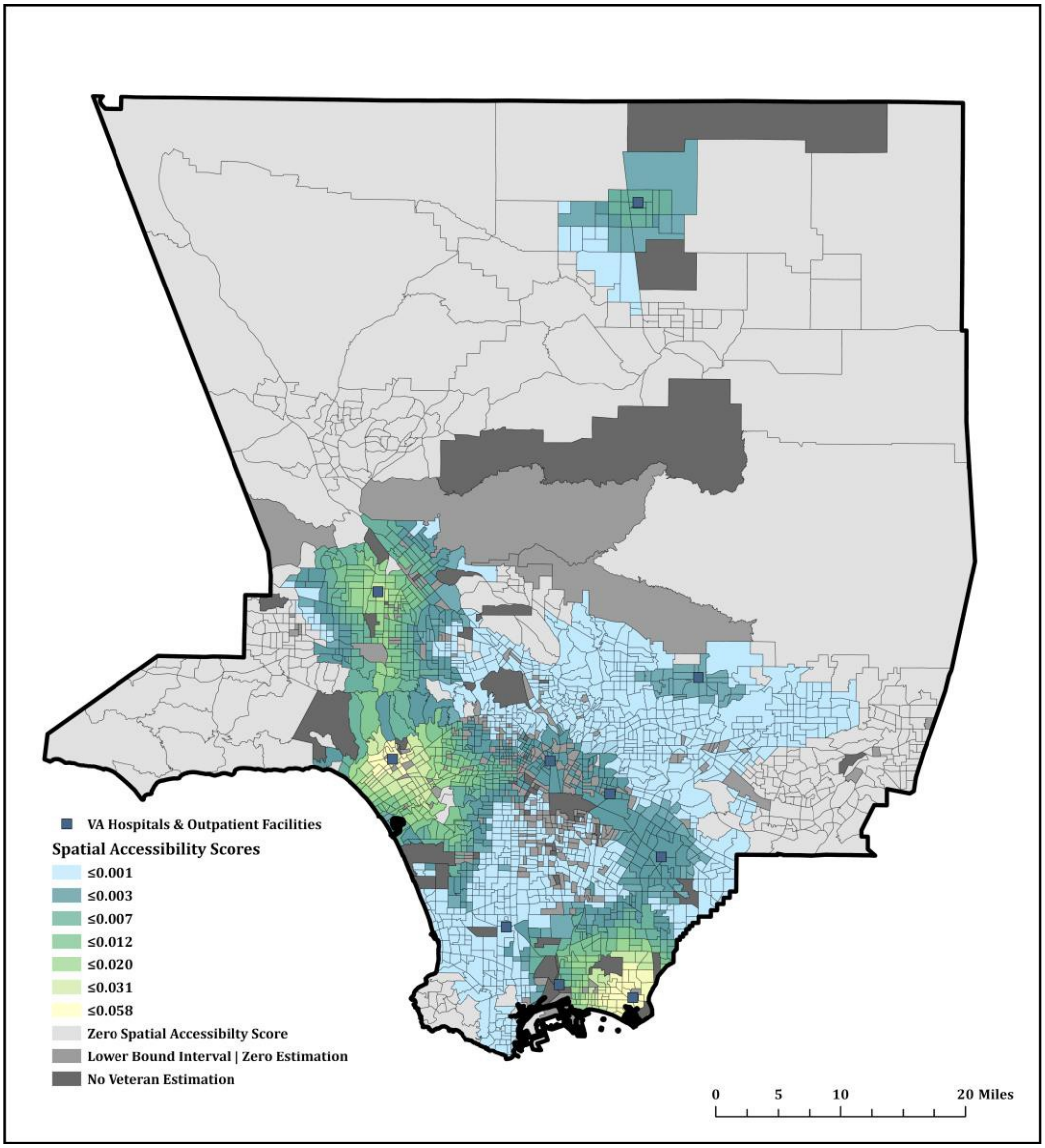

Figure 20. Upper Boundary Interval Map

4.4. Supply Volume Increase – San Gabriel Valley VA Clinic

One of the objectives of this study was to help VA administrators understand how the E2SFCA model could be used to assess changes in service levels or if expanded locations for VA primary care in Los Angeles County is warranted. The San Gabriel Valley VA clinic located in the city of Arcadia became part of the focus for assessing the lack of accessibility in the eastern portion of the county because it is an existing location with a relatively low service capacity equivalent to two physicians or nurse practitioners. There were an estimated 24,845 veterans that were dispersed throughout 182 census tracts that made up a catchment of 15-minutes of drive time closest to the San Gabriel Valley Clinic. In the analysis of increased volume at that location, two iterations using the core model parameters were undertaken which used volume as a variable which increased with each test. The results were analyzed, and SA scores were partitioned into drive time increments.

