SIDEWALKS TO NOWHERE:

A TOOL TO PRIORITIZE PEDESTRIAN IMPROVEMENTS

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ABSTRACT

Sidewalks to Nowhere:

A Tool to Prioritize Pedestrian Improvements

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Walkability as a concept that captures the ability to walk from one place to another has multiple dimensions. Between traversability to being a proxy for better urban places, there are also numerous measurements of walkability that attempts to quantify certain or all aspects of walkability. It is, however, unclear, through a review of available literature, how these measurements of walkability relate to each other statistically. This methodology focuses on generating a framework for analysts to evaluate and prioritize pedestrian infrastructure. WalkScore™ (WS), HCM Pedestrian Level of Service (PLOS), Average Nodal Degree (AND), and Intersection Density are the four metrics selected for this analysis that focuses on distinctive aspects of walkability (proximity, amenity, network-connectivity, respectively). A sample of 51 street segments from the County of San Luis Obispo is selected according to their respective Average Daily Traffic (ADT) volumes. Pearson's Correlations between the six combinations of relationships are measured, and the strongest correlation between the six relationships is between WalkScore™ and Intersection Density with an R^2 of 0.44.

A regression model that includes external factors such as population and adjacent land use is used to analyze and predict PLOS of the street segment. Although the model is not statistically significant, the goal of this research is to identify gaps in current and potential walkability of street segments in the sample. Therefore, this framework of using established walkability metrics to predict PLOS, and then distinguishing places for improvements is proposed as a result of this research to be used by government agencies to prioritize pedestrian infrastructure.

Keywords: Walkability, Prioritizing, Pedestrian infrastructure, WalkScore™, Pedestrian Level of Service, Average Nodal Degree, Proximity, Amenity, Network-connectivity

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1 INTRODUCTION

Pedestrian infrastructure is imperative to one's daily activities and a huge contributing factor to sense of place. The importance of pedestrian infrastructure largely stems from three major aspects of planning: transportation, environment protection, and health.

The California Complete Streets Act of 2008 requires revisions of any city or county general plan or circulation element to accommodate all roadway users (AB - 1358, 2008). This is because of the lack of inclusivity of all transportation modes that is the existing condition at many California streets, which is primarily geared and designed to accommodate motor vehicles. Improvements on pedestrian infrastructure can reduce car dependency, lower the number of vehicle miles traveled, increase the choice of walking for shorter trips, increase pedestrian activity, lower the demand for parking in urban areas, and much more. In terms of environment protection, replacing short car trips with walking can reduce greenhouse gas emissions, in which car travel represents a large percentage of all greenhouse gas emissions. Replacing short car trips with walking is also good for public health, because increasing activity and opportunities for exercise is directly related to improving health, decreasing probability of developing chronic diseases, and improving mental health. In essence, improving pedestrian infrastructure increases the livability of a community, therefore having a methodology to select and prioritize pedestrian improvements provide a guide for realizing the vision of a more walkable city.

1.1 Purpose of Research

It has been long established that level of service (LOS), essentially measuring vehicle density and travel time delay, is the golden rule for evaluating the quality of vehicle travel. However, it is highly debatable that street performance for non-automobile modes, in this research pedestrian travel, can be measured by the same standards. There have been many researchers and agencies that established many metrics and indices that take into account different aspects and utilities that affect the decision to or the experience of walking at various degrees. Walkability, as a term, also has many various definitions: traversability, proximity, a projection of better outcomes, and a proxy for better urban places (Forsyth, 2015). As such, one place that is measured walkable for one metric may not be equally walkable for another metric. Theoretically, a place is only truly walkable when all aspects of walkability are met at a high standard. Places that are highly walkable in terms of proximity and street connectivity have the greatest potential to benefit from improvements, because infrastructure changes are easier to implement than built-environment factors. The purpose of this research is to demonstrate the feasibility of a methodology to identify locations and prioritize investment in pedestrian infrastructure improvements.

The process of this research is to select three out of the numerous published and accessible methods and feed a list of selected street segments through to see how these metrics compare to one another in order to generate a prioritization methodology. It is imperative that the three tools focus on different aspects of walkability. For example, Walk Score focuses on proximity (Carr, Dunsiger, & Marcus, 2010), pedestrian LOS

(PLOS) focuses on amenities and design characteristics (Brozen, Huff, Liggett, & Wang, 2014), and a pedestrian corridor improvement index focuses on capturing all four pillars of walkability: (1) infrastructure; (2) location; (3) mobility; and (4) safety (Oswald Beiler & Phillips, 2016). This research is interested in seeing how separate tools rate and rank streets differently, and identify places of rank discrepancies as places for improvements in pedestrian infrastructure.

This thesis aims at providing a tool for agencies to prioritize pedestrian improvements using three well-developed walkability metrics. The methods include evaluating existing pedestrian infrastructure in the County of San Luis Obispo using different scoring tools and measuring the correlation between each tool. There are many indicators that rank and evaluate the quality of pedestrian infrastructure, but in what ways they do relate to each other is unclear. Therefore, multivariate regression is used to find out the degree of correlation and to predict a PLOS score based on the built-environment. Although the correlation is not significant and the goodness of fit of the model is not high, this thesis demonstrates that street segments where the predicted PLOS score is better than actual PLOS are places with the highest potential to improve pedestrian infrastructure.

1.2 Research Tasks

The analytical approach or research methodology to be followed are listed as follows:

1. Select a sample of 51 points of interest by picking three street segments in all 12 unincorporated communities and 7 incorporated cities within the County of San Luis Obispo using the most recent traffic volumes.

2. Using Walk Score, Pedestrian Level of Service, and Average Nodal Degree, the respective scores of the sample points yields a table of 51 numbers each in three columns.
3. Conduct a coefficient of correlation analysis by raw score and ranking.
4. Conduct a coefficient of determination analysis by raw score and ranking.
5. Conduct a multivariate regression analysis to measure the relationship between PLOS and the built environment and predict a PLOS based on input independent variables.
6. Determine statistical significance of the results, and analyze results to identify places where the predicted PLOS has the biggest difference with the calculated PLOS.
7. Determine the list of places where building pedestrian infrastructure would generate the biggest benefits.

1.3 Organization of the Thesis

The chapter following this introduction is a review of existing literature on different aspects of walkability and measures of walkability. 0 details the source of the data, and the order and methods this quantitative analysis on walkability is going to be carried out. The next section as 4 provides the results and includes a detailed discussion of the data. Finally, 5 is the conclusion chapter where further discussion of the results, the limitations of this research, and the proposed next steps are addressed.

2 LITERATURE REVIEW

This chapter begins with an in-depth discussion of the three types of walkability metrics: those based on proximity (including WalkScore^{TM}), those based on infrastructure (including pedestrian level of service), and those based on route directness (including average nodal degree). Walk Score, Pedestrian Level of Service, Average Nodal Degree are particularly emphasized because they form the basis of the analysis presented later in this thesis. Finally, the chapter covers literature on methods of prioritizing pedestrian infrastructure, and includes previous research that sought to compare and identify relationships between existing pedestrian walkability metrics.

2.1 Walkability

The phrase "walkability" can be broken down into two components: "walk" and "ability". In short, the word describes the ability to walk. "Walkability" itself as a phrase, however, is not a word in the Oxford English Dictionary. Instead, "walkable" is an adjective describing places "of terrain, a road, path, environment, etc.: that is suitable, fit, or safe for walkers" that was in use by 1736 at least (Forsyth, 2015). In similar sources such as Merriam-Websters and Dictionary.com, the word "walkable" has comparable meaning that describes places that are "capable of being traveled". The definition of walkability, though, is very different depending on the context. Walkability can be used in professional, research, and public debates with varying understandings. Forsyth's (2015) review of the debate on walkability reveals three general usages of the term.

Walkability can focus on the "means of conditions by which walking is enabled", which describes the existence of infrastructure that allows walking activity (Forsyth, 2015). This rather physical and literal understanding of walkability captures the definition of "walkable" from the dictionary. In this dimension, walkability is about the basic physical infrastructure that allows traversability in a relatively safe fashion with "reasonable surface and no major hazards" (Forsyth, 2015).