Table 9. San Gabriel Valley VA Clinic Drive Time Analysis using Decay Bandwidth 50

Drive Time in Minutes & Census Tract Count	Core Model Supply Volume 2 Spatial Accessibility Scores		Supply Volume 3 Spatial Accessibility Scores		Supply Volume 5 Spatial Accessibility Scores		Veteran Estimation
	Low	High	Low	High	Low	High	
0 - 5 22	0.00183	0.002642	0.002754	0.003963	0.004575	0.00660	3,009
5 - 1 0 71	0.00050	0.00180	0.00075	0.00270	0.00125	0.00451	9,170
10 - 15 89	0.00005	0.00086	0.00008	0.00109	0.00016	0.00154	12,666

In Table 8 above, drive time intervals of 0-5, 5-10, and 10-15 minutes of drive time from supply were assessed. SA scores from low to high along with veteran estimations and census tract totals were compared. The building footprint at the San Gabriel Valley VA appeared unable to accommodate more than five practitioners due to size, therefore testing was not done with a supply volume higher than five. The 0-5-minute high SA score was 0.002 and was improved to a higher SA score of .006 when the volume of 5 was added. The 5-10-minute drive time interval had a high score of 0.001. When the supply volume was increased to five physicians or nurse practitioner at that location, the high score improved to a value of 0.00451. By adding more supply volume, the access became better to the estimated 9170 veterans in the drive time interval of 5-10 minutes. The 12,666 veteran estimate occupying the 10-15-minute drive time interval had a high score 0.00086 for a supply volume of two. An increased volume to five in that same drive interval increased the SA score to 0.00154.

The volume of three was also chosen to test as it is the average number of practitioners (volume) of the identified primary care facilities in Los Angeles County. The total outpatient supply volume of twenty was divided by the total amount of primary care facility which equaled 2.8 practitioners per primary care facility. This value was rounded up to three to make a simple modeling estimate. In Figure 21 below, the map shows increased supply volume at the San Gabriel Valley VA Clinic. All three maps used the same parameters from the core model analysis. The only variable changed was increasing the supply volume between iterations. The bottom right square shows the legend and symbology that all three maps share which were seven classes using graduated colors, natural breaks (Jenks).

There is a 15-minute catchment boundary represented by the time it took to reach a demand centroid from the San Gabriel Valley VA supply point. They grey census tracts that extend past the catchment boundary were tracts that did not receive a SA score. In the map on the top left, VA location name is shown for visual reference. The top left map (A) uses seven classes with Jenks classification. It showed that there were nine census tracts greater than a value of 0.002 and less than a value of 0.006. When the supply volume was increased to three, shown on the map on the top right (B), there were 39 census tracts that had values less than 0.006 and greater than 0.002. Increasing the supply volume to five (C) showed there was a total of 64 census tracts had SA scores that ranged from 0.002 and 0.006488. The census tract the San Gabriel Valley VA occupies had a score that now ranged from 0.006 to 0.013. The score for that census tract using a supply volume of two was 0.002. When the volume was raised to three, the score improved to a 0.003. The increase in supply using a volume of 5 showed that the census tract with the VA clinic was raised to 0.006 SA score.

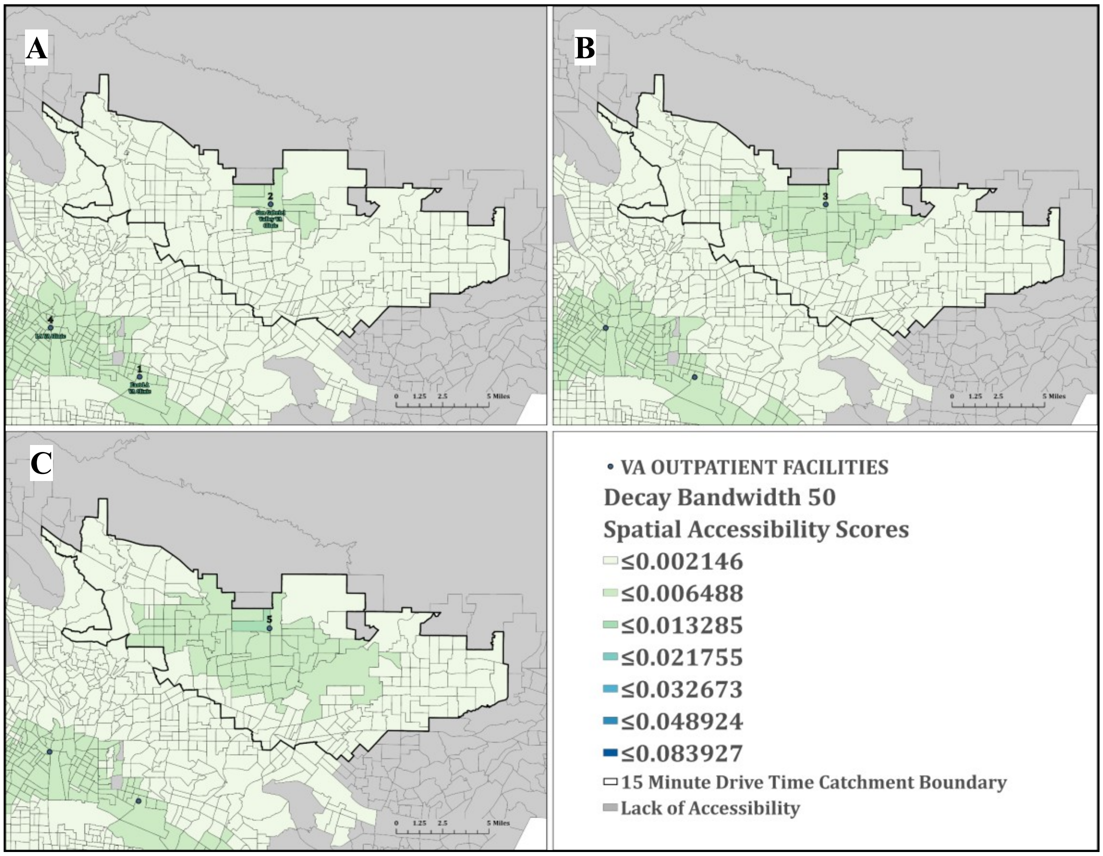

Figure 21. San Gabriel Valley VA Clinics with Increased Supply Volume.

4.5. Review of Additional Accessibility Location

As the result indicated above at the San Gabriel Valley VA Clinic, changing supply volume can increase accessibility. Adding additional locations in the south eastern portion of Los Angeles County can also be used to test improving veteran accessibility. This author also reviewed VA medical center locations and primary care facility locations outside of the Los Angeles County borders. This was accomplished by assessing the distance of the cities nearest the Los Angeles County borders to the next closest primary care facility location within a bordering but different county. The findings are driving distances in miles using Google Maps.

Reviewing the nearest VA location in Ventura County that borders the west side of Los Angeles County is a VA primary care facility in Oxnard which is 25-28 miles to the western portion of Los Angeles County border. The closest VA primary care facilities on the northern portion of Los Angeles County is in Bakersfield which is in Kern County. The distance to that facility is 89 miles from Lancaster and 48 miles from Gorman, two rural cities in the Antelope Valley of Los Angeles County. Orange County borders Los Angeles County on the southeast section of the county. The VA primary care facility closest to that border is in Anaheim. From the various cities along Los Angeles County border with Orange County, the distance is 5-21 miles. The closest location outside of Los Angeles County where the coverage gap was identified in this project is located on the eastern side of the county and borders San Bernardino County. It is the VA primary care facility PCF in Rancho Cucamonga which is 12-21 miles from the cities located in the east portion of Los Angeles County.

A short discussion of an additional site to consider improving veteran access to primary health care based on the outcome of this research project is worth reviewing within this thesis. Site selection involves identifying criteria and analyzing suitable sites within Los Angeles County. Mishra et al. (2019) identified five criteria to evaluate a potential suitable site for healthcare purposes. They included distance to the nearest facility, accessibility to existing healthcare locations, the ratio of the supply to the demand population, the actual population of the area to be served, the ease of access using road transportation and the health needs of the population to be served. Parvin et al. (2020) completed a study of accessibility and site suitability in a location in India with the objective of using GIS with spatial and non-spatial data. They indicated that analyzing accessibility is the first consideration to evaluate a potential new site for a healthcare facility. As written in the thesis, although not as a site suitability study, the use of spatial models and non-spatial dimensions took into consideration accessibility along with availability of existing primary care services and distance decay from supply to demand. Other considerations not discussed in this project to analyze site suitability are zoning regulations for the proposed site, and the size of the land parcel under consideration (Sarain 2019). Also, if proposing to use an existing physical location, does the site have capacity to accommodate practitioners, and demand volume. The ease of use to either public transportation or road access is another consideration.

An existing potential site location that the VA could explore for additional veteran primary care can be viewed in Figure 22. The map is a broad overview of Los Angeles County that showed how county wide SA scores would look when visualized with a new location added in the city of Diamond Bar. The study area below used the same symbology as the core model with a decay bandwidth of 50. Although this study did not have a full site suitability analysis, some suitable exiting locations for expanded veteran primary were analyzed. The most suitable existing locations that have medical offices and offer other outpatient services, including a pharmacy, was the Kaiser Permanente location in Diamond Bar. Three practitioners were the average from the total supply volume of all the outpatient VA clinics and this number was used when assessing the potential Diamond Bar location. The lower bound interval assessment illustrated there was 265 tracts with negative lower bound scores and thirty-one zero scores. From those scores only five census tracts with negative lower bound intervals ended up in a 15-minute drive time catchment centered around the Kaiser location. In comparison to 79.41% of coverage from the core model the new location using the core model parameters lifted coverage to 85.02%, with 123 census tracts that now routed to a supply point within a newly created floating catchment of 15-minutes around that Diamond bar location.

The analysis from the core model proved useful as baseline results. Moreover, it was useful to compare scores from the results of the sensitivity analyses to determine what bandwidth values was appropriate. Increasing the supply volume at the San Gabriel Valley VA clinic showed that scores did improve when supply volume was raised. Adding a location in the eastern portion of the county proved that adding a supply point improved accessibility.