Walkability can be a projection of desired "outcomes or performance" as well, which is more about the associated benefits with walkable environments such as vibrant urban areas with active social interactions and improved physical health (Forsyth, 2015). The Centers for Disease Control and Prevention encourages walking as an excellent way for people to become more active in their daily life and improve their health (CDC, 2017). Walking is the most common form of physical activity after all, and a community designed for walkability makes the decision to choose walking as a mode of transportation to reach their destinations that much easier, which in turn is positively related to increase in physical activity and healthier communities (Lawrence D. Frank et al., 2006).

Walkability is also used by urban designers as a "proxy for better urban places" in some cases to be the solution to a variety of urban problems. Ewing and Handy (2009) related walkability to urban design qualities by developing a measurement tool that quantifies variables that makes a desirable walking environment. They were able to operationalize five urban design qualities: imageability (Lynch, 1960); (Gehl, 1987) enclosure (Cullen, 1995), human scale (Carmona, Heath, Oc, & Tiesdell, 2012), transparency ((Ewing, Handy, Brownson, Clemente, & Winston, 2006; Heath et al., 2011; Madanipour, 1999). and complexity (Ewing et al., 2006;Rapoport, 1990), and identify significant physical features that are measurable with field work. The model is based on the idea that a walkable space should be interesting, visually enticing, and convenient to walk as well (Gehl, 1987; Speck, 2012).

Lastly, Forsyth (2015) points out that the varying definitions of walkability creates confusion in discourse. The term walkability entails different levels of expectation when used to convey walkability outcomes. While this thesis explores the relationship between three metrics that has a clear focus on their own aspects of walkability, it will not analyze the accuracy or ability of such metrics in predicting actual walking activity. The following sections will feature a selection of established walkability metrics under three broad definitions: (1) Proximity; (2) Infrastructure; and (3) Network Connectivity.

2.2 Proximity / Distance (Walk Score™)

Proximity refers to the distance between places of origins, usually residences, to destinations such as stores or work places (Owen et al., 2007). It is established that the built-environment are highly related to the amount of physical activity, in this case the amount of walking (G. W. Heath et al., 2006). A study on urban adults using travel diaries found that distance to retail activity is important in predicting the amount of walking at a close distance (within 200 meters) (Krizek & Johnson, 2006).

The Neighborhood Environment Walkability Scale (NEWS) measures built-environment factors that are perceived to have an effect on the decision to walk (Cerin et.al., 2006; Saelens et. al., 2003). It is a 68-item survey instrument that is designed to assess residential density, proximity to nonresidential land uses, access to nonresidential land uses, etc. Proximity is recorded in terms of walking distance in minutes from home to various nonresidential land uses. A study by Cerin et.al. examined and confirmed the validity of the metric, using multilevel confirmatory factor analysis, and developed an abbreviated version (NEWS-A) for an expedited research process (2006). Another research team conducted the study in Hong Kong also found this instrument to be reliable for cross-national study, indicating NEWS' applicability in evaluating the effect of built environment on walking in different geography and cultures (Cerin et al., 2006).

Walk Score™ is a tool established by Front Seat Management, LLC as an index to be utilized by real estate professionals for measuring the proximity to different amenities from any address in the US, Canada and Australia. It is widely used in real estate listings and a high walk score can add significant value to the property. Walk Score™ uses data from the Google™ AJAX Search application program interface and a geography-based algorithm to identify the location and density of amenities, in 13 different categories, with respect to a specific address to calculate a "score of walkability" (Heath et al., 2006). The score ranges from 0 to 100, with 0 being the worst and 100 being the best.

Walk Score™'s algorithm is largely based on three components: amenities, proximity, and pedestrian friendliness. The distance decay function in the walk score methodology relates to amenities and proximity: a destination gets the category's full score if it is located within .25 miles of the origin; at one mile the destination would only receive 12% of the full score; at 1.5 miles the destination will not be counted towards the full score at all (Walk Score, 2011). There are different weights assigned by the WalkScore™ developers to the different amenities and the numbers listed for each category represents the assigned weight and number of counts of that destination. When there is more than one count of such destination within 0.25 miles, the second nearest destination will receive the second highest weight associated with such destination, and so forth. As such, a grocery store that would normally receive 3 points will receive a discounted score of 2.6 points at a distance of one mile. The amenities that WalkScore™ chose, and their respective assigned counts and weights are selected according to the developers' interpretation of current walkability research (WalkScore™, 2011).

The methodology listed a few studies that analyzed the relationship between walking activity and presence of amenities (Lee & Moudon, 2006; Moudon et al., 2006; Iacono, Krizek, & El-Geneidy, 2010; El-Geneidy & Levinson, 2011). The available research found grocery stores to be the drivers of walking (Lee & Moudon, 2006) and the most common destination in surveys (Cerin, Leslie, Toit, Owen, & Frank, 2007), hence it was assigned to bear the most weight in WalkScore™. These surveys also reflected restaurants/bars, shopping, coffee shops, banks, and parks to be common destinations by walking. Variety was the main consideration in assigning the number of counts allowed to be factored in the final tally. This is echoed by having ten allowable counts for dining options, five allowable counts for shopping; and two allowable counts for coffee shops. The methodology does not clearly indicate the consideration for assigning a total weight of 1 for other amenities (WalkScore™, 2011). The availability of parks, however, should be weighed more in any walkability metric because of its high correlation to improved physical and mental health.

The pedestrian friendliness portion of WalkScore™ contains two pieces: calculating intersection density (intersections per square mile) and average block length (meters), which related to network connectivity (WalkScore™, 2011). The methodology determines that areas with poor pedestrian friendliness to be penalized of up to 10% of the total score after initial calculations based on amenities and proximity (Saelens, Sallis,

& Frank, 2003); Ewing & Cervero, 2010; Lee & Moudon, 2006; Leslie et al., 2005; Berrigan, Pickle, & Dill, 2010.The Walk Score method is intuitive and easy to use. It only requires inputting an address to an online tool for the algorithm to calculate and can be done in minutes.

There is a lot of available scholarly research that measured and validated the ability of WalkScore™ in predicting actual walking activity (Carr et al., 2010), associated health benefits (Duncan, 2013), the anticipated increase in property value (Gilderbloom, Riggs, & Meares, 2015), etc.

Carr, Dunsiger, & Marcus (2010) manually calculated the WalkScore™ of 296 residential addresses in Rhode Island using GIS and publicly available data and then comparing those scores to numbers calculated by the WalkScore™ website by using Pearson's correlation to check to what degree the results match each other. The results indicated "significant positive correlations between WalkScore™ and several objectives" related to a desirable urban living environment, including street connectivity and residential density (Carr et al., 2010). Those objectives included street connectivity, residential density, access to public transit, crime, etc. While the validation of WalkScore™ as an indicator of desirable features of the living environment is demonstrated by strong and significant correlations above 0.5, the fact that similar results are found between WalkScore™ and crimes reported led the authors to conclude that WalkScore™ can be a proxy for estimating density and amenities rather than a measure of comprehensive neighborhood walkability or desirability (Carr et al., 2010).

Duncan, Aldstadt, Whalen, Melly, & Gortmaker (2011) continued and expanded the previous study by Carr et. al. about validating the ability of the WalkScore™ in predicting neighborhood walkability. This research collected and calculated data for four US metropolitan areas with 733 residential addresses from families with children aged 5-11 years that were participants of the YMCA-Harvard After School Food and Fitness Project. Researchers evaluated the validity of WalkScore™ in assessing neighborhood walkability versus GIS-based indicators on several levels of street network buffer distances (i.e., 400-, 800-, and 1600-meters) and found correlations to be stronger as the spatial scale increases, hence confirms the generalizability of WalkScore™ as a valid measure that is free and highly accessible for the public (Duncan et al., 2011).