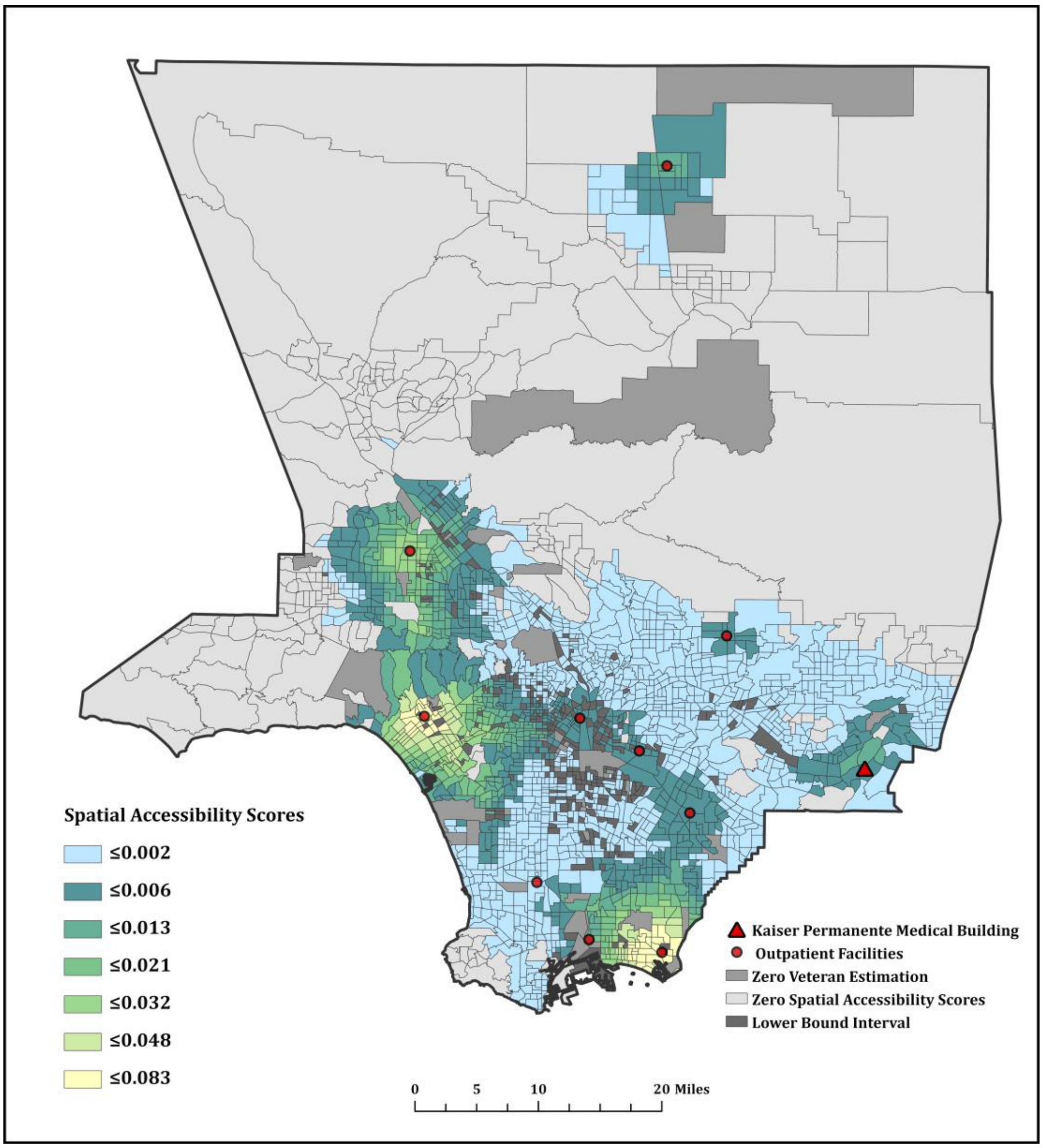

Figure 22. Additional Outpatient Facility Location.

4.6. Overall Summary of Results

In summary, the results of the E2SFCA showed supply to demand accessibility gaps for veterans in the eastern portion of Los Angeles County. Based on the E2SFCA methodology using drive time decay of 15-minutes to access primary care in Los Angeles County, gaps were identified. Accessibility scores were not only the result of the distance to a supply location but also the supply number compared to the veteran estimates in the closest and nearby census tracts. The addition of testing increasing supply volume in one location had improved accessibility. The potential addition of another site also changed veterans' accessibility scores in census tracts surrounding a new location within the 15-minute catchment.

Chapter 5 Discussions and Conclusions

This thesis was designed to assess if gaps exist in veteran primary health care access in Los Angeles County based on supply and demand of the services needed. The VA has mandated drive time limits in order to provide veterans with healthcare in locations that are both accessible and available. The E2SFCA method resulted in detailed spatial accessibility scores in the context of underlying uncertainty of veteran estimates in the ACS data. The results were determined through sensitivity analysis. The results indicated that the area around the San Gabriel Valley VA had the least supply volume to meet the estimated veteran demand. Corresponding neighborhoods to the east of the San Gabriel Valley VA clinic also had low SA scores. In addition, the eastern part of Los Angeles County had the largest area with low accessibility scores. Census tracts with high spatial accessibility scores were all centered around the three main hospitals with high supply volume. In addition this project offered a location of an existing healthcare facility that has potential for use by the VA decision makers to provide additional primary care. This chapter discusses the methods used in this thesis with results discussed in Chapter 4. The next section analyzed in detail the limitation of this project. The last section discussed future research and reviewed conclusions.

5.1. Review of The Methods

The methodology, as stated above, that was used in this study was the E2SFCA gravity model with the use of the Gaussian distribution function to simulate travel time distance decay. This gravity model was chosen as it integrates the availability and accessibility as a measure of healthcare service from a spatial level. The choice of the E2SFCA method incorporating a Gaussian distance decay function and utilizing the USWFCA2 accessibility tool was the methodology used to perform the testing. As discussed earlier in this thesis, the use of the

USWFCA2 accessibility tool and decay bandwidth settings allowed for classification of drive time zones of 0-5, 5-10, and 10-15 minute distance decay from the demand to each supply point. The Gaussian model was used to simulate the distance decay function. The primary purpose of the USWFCA2 accessibility tool established the rate of decay using the Gaussian model and was used to facilitate the computation of the E2SFCA measure of spatial accessibility. Langford (2015) discussed the Gaussian model typical decay bandwidths and the use of the USWFCA2 accessibility tool to simulate distance decay. According to Langford (2015), 50 is the most typical decay bandwidth used, but using values from 20-50 can also be acceptable depending on the research. This researcher initially tested a bandwidth of 20 when assessing which value would best simulate the distance decay parameters for this thesis. The result of the Gaussian model 20 decay bandwidth tested produced a steep rate of decline in the middle, and there were no veteran estimates beyond 10 minutes. Examining the decay bandwidth of 50 produced the results that showed the best coverage. The creation of the VA hospitals and primary care facilities layer was obtained from the most up to date data sources. The supply volume numbers that included physicians and nurse practitioners were acquired from telephone calls to the facilities. The demand volume was represented by the veteran estimates in each census tract in the county. This thesis will give future researcher information to understand better the spatial complexities of evaluating healthcare accessibility from many different viewpoints.

5.2. Limitations

The limitations identified in this thesis can provide information to future researchers assessing and analyzing healthcare accessibility in different locations. The limitations discussed below include the MAUP, ACS, and the uncertainty, 15-minute catchment threshold, closest facility catchment, accuracy of travel time routes, and neighborhood centroids.

5.2.1. Modifiable Areal Unit Problem (MAUP) and ACS Data and Uncertainty

One limitation worth discussing is the issue of modifiable areal unit problem (MAUP). MAUP is an issue identified in spatial and geographical studies and needs to be considered when measuring accessibility. According to Tuson et al (2019), counts from census tracts and boundaries of many areas can be affected by the scale of the data aggregated. MAUP can occur when geographical units are changed, or if census tract boundaries are be redrawn when census counts are undertaken. MAUP has two forms; the scale and the zone effects. The scale effect occurs when the size of the aggregation of units is changed but the analysis is applied to the same data. With larger units the variation of the data decreases which will affect the spatial accessibility. The zone effect is when the scale of the analysis is fixed but the zone or shape of the aggregation units are changed. The zone effect can be the analysis of the zone and not the data. The focus is on the aggregation of results from the spatial accessibility as a result of the zone changes. Since this is an ongoing issue in GIS, the results from spatial accessibility studies should state the reasons for boundary change decisions. The researcher needs to be mindful of the MAUP when quantifying the data. This study utilized census tract veteran estimate data and did not change geographical units or existing census tract boundaries. The veteran data estimates used was obtained from the ACS for a 5-year period from 2012-2017. Although it was the most accurate, and up to date information to use when this study was written, there is the inherent issue of the uncertainty of the MOE. The unit of veteran estimation was represented by each census tract and therefore contained different veteran estimations and MOE for each tract. As indicated in other limitations listed below tracts were not combined to reduce the MOE even though combining census tracts into regions can reduce the ACS MOE uncertainty. But if tracts are combined to reduce the MOE, the issue of MAUP must be considered by future researchers.

5.2.2. 15-Minute Catchment Threshold Assessment

Using a 15-minute catchment threshold excluded 57,642 veteran estimates in 372 census tracts. The mean value of veterans per census tract was 119.6 and was determined by dividing the total estimates of veterans which was 280,012 by the total number of census tracts value 2341. In Figure 23 below, the area around the Antelope Valley VA had veteran estimates that were above the mean value of 119.6. The Antelope Valley VA had numerous census tracts with above average veteran estimates that were not analyzed in this study since they were outside the 15-minute catchment. The 15-minute drive time threshold that was set during the addin tool setup procedure excluded all tracts that were beyond the catchment boundary from being assessed. For example, there were 82 census tracts that were assigned to the Antelope Valley VA Clinic as the closest supply point. Of those 82 census tracts only 36 were counted during the analysis using the core model parameters. There were 46 census tracts that were not included in that areas. The excluded tracts were ones that fell outside the 15-minute threshold. In those 36 census tract that were inside the 15-minute threshold there were total veteran estimation of 9172. The 46 tracts that fell outside the catchment had a veteran estimation total of 10,082.