There are, however, limitations to the WalkScore™ methodology that are worthy of discussion. For example, WalkScore™ does not differentiate between small corner shops and a full service grocery shop (Reyer, Fina, Siedentop, & Schlicht, 2014). It also does not account for proximity to transit, but instead separate that calculation in a separate methodology called Transit Score. WalkScore™'s algorithm assumes the availability of sidewalks based on the existence of a roadway, which is an important factor when it comes to making the decision to walk. Factors such as safety, how many lanes of traffic one must cross, topography, roadway design, etc., are all not part of the WalkScore™ methodology (Washington, 2013).

2.3 Infrastructure / Design Characteristics (Pedestrian Level of Service)

HCM MMLOS is a level of service index developed by the Florida Department of Transportation for the Highway Capacity Manual update in 2010 that specifically evaluates forms of transportation outside of motor vehicles, namely transit, bike, and walking. "The HCM uses four units of analysis: intersections, links, segments, and facility. The LOS estimation requires information about demand, control, and geometry.

The equations provide a numerical score that is converted into a letter [grade from A to F]”, where the letter A is associated with the least delay (or best quality of service) while the letter F is on the opposite end of the spectrum (Brozen et al., 2014). The HCM method requires extensive training and technical knowledge, as well as in-depth field work but it is based on a strong research background that is widely recognized. It also includes both the intersection and the link in its analysis (Zuniga-Garcia, Ross, & Machemehl, 2018).

Historically, the Level of Service (LOS) concept in the Highway Capacity Manual from 1965 reflected a motorist perspective with emphasis on traffic delay in seconds, as well as density and speed. It is the most widely recognized method to measure roadway operational performance in the transportation planning and traffic engineering discipline. The LOS method is embedded in analytical software that evaluate roadway performances and used as the standard for circulation studies, traffic fee updates, and even the traffic impact portion of environmental review processes such as CEQA and NEPA. LOS only accounts for vehicle delay and neglects the interaction between motor vehicles and pedestrians, cyclists, and transit users.

In 2010, the 5th edition of the Highway Capacity Manual included a multimodal analysis framework for level of service for the first time(HCM 2010, 2010). The HCM adopted the multimodal LOS methodology, which includes a Pedestrian LOS and Bike LOS separately, that was developed by the Florida Department of Transportation as an attempt to provide a more comprehensive approach to traffic engineering. Like the traditional motor vehicle LOS method, MMLOS is labor-intensive with numerous variable that are heavily technical but not commonly used by practitioners. MMLOS also requires a lot of data that are not widely available and regularly collected, which makes manual calculations a time consuming task and a difficult method for resource-constrained agencies. The most recent update of the Highway Capacity Manual in 2016 for its 6th edition included changes to both pedestrian and bike LOS that are segment specific. In the current version, segment LOS score is based on weighted average of intersection and link LOS scores, with link weighted by travel time and intersection weighted by intersection delay.

Huff and Liggett (2014) provides a comprehensive overview of how the HCM MMLOS methodology is made up of various components, what these components mean, how important each variable is in determining the final LOS assignment, etc. The authors also reflected on the methodology and pointed out problems and criticisms with the methodology itself but in terms of individual variables. There are many situations not covered by the pedestrian LOS given its robust and lengthy process. For example, Ped LOS does not account for topography, midsegment unsignalized crosswalks, railroad crossings, unsignalized intersections controlled by stop signs and roundabouts, etc., just to name a few.

Oswald Beiler's (2016) article provided an insight into what street elements and characteristics, when chosen in degrees of intensity, will be able to capture the most holistic view of the various street designs in existence. In terms of pedestrian infrastructure, both physical conditions and designs of the roadway are factored into the calculation. Metrics such as walkway width, ADA access, aesthetics, surface condition, slope, and pedestrian amenities are part of the formula. For example, for the vehicular speed metric, the scale is divided into five categories with their respective assigned scores. After the scores were assigned to each metric, a factor weight is applied to result in possible points to contribute to the overall pedestrian corridor improvement index (PCII) value of a street segment.

2.4 Street Connectivity (Average Nodal Degree / Intersection Density)

Average Nodal Degree is an index that quantifies the density of street networks. By dividing the number of street segments over intersections, this method evaluates the street connectivity in any given spatial area. This is derived from the notion that well-connected streets are more inducive to increased walking or biking activities, which are important factors to making a healthy community (Oakes, Forsyth, & Schmitz, 2007). It is also a key consideration in good neighborhood design. Intersection density, on the other hand, quantifies the distribution of intersections in any given spatial area. A higher intersection density value corresponds to shorter block lengths, more direct routes, and better street connectivity.

Barrington-Leigh & Millard-Ball (2015) examined the relationship between street connectivity and sprawl in the United States from 1920 to 2015. They defined sprawl as low connectivity, and used nodal degree as a measurement to quantify the history of sprawl through the decades (Barrington-Leigh & Millard-Ball, 2015). The authors concluded that the pattern of sprawl has begun long before private car ownership became an inseparable part of American life. The rise of sprawl began in the early 1920s with the cul-de-sac design from Radburn, New Jersey starting to become popular, and the trend continued well into the 1990s with a decrease in average nodal degree. This type of street design featuring a lot of dead-ends that lowers connectivity was also recommended by various influential publications at the time (Barrington-Leigh & Millard-Ball, 2015).

With sprawl peaking in 1994, newer street designs returned to being more connected and grid-like. The authors found that by mean nodal degree, sprawl fell by 9% from 1994 to 2012 (Barrington-Leigh & Millard-Ball, 2015).

Dill's (2004) research evaluated several measures of connectivity to the Portland region for the purpose of increasing walking and biking. This is because previous research has been focused on overall street network but not specifically on active travel, which is a strongly recommended strategy for reducing vehicle travel and greenhouse gas emissions. The paper's first part included a review of existing measurements related to street connectivity from different disciplines (Dill, 2004). The identified measurements include block length, block size, block density, intersection density, connected node ratio, link-node ratio, pedestrian route directness, etc. (Dill, 2004). The second part focused on using four of the above measures to measure connectivity in 219 census tract in the Portland region. Using street network density, connected node ratio, intersection density, and link-node ratio, Dill found the measures to be positively correlated but not consistently comparable for a tract (2004). Future calibration of the method and further research is needed.

Street permeability is another concept related to connectivity. Referring to the ability to walk to nearby destinations in a direct route, the Walking Permeability Distance Index (WPDI) calculates the ratio between the direct distance between origin and destination to the actual distance by the most practical route (Allan, 2001). A WPDI = 1 is the ideal scenario where there is no difference between direct distance and actual route. The perfect score would imply that the network is highly permeable for pedestrian to walk from origin to destination without much hinderance (Allan, 2001).

Oakes et al. (2007) have sought to measure the association between street connectivity and active transportation. The authors conducted a multilevel study in Twin Cities, Minnesota to investigate the effect of neighborhood density and street connectivity on physical activity (Oakes et al., 2007). It was a rigorous study that sampled 716 adults in 36 randomly elected neighborhoods across four strata based on density and street connectivity. The results indicated increased odds of travel walking in high-density areas and leisure walking in low-connectivity areas. However, neither density not street connectivity are related significantly to miles walked per day or increased total physical activity, which is contrary to previous research results that find positive relationships between density / connectivity and walking.

Berrigan, Pickle, & Dill's (2010) research focused on studying the associations between street connectivity and active travel by adding a geographic perspective to account for spatial distribution in research methods. This paper also studied the propensity and duration of active travel separately using a multivariate distribution to "provide statistical power to detect covariates associated with both elements of active travel" (Berrigan et al., 2010). Over 50,000 households from the California Health Interview Survey were randomly surveyed by telephone with around 10,000 final responses used in the analysis. A handful of connectivity-related measures, like link-node ratio, connected node ratio, intersection / street / block density, average block length, etc, were calculated based on the respondents' closest intersection location, and then Spearman correlations were calculated (Berrigan et al., 2010). The results suggest that about 85% of the variance in nine measures of street connectivity are accounted for by places with short blocks and dense nodes and places with longer blocks but still have a grid-like street network. From this study, it can be concluded that aggregate measures of street connectivity are statistically significant and correlate active travel with a number of neighborhood street characteristics (Berrigan et al., 2010).