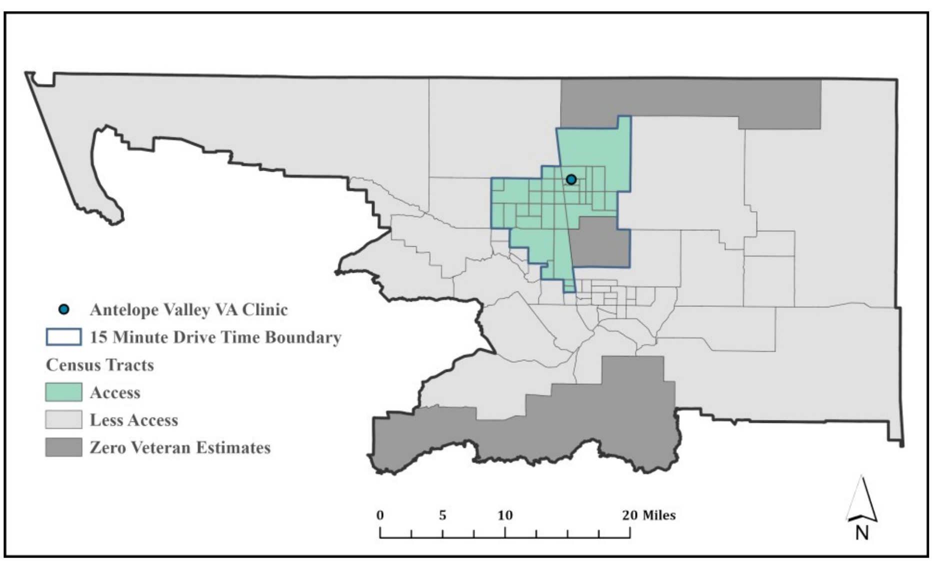

Figure 23. Antelope Valley Catchment.

The map in Figure 24 showed numerous census tracts that were not included in the analysis because of the 15-minute threshold, these were colored in light grey and considered less access. The Antelope Valley VA in the northern part of LAC is somewhat isolated from the rest of the county. This area became a reference guide to the limitation of a 15-minute catchment results when analyzing limitations with the parameters that were set. The map below Figure 20, shows a zoomed-in extent of the Antelope Valley VA Clinic. It serves as an example to show how many census tracts with high veteran estimations. That fell just outside the 15-minute catchment boundary and were not included in the analysis and thus lacked accessibility.

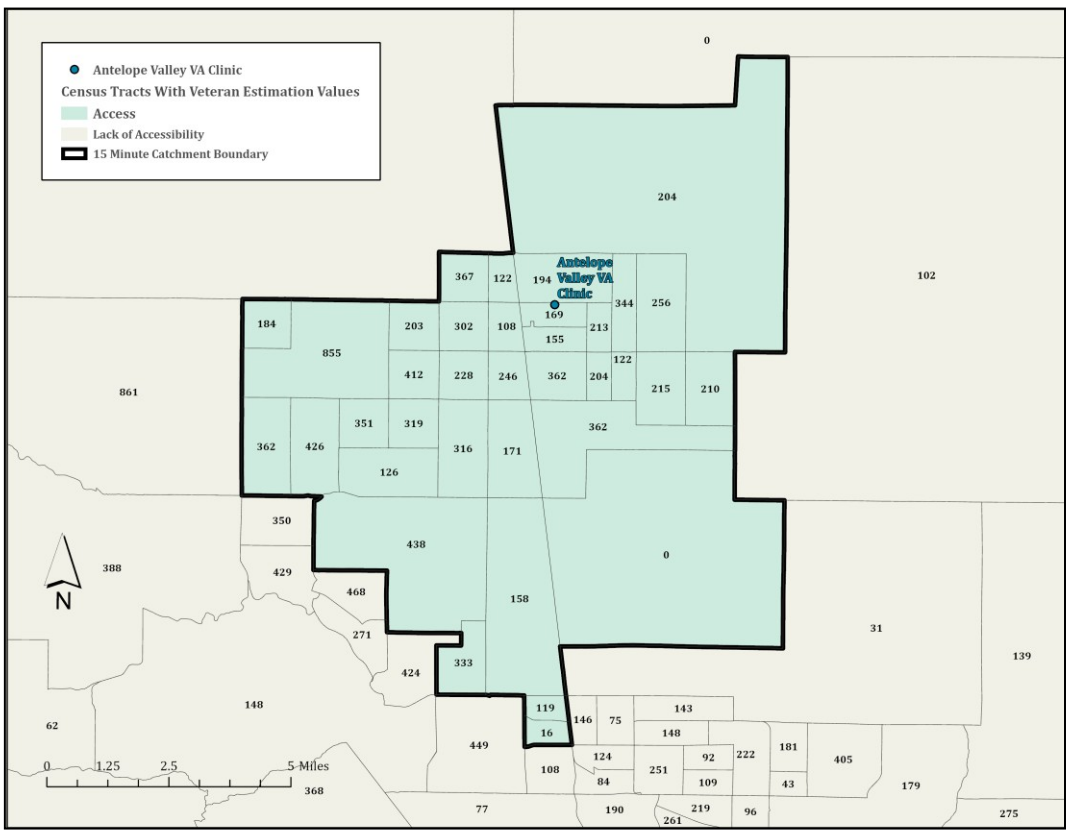

Figure 24. Antelope Valley Veteran Estimations Values.

5.2.3. Closest Facility

The closest facilities were found using drive time as impedance. The limitations of this data produced results there were not as accurate as it could have been as it did not consider types of transportation options. It did not consider traffic, stop signs, or red lights that occur when traveling from an origin to a destination. This would undoubtedly add more travel time when assessing quickest routes. Public transportation such as trains or bus routes were not assessed. Los Angeles County has over 15,000 bus stops (Rideshare LA County 2017), and the Metrolink has 62 train stations (Metrolink 2020). Using that data could have produced SA scores with higher values in neighborhoods that are spatially located close to train pick up locations, or a bus stops where a quicker route may have been utilized.

5.2.4. Precision of Travel Times on Routes

An example of a limitation on travel time routes is seen in Figure 25. The route in blue represented a drive time from the Antelope Valley VA clinic to its corresponding demand centroid with a total drive time of 15.2 minutes. The other route in red showed a drive time of 15.7 minutes to its demand centroid. Perhaps there is imprecision in the drive time data and both census tracts just outside the 15-minute drive time threshold should have been counted in the analysis. Considering the isolation of that area all census tracts with veteran estimates would most likely use the Antelope Valley VA clinic.

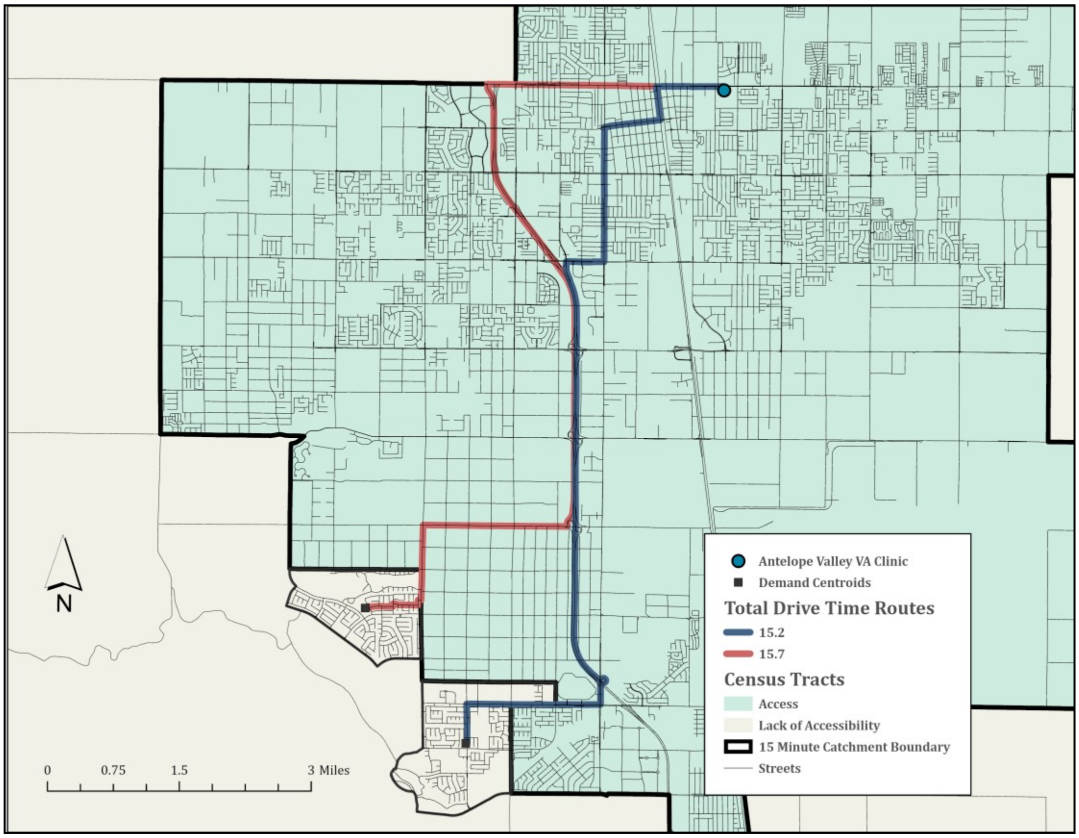

Figure 25 Total Drive Time Routes.