2.5 Infrastructure Prioritization

PCII stands for pedestrian corridor improvement index, and it is developed in 2014 in an attempt to help transportation agencies prioritize pedestrian infrastructure implementation using a "quantitative decision analysis approach" (Oswald Beiler & Phillips, 2016). It is a comprehensive index that draws on existing federal design guidance, and uses GIS and uses an analytical hierarchy process to define factor weights. One of the biggest differences between PCII and HCM MMLOS is that PCII takes into consideration more planning-related factors than HCM MMLOS, which is largely technical and engineering based. Other factors, like mixed land use, school zone proximity, population density, environmental justice, pedestrian wait area, lighting, shading, aesthetics, etc. are just some of the considerations included in this index.

Moudon's (2001) report included three tools for identifying and prioritizing pedestrian infrastructure improvement. The first two tools, Pedestrian Location Identification tools 1 (PLI-1) and 2 (PLI-2), recognize suburban areas that do and do not have potential for walking (Moudon, 2001). PLI-1 uses socio-demographic census data, like population and housing, and aerial photos to identify and delineate potential cluster blocks for high walking potential. The goal of PLI-1 is to identify blocks of medium density residential development, blocks with more multi-family than single family housing, and the presence of large apartment complexes. PLI-2, instead, utilizes parcel data with attribute data including land-use information and GIS raster tolls to establish high priority areas. PLI-2 is less time-intensive and delivers more precision to the analysis if a complete data set is available. The third tool, Pedestrian Infrastructure Prioritization (PIP) decision system, requires analysts to evaluate each identified cluster through a four-component approach to rank clusters and determine which is expected to yield the highest benefits (Moudon, 2001). These four components are: area-scale considerations, transportation facility scale considerations, policy conditions, and total conditions, which is a summary of the previous three categories (Moudon, 2001). By assigning different weights and ranges to each sub-criteria, jurisdictions or agencies can choose to prioritize pedestrian projects that most align with their goals and objectives (Moudon, 2001).

2.6 Safety

The concept of safety can be regarded as perceived or actual safety, and its effect on one's decision to walk should not be underestimated (Loukaitou-Sideris, 2006). An objective criteria of measuring actual safety in terms of pedestrian mobility could be the number of crashes per intersection, the number of pedestrian fatalities per capita within a neighborhood, either of which are daunting statistics that can dissuade one from choosing to walk. Perceived safety, however, is more associated with a state of mind that assumes the possibilities of unsafe situations. Both design (e.g. lighting) and infrastructure (e.g. sidewalk condition) components can contribute to a perceived risk and also deter pedestrians. Loukaitou-Sideris' article cites many past research that found a link between the decline of walking and safety concerns (2006).

Grossman, Rodgers, Xu, Guensler, & Watkins, (2019) collected over 133 survey responses from government agencies on the topic of bicycle and pedestrian treatment planning, prioritization, and implementation. Also, the survey questions whether these agencies have dedicated staff to deal with issues related to active transportation. Results indicate that safety is the primary considering factor when it comes to implementing active transportation infrastructure, but one-third of the responding agencies do not collect any data on traffic volumes and hence do not have enough evidence to support robust safety studies for the construction of adequate active transportation infrastructure (Grossman et al., 2019).

PCII also included safety considerations into the methodology of prioritizing pedestrian infrastructure (Oswald Beiler & Phillips, 2016). PCII ranks crash rate (safety) at the top of the list with a raw weight of 1, indicating the metric’s emphasis on the importance of safety towards pedestrian infrastructure development.

Safe Routes to School (SR2S) programs have been a popular tool for local agencies to use available grant funding for significant improvements to pedestrian and bicycle infrastructure immediately surrounding schools. Boarnet et. al. found, through surveys and observations of traffic behavior, that at most locations the amount of child walking has increased after sidewalk or traffic signal improvement projects. The outcomes of this study indicated that sidewalk gap closures and replacement of four-way stops with traffic signals have the highest potential for success (Boarnet et al., 2005).

A study that included walking and biking data from California cities, Danish towns, European countries, Netherland cities, etc., compared the relationship between the amount of pedestrian and bicyclists to the number of injuries in collisions with motor vehicles (Jacobsen, 2003). Researchers found that the likelihood of a pedestrian or cyclist being struck by vehicles is inversely proportional to the actual amount of walking and biking. This conclusion is also consistent through all the geographies included in this study. It is concluded that the increased visibility of a platoon of people is associated with the decreased risk of not being seen by motorists (Jacobsen, 2003).

2.7 Relationships among walkability metrics

Researchers at the University of California Transportation Center did an analysis of how different types of MMLOS metrics relate to each other (Brozen et al., 2014). This working paper examines the street performance for non-automobile modes at five street segments. Using four multimodal level of service metrics by the City of Fort Collins, CO, City of Charlotte, NC, City of San Francisco's Public Health BEQI/PEQI, and the HCM MMLOS and analyze how the scores produced by each metric compare with each other. The researchers selected five street segments in Santa Monica, California that have existing traffic counts because that is one of the key variables / inputs required to calculate MMLOS. Each segment analyzed includes three intersections and two connecting streets known as links. By comparing the ranking of each segment that is evaluated in three separate methodologies, the researchers were able to conclude that different methodologies are better at evaluating different street performance characteristics. In general, if a street is of good quality, the scores ranked similarly; however as the existing conditions deteriorate, the scores from each tool became increasingly different from each other. The HCM MMLOS is better at evaluating multimodality; the Charlotte LOS is better at evaluating safety and geometric design; and the BEQI/PEQI is relatively easy to use and cheaper to incorporate. One interesting addition, in terms of level of analysis, in this research is the measure of how sensitive each tool is to on-the-ground change. In other words, the researchers tried to create innovative redesign scenarios like road diet to see how the metrics scored before and after changes. They concluded that these metrics had limited ability to measure the effectiveness of innovative treatments.

More recently, researchers at the University of Texas, Austin applied eight different multimodal level of service methodologies to one arterial corridor section in Austin (Zuniga-Garcia et al., 2018). The eight methodologies are: Highway Capacity Manual; Transit Capacity and Quality of Service Manual; Charlotte, NC, Urban Street Design Guidelines; pedestrian and bicycle environmental quality indices; assessment of level of traffic stress; bicycle compatibility index; deficiency index; and Walk Score®, Bike Score®, and Transit Score®. There is a table towards the end of the paper that compares and contrasts the pros and cons of each methodology. This is a comprehensive overview for general practitioners or researchers to pick and choose between methodologies for their research purposes. They concluded that one overall MMLOS that was able to effectively analyze performance across all modes is not identified in this analysis.

2.8 Conclusions from Literature Review

The literature indicated the strong relationship between the characteristics of walkability and the actual amount of walking activity. Since WalkScore™, improved safety, and street connectivity are associated with more walking, it is likely that places with high walk scores and connectivity but low PLOS, due to lacking infrastructure, are likely to benefit the most from improvements.

For the associations between proximity and walking, there is scholarly research that measured and validated the ability of WalkScore™ in predicting actual walking (Carr et al., 2010). As for street connectivity, Oakes et. al. (2007) found increased odds of travel walking in high-density areas and leisure walking in low connectivity areas.

A study to investigate relations of walkability to total physical activity in youth, using land use characteristics and intersection density as factors, found positive relationships between neighborhood walkability to intersection density and residential density respectively (L. D. Frank et al., 2010). Participants in highly walkable neighborhoods had 92% more walking than other neighborhoods in the study, and intersection density was the most consistent component associated with increased walking (Carlson et al., 2015). Villanueva et al. also found a higher likelihood of adults walking in more walkable neighborhoods using variables such as land use mix and street connectivity, and correlating with self-reported total minutes of walking (2014).