5.2.5. Census Tract Centroids

When assessing limitations using census tract centroids one must consider that using the center of a census tract does not accurately depict true drive time from supply to demand locations because of urban sprawl in the area. One example in Figure 26 below showed that a demand centroid was not centered around the population and the location was in the middle of a forested recreation area. Figure 24 with a zoomed extent of the study area shows the supply location at the San Gabriel Valley VA in the city of Arcadia. A census tract with 209 estimated veterans was isolated and then symbolized with an Environmental Systems Research Institute (ESRI) base map to show the center of that census tract. That census tract is 9.3 square miles with a major portion occupying a forest and recreation area. The vast majority of the population of that census tract is located in residential zones along the foothills. The green supply to demand route has a total drive time of 8.4 minutes. That route time could be shortened if the demand points were centered more around the population in the foothills.

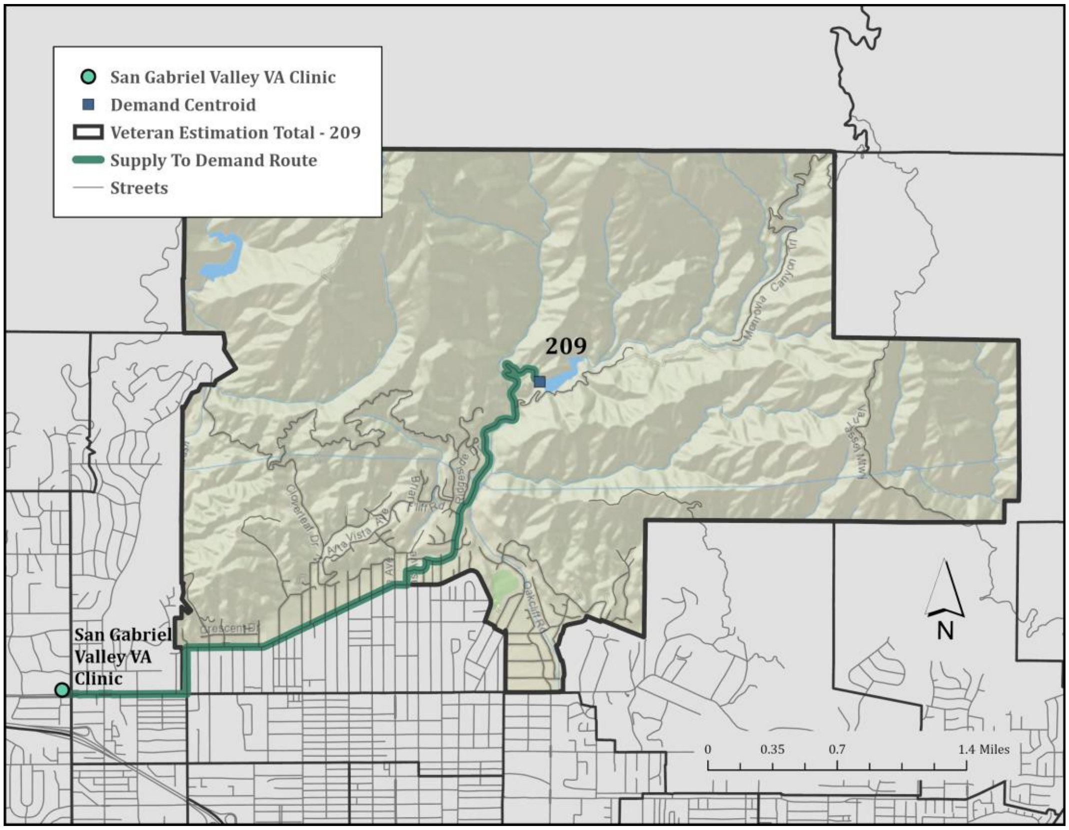

Figure 26 Demand Centroid Limitations.

5.3. Conclusions

This thesis was undertaken to analyze if gaps in primary healthcare coverage for veterans in Los Angeles County existed based on drive time impedance. The thesis provided an analysis of veteran access to exiting primary care VA locations using census tract information. The major finding of this study indicated gaps in accessibility based on drive time existed in the eastern portion of the county. The study also resulted in an interesting finding that veteran estimate concentrations have an impact on accessibility to existing supply sites. The results of this project could facilitate the VA with the ability to monitor accessibility on a re-occurring schedule based on changes in census data. The analysis also projected a theoretical additional site location in the southeast portion of the county to increase accessibility. The analysis of the identified limitations in this study may give future researchers tools to study to improve the spatial accessibility results of the veterans' access to primary care. Through the use of data and GIS technology, this thesis identified the spatial relationships between the veterans and the primary care locations to give VA planners a better understanding of reviewing where supply may not adequately serve the veteran demand. Moreover, census tracts were the areal unit used in this analysis. In closing one could surmise that using a smaller aggregation of data such as blocks groups would improve accuracy and spatial accessibility.

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