It is to note that based on this extensive literature review, a robust and quantitative investigation of relationships between different walkability metrics is absent. The most relatable one is by Zuniga-Garcia, Ross & Machemehl (2018) which analyzed eight multimodal level of service methodologies qualitatively and quantitatively but not statistically. The degree to which different walkability metrics (i.e. destination-based, design-based, network-based, etc.) relate to each other statistically, however, is a gap in the literature. This establishes a need for research to connect the currently missing links and generate knowledge about the relationship between the plethora of metrics that claim to all measure “walkability” but seem to focus on the respective definitions of walkability. Most importantly, to identify places where one metric does not tell the whole story about the walkability of the location, and proposes this method to prioritize pedestrian infrastructure improvements.

3 METHODOLOGY

This chapter seeks to identify locations where pedestrian infrastructure improvements have the highest potential to increase walking activity. Using Pearson's correlation and regression, I analyzed and compared the scores and rankings of 51 sample points generated by four walkability metrics, as referenced in the previous literature review chapter. These metrics are 1. Walk Score; 2. Pedestrian LOS; 3. Average Nodal Degree; 4. Intersection Density. Although these are all "walkability" metrics, walk score measures proximity, pedestrian LOS measures infrastructure, and average nodal degree and intersection density both measure network connectivity. The process of applying these metrics to selected sample points in the County of San Luis Obispo allows a fair comparison across the board.

3.1 Selecting the Sample

The County of San Luis Obispo has a diverse mix of geography and a large differential in degrees of urbanization. It is assumed that most pedestrian activity, and streets that have the most potential for pedestrian activity, are fairly urbanized areas, and thus would have sufficient traffic volume to warrant a traffic count. The HCM methodology of calculating Pedestrian Level of Service also requires traffic volume as an input. Therefore, I compiled a list of all traffic volume counts conducted from 2016-2018. I obtained traffic volumes for unincorporated communities from the County of San Luis Obispo and data regarding incorporated cities is obtained via the City of Paso Robles and the San Luis Obispo Council of Governments. I formed a list by picking three street segments in 10 unincorporated communities and 7 incorporated cities within the County of San Luis Obispo: San Luis Obispo, Arroyo Grande, Atascadero, Paso Robles, Morro

Bay, Grover Beach, Pismo Beach, Oceano, Santa Margarita, Shandon, Templeton, Nipomo, San Miguel, Los Osos, Cayucos, Cambria, and Avila Beach. The process is to find and sort from high to low all the streets that have a record of traffic volume in each respective community. Then, three street segments with traffic counts at the 15th, 50th, and 85th percentile will be picked for this analysis. There are 51 points of interest in total for this analysis, the list is as follows Table 1:

Table 1: List of 51 sample points and respective ADT

Community	**Selection**	**Road Name**	**Nearest Cross Street**	**A D T**
Arroyo Grande	15th Percentile	Tally Ho Rd	S James Way	2581
	50th Percentile	Thompson Ave	NB US 101	5401
	85th Percentile	Huasna Rd	E Branch St/ SR 227	8137
Atascadero	15th Percentile	Atascadero Ave	S Santa Rosa Rd	1722
	50th Percentile	Curbaril Av	W US 101	6608
	85th Percentile	Curbaril Ave	E US 101	12981
Paso Robles	15th Percentile	S. Vine St	S of 1st St	5109
	50th Percentile	Union Rd	E of Golden Hill Rd	8820
	85th Percentile	Niblick Rd	E of Melody Dr	15289
Morro Bay	15th Percentile	Quintana Rd	W South Bay Blvd	2353
	50th Percentile	Morro Bay Blvd	W Quintana Rd	11637
	85th Percentile	Main St	S Radcliff Ave	11737
Grover Beach	15th Percentile	Farroll Ave	Oak Park Blvd	5116
	50th Percentile	4th St	N Grand Ave	11548
	85th Percentile	Grand Ave	W 4th St	11968
Pismo Beach	15th Percentile	James Way	E 4th St	5325
	50th Percentile	Price Canyon Rd	N Solar Way	9460
	85th Percentile	Price St	S Hinds Ave	16496
Oceano	15th Percentile	Twenty-Third St	N of Paso Robles St	951
	50th Percentile	Twenty-Second St	S of The Pike	3130
	85th Percentile	Halcyon Rd	S of Arroyo Grande Creek	9239
Santa Margarita	15th Percentile	I St	W of Highway 58	272
	50th Percentile	San Antonio Rd	S of Santa Barbara Rd	1565

	85th Percentile	El Camino Real	N of SR 58	3850
Shandon	15th Percentile	Second St	S of Highway 41	229
	50th Percentile	Center St	S of Highway 46 (east)	745
	85th Percentile	Center St	W of El Portal Dr	1810
Templeton	15th Percentile	Santa Rita Rd	W of Ridge Road	506
	50th Percentile	Florence St	W of Old County Rd	1741
	85th Percentile	Vineyard Dr	W of US Highway 101	7147
Nipomo	15th Percentile	Sandydale Dr	W of Frontage Rd	550
	50th Percentile	El Campo Rd	S of US Highway 101	1774
	85th Percentile	South Frontage Rd	S of Tefft	6962
San Miguel	15th Percentile	Wellsona Rd	W of US Highway 101	370
	50th Percentile	River Rd	N of Paso Robles City Limit	1030
	85th Percentile	Mission St	N of Fourteenth St	2861
Los Osos	15th Percentile	Palisades Ave	N of Los Osos Valley Rd	963
	50th Percentile	Tenth St	N of Los Osos Valley Rd	3058
	85th Percentile	Los Osos Valley Rd	W of Clark Valley Rd	14731
Cayucos	15th Percentile	Montecito Rd	E of Old Creek	98
	50th Percentile	Pacific Ave	N of Thirteenth St	666
	85th Percentile	South Ocean Ave	N of Thirteenth St	4009
Cambria	15th Percentile	Main St	E of Windsor Blvd	759
	50th Percentile	Pineridge Dr	E of Burton Dr	3063
	85th Percentile	Tamsen St	N of Main St	5245
Avila Beach	15th Percentile	Cave Landing Rd	E of Avila Beach Dr	859
	50th Percentile	San Luis Bay Dr	W of Ontario Rd	8510
	85th Percentile	Avila Beach Dr	W of San Luis Bay Drive	11460
San Luis Obispo	15th Percentile	Tassajara	Foothill to Ramona	1750
	50th Percentile	Grand	101NB to Mill	6644
	85th Percentile	Madonna	LOVR to Pereira	19162

The selected sample points can also be represented spatially, as in Figure 1 below. It is evident from the map below that the County of San Luis Obispo is geographically expansive, with small urbanized pockets concentrated on the western side of the county.

This analysis is therefore focused on analyzing walkability in these urbanized areas that have potential for pedestrian activity.

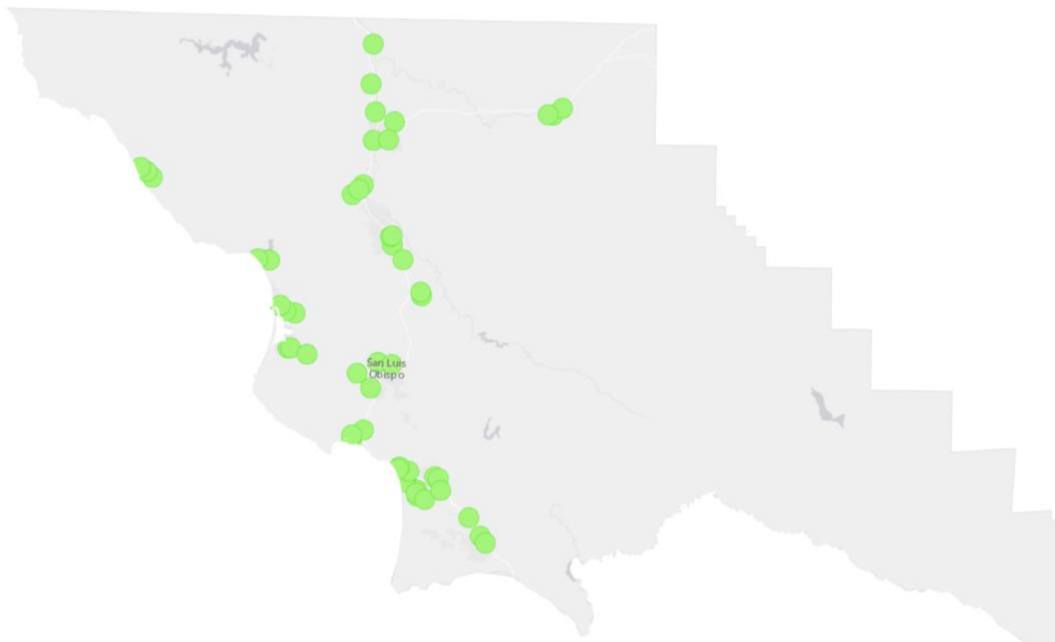

Figure 1: Map of 51 Sample Points

3.2 WalkScore™

WalkScore™ is a proprietary algorithm, owned by real estate listing company Redfin, of which the exact calculation method or formula is inaccessible. However, the WalkScore™ for and location can be calculated through the publicly available WalkScore™ website via the following url: https://www.walkscore.com/score/loc/lat=*xx*/lng=*yy*, where *xx* is the latitude of the location , and *yy* is the longitude. Using this url, I generated WalkScore™ values for all 51 locations in my study sample.

3.3 Pedestrian Level of Service

The Highway Capacity Manual's Pedestrian Level of Service determines walkability by a formula that considers a number of elements regarding street infrastructure, adjacent traffic, separation from traffic, etc (HCM 2010, 2010). The complete Ped LOS methodology consists of eight steps and calculates a score for the street segment, which is comprised of the street link and intersection. Due to limited resources, only the link portion of the LOS methodology is calculated. Of the various data points that are required to do the calculation, some are obtained by doing measurements on google maps while others are based on assumptions of average scenarios. For example, the motorized vehicle volume adjustment factor is calculated based on the traffic counts. The variables that go into calculating cross-section adjustment factor - width of outside through lane, bicycle lane, shoulder, parking lane, and sidewalk are collected from google maps. On the other hand, the proportion of on-street parking occupied is assumed to be 50% when there is available on-street parking, or otherwise 0%. Also, the midsegment demand flow rate is estimated based on ADT divided by 10. Although the Ped LOS methodology stratifies raw scores into six letter grades ranging from A to F, in this analysis only the raw score is used. This is to allow a level comparison of ordinal data with the outputs of other walkability metrics used in this research. All of the calculations were done using excel and the HCM 2010 LOS methodology, specifically Step 6 that determines Pedestrian LOS score for link, is used.

3.4 Average Nodal Degree

The last walkability metric to be evaluated is the average nodal degree, which measures network connectivity and assigns a score from 0 to 4. In a perfectly laid out street grid system, the average nodal degree will be 4 (Figure 2). On the other hand, in suburban areas where there are more dead-end streets because of cul-de-sacs, the average nodal degree usually ranges from 2-3. The process of calculating average nodal degree involves a simple formula: the number of street segments (legs) divided by the number of street intersections (nodes).

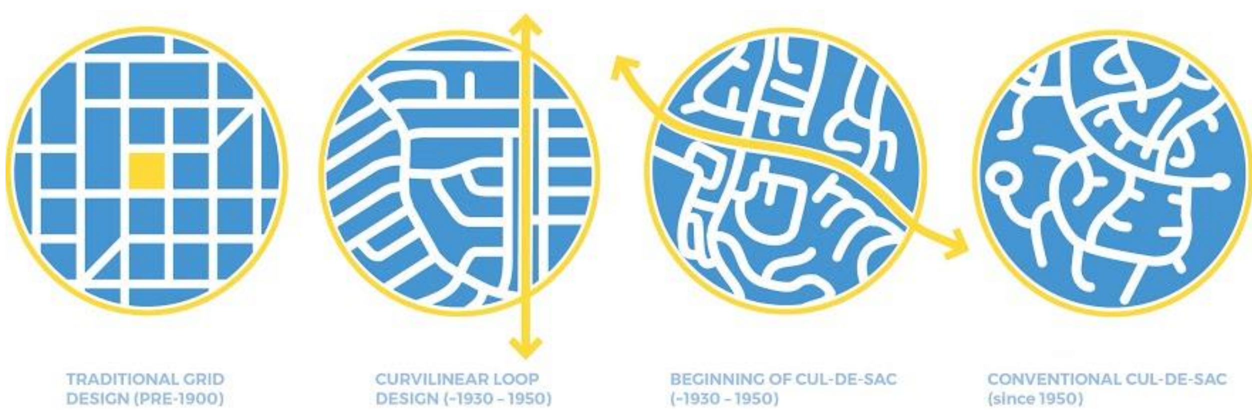

Figure 2: Street Network Typologies. From Congress for New Urbanism, https://www.cnu.org/our-projects/street-networks/street-networks-101.

However, to gather the number of legs and nodes in a designated area can prove to be burdensome if counted manually. In this step of the research, ArcGIS is used to designate a one-mile buffer from each point of interest and to calculate the number of nodes and legs that connect to each node within each buffer.

Using a shapefile from http://opendata.slocounty.ca.gov/ that is the "combined collection of the street centerlines created by the San Luis Obispo regions various GIS agencies within the county", a one-mile buffer from each sample point is created using the buffer tool in the geoprocessing menu. Next, the clip tool is used, also in the geoprocessing menu, to clip the underlying layer to only present roads within each buffered area. The result of this step is demonstrated in Figure 3 below.

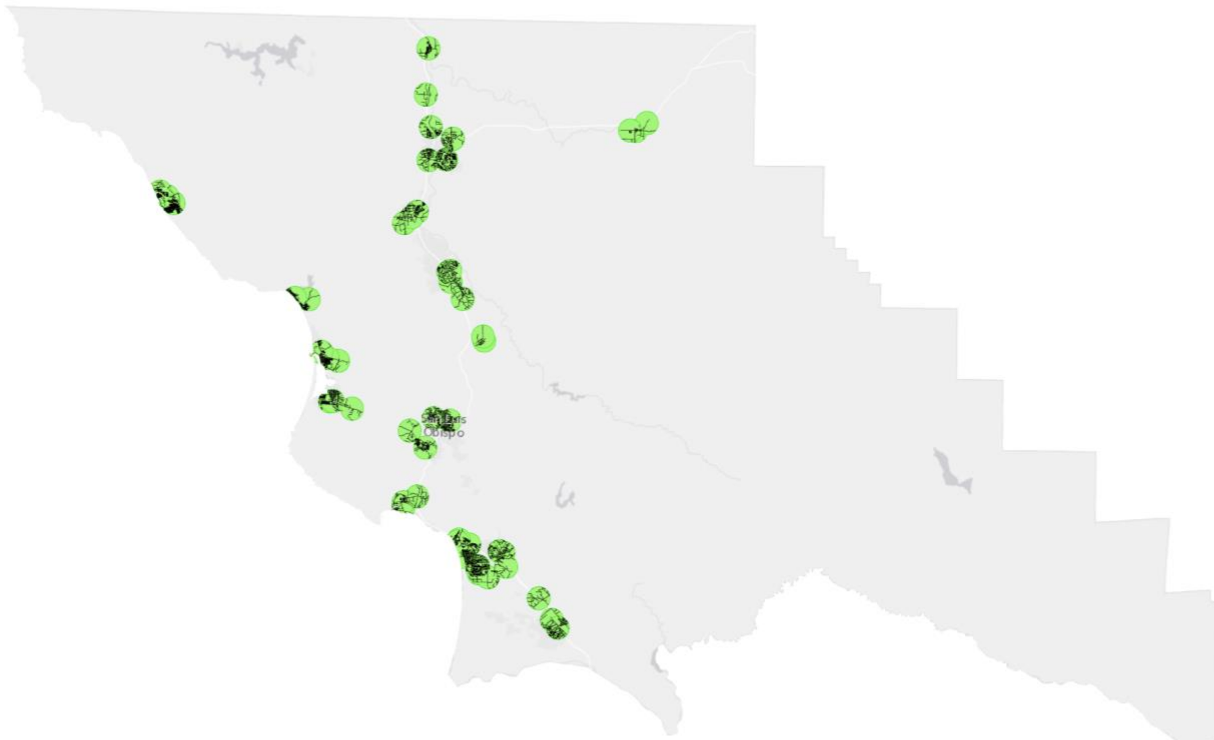

Figure 3: Roads within each 1-mile buffer

Another point worth mentioning is that the roads file contains all varying types of roads, including freeways, freeway ramps, trails, paper roads, driveways, etc. Since this research is about pedestrian and walkability, it is safe to assume that the above-mentioned types of roadways should not be taken into consideration as available for pedestrian access. Therefore, in the analysis, only local roads, park roads, and alleys are included, where everything else, including freeways and highways, is filtered out. Next, the feature vertices to points tool is utilized to “create a feature class containing points generated from specified vertices or locations of the input features” (ArcGIS Desktop, n.d.). This tool analyzes the input line layer and creates a point where lines intersect each other. It also allows a selection of different types of points to be created depending on the need of the analyst. With reference to Figure 4, “all” selects points that are at both ends, including dangle points. For this research, the “all” option is selected to be the output point type. This is because an accurate representation of average nodal degree should include dangles, which are prevalent in suburban street design with cul-de-sacs. It is also worth noting that the process of clipping roads to buffers should happen after nodes are identified. This is due to the fact that roads with start and end points outside the buffer boundary should be counted as unconnected roads in the network, which does not increase the ease of walking (Figure 4). Clipping roads before counting nodes would result in adding two more nodes to the area and increasing the average nodal degree that is not accurate.

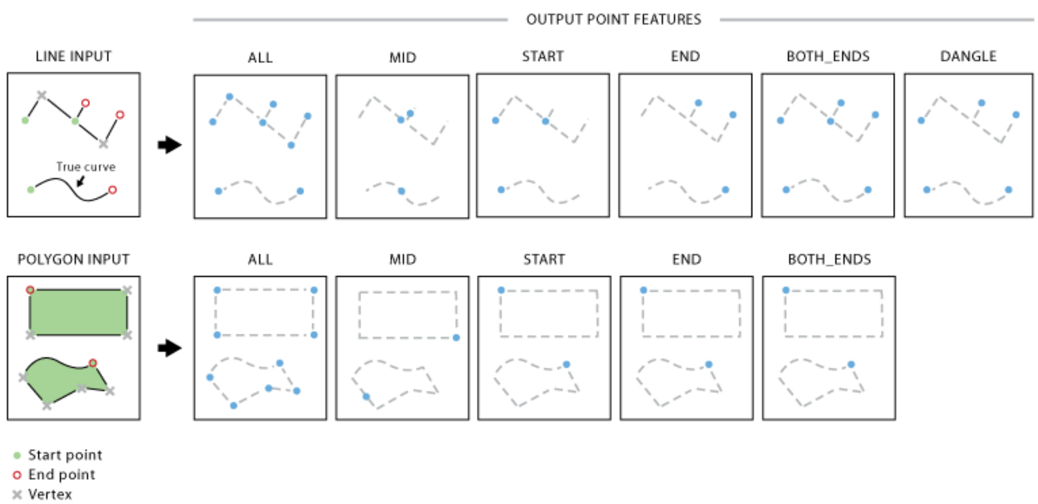

Figure 4: Output Point Features Characteristics in ArcGIS. From https://pro.arcgis.com/en/pro-app/tool-reference/data-management/feature-vertices-to-points.htm

The next step in process is to figure out how many segments connect to each node. ArcGIS’ joins and relates tool has the capability to calculate the number of lines (segment) that “touch” each point (node). It is important to note that simply taking the number of lines within a buffered area from the attribute table then dividing that number by the number of nodes will not yield an accurate average nodal degree result. For two immediately adjacent intersections, in a grid system, the number of segments that leads up to each node is four. The methods to calculating Average Nodal Degree are displayed in Equation 1 and Figure 5:

Equation 1: Average Nodal Degree

$$\frac{4+4}{1+1} = \frac{8}{2} = 4$$

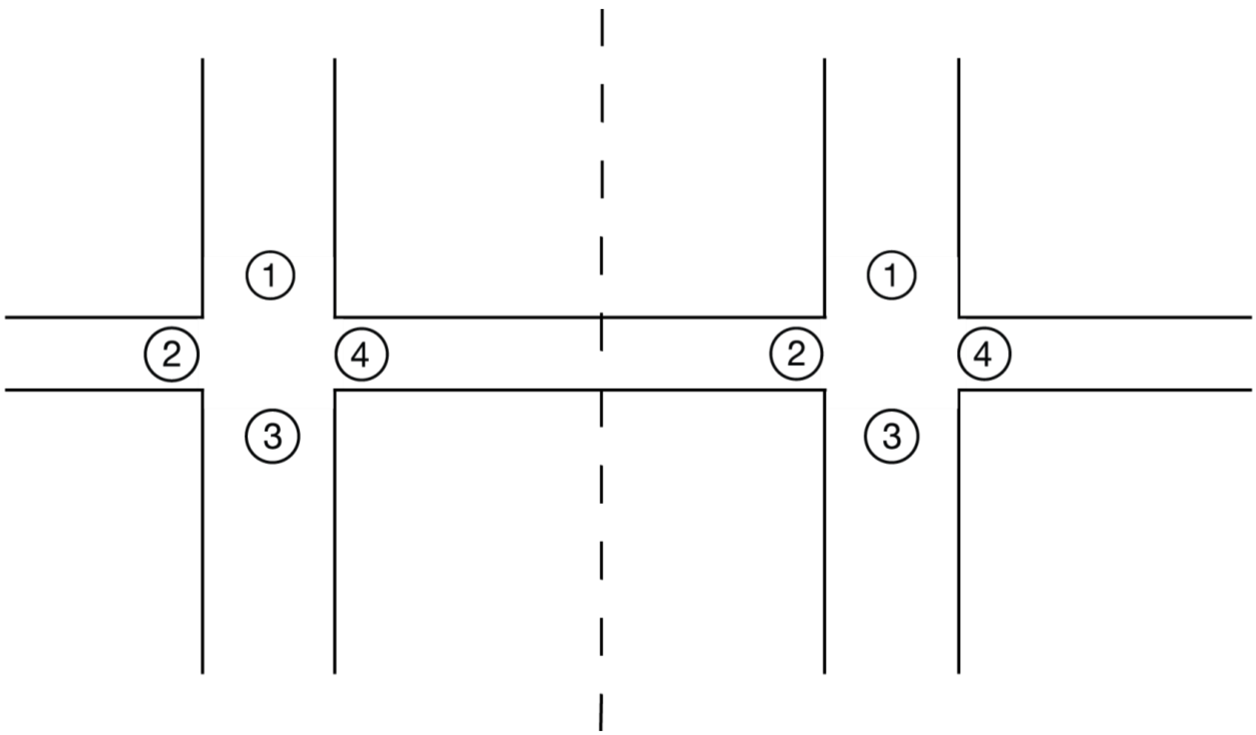

Figure 5: Example of calculating Average Nodal Degree

The following example, Figure 6, is from the sample point at Wellsona Road in the community of San Miguel, located in the northern portion of the county. This example is selected because of its relatively simple network, which makes manual calculation and demonstration in this paragraph easy. There are 29 nodes in this buffered area and 71 segments, which makes the average nodal degree for this area to be 71/29 =2.45.

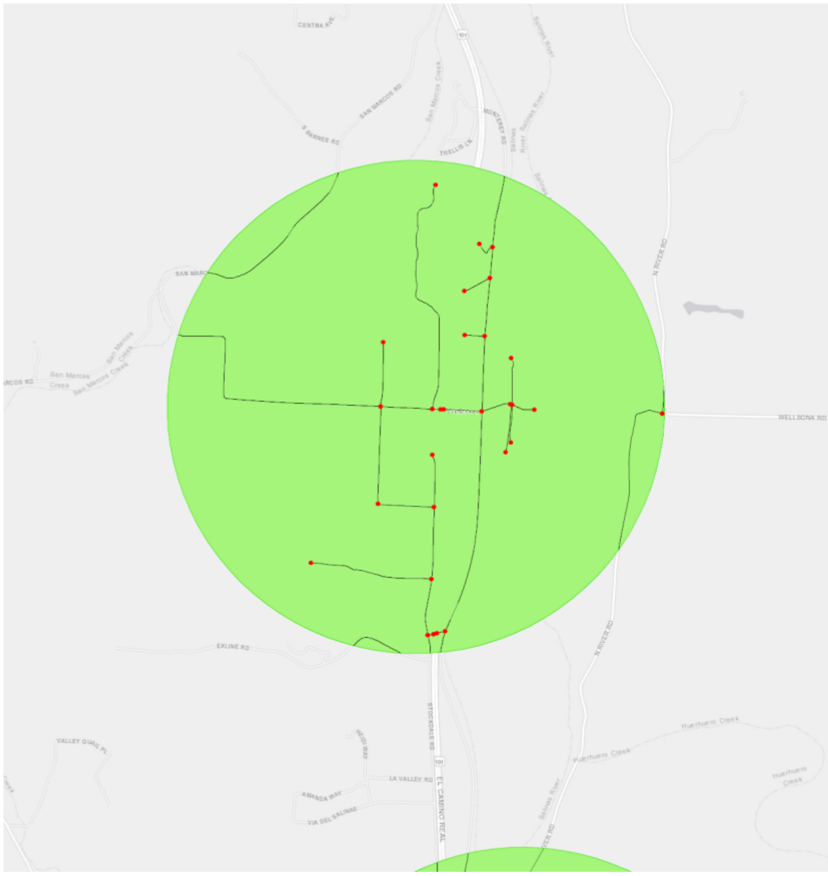

Figure 6: Number of nodes within a 1-mile buffer of Wellsona Road in San Miguel

3.5 Intersection Density

Intersection density highly related to block length, and is calculated by dividing the number of intersections (nodes) within each 1-mile buffer by the area of each 1-mile buffer. The data for number of intersections is already obtained during the previous process of calculating AND. The biggest difference between Average Nodal Degree and Intersection Density is the fact that the latter accounts for the relationship between closeness of intersections and potential for walking. For example, the presence of only one four-legged intersection in a 1-mile buffer yields a perfect average nodal degree score of 4, but the same scenario results in an intersection density score of only 0.32 intersections per square mile. Therefore, adding intersection density into the research ensures the incorporation of one more definition, or aspect, of walkability.

3.6 Pearson's Correlation

Upon completion of calculating all sample points using the three different walkability metrics, the next step involves establishing a ranking and correlation for further analysis.

I calculated the rankings in Excel using the =RANK() function. It is important to note that, however, to rank the list in descending order for Walk Score, Average Nodal Degree, and Intersection Density. This is because for both metrics a higher score indicates a better walking environment, versus Ped LOS which is the reverse.

As for correlation between the four metrics, the =CORREL() function in excel is used. Correlation is calculated between Walk Score and PLOS; PLOS and Average Nodal Degree; Walk Score and Average Nodal Degree; Walk Score and Intersection Density; PLOS and Intersection Density; and Average Nodal Degree and Intersection Density. Since a ranking is created earlier, the correlations between the six scenarios in terms of both calculated score and ranking are calculated.

3.7 Multivariate Regression

A regression model is estimated to predict Pedestrian Level of Service (PLOS) for comparison with existing, calculated PLOS in order to identify street segments with the highest potential for improvements. The model is controlled for five continuous independent variables (WS, AND, Intersection Density, population, intersection density) and one categorical variable, which indicated whether the adjacent land use of the street segment was residential, commercial, or other. All continuous independent variables are normalized and mean-centered to better facilitate the interpretation of results. The predicted PLOS from the regression analysis is to highlight the difference between calculated PLOS, which represents actual PLOS; and predicted PLOS, which represents what PLOS should have been given the number of destinations and street network connectivity. The intercept estimate represents the expected PLOS under average conditions of the independent variables among the sample street segments. Coefficient estimates for each independent variable represents the change in PLOS with the difference of one standard deviation in the independent variables.

Besides walk score, average nodal degree, intersection density, variables such as intersection density, population and land use are added to capture the different elements that makes up an overall walking environment. I calculated intersection density by dividing the number of intersections by the area of each one-mile buffer. The number of intersections was available to me during the process of calculating Average Nodal Degree. I collected population data from the US Census for the 17 communities previously mentioned. Since there are three samples from each community, the input for population is repeated for points within the same area. As for land use, sample points are identified as either commercial or residential or neither by judgement based on looking at Google's Streetview service.

Table 2 summarizes the values of the independent variables.

Table 2: Summary statistics of independent variables included in regression model

Independent variable	**Average**	**Standard Deviation**
Continuous (raw values)	-	-
Population	13048.3	12436.1
WalkScore	37.8	24.7
Average Nodal Degree	2.63	0.213
Intersection Density	73.8	46.8
Continuous (normalized)	-	-
Population	0	1.0
WalkScore	0	1.0
Average Nodal Degree	0	1.0
Intersection Density	0	1.0
Categorical	**Count**	**Percentage**
Residential (base)	22	43%
Commercial	15	29%
Other	14	28%
Total	51	100%

4 RESULTS

This chapter discusses the results from the analysis of walkability using Walk Score (WS), Pedestrian Level of Service (LOS), and Average Nodal Degree (AND) using Pearson’s correlation. The analysis will be conducted on both the raw score and the ranking. Both results are analyzed by Pearson’s R to find out the statistical significance and relationship between different metrics using the same sample.

4.1 Coefficient of Correlation

4.1.1 Relationships using Raw Scores

As previously mentioned, the results from the analysis using three walkability metrics are measured for their relationship by Pearson’s correlation function in excel. In this analysis, the coefficient of correlation is calculated in six relationships: Walk Score and PLOS; PLOS and Average Nodal Degree; Walk Score and Average Nodal Degree; Walk Score and Intersection Density; PLOS and Intersection Density; and Average Nodal Degree and Intersection Density. Table 3 below shows that the coefficient of correlation for Walk Score versus Level of Service and Level of Service versus Average Nodal Degree are both in negative. The inverse relationships between WS vs LOS (-0.38) and LOS vs AND (-0.31) indicate that one metric cannot explain the results of another in such relationships. On the other hand, there is a moderately positive correlation between WS against AND (0.57).

Table 3: Coefficient of Correlation by Score

	WS	LOS	AND	Int.D
WS	1			
LOS	-0.38	1		
AND	0.57	-0.31	1	
Int. D	0.55	-0.32	0.37	1

4.1.2 Relationships using Rankings

It is important to note that the four metrics contribute to the walkability result differently. In this research, the higher the WS and AND scores, the more desirable result. Unlike LOS, the lower the LOS, the better the walkability ranking. Therefore, the nature of these metrics may have contributed to the negative correlations using raw scores. The correlation between the results is also analyzed using a ranking system to make the coefficient of correlation results more comparable. The coefficient of correlation using ranking is shown in Table 4 below.

Table 4: Coefficient of Correlation by Ranking

	WS	LOS	AND	Int.d
WS	1			
LOS	0.34	1		
AND	0.60	0.33	1	
Int.D	0.66	0.34	0.47	1

It is evident that using the ranking to measure correlation yielded very different results from using calculated scores, especially where there were the negative coefficients of correlation with WS vs LOS and LOS vs AND. Using rankings, all six relationships recorded positive correlations, ranging from 0.33 to 0.66. In this scenario, both WS vs LOS and LOS vs AND went from inversely related to positively related, although it is only of moderate effect. In addition, WS vs AND and WS vs Int.D have the strongest correlation of the six relationships with a 0.6 and 0.66 respectively.

4.2 Coefficient of Determination

The coefficient of determination (R^2) allows analysts to state how much of one variable is predictable from the other variable. It also represents the percent of the data that is closest to the line of best fit, also known as the regression line. Analyzing the results from this research using the coefficient of determination will show the accuracy of one walkability metric in predicting the results of another walkability metric. Similar to the process above, this calculation is done in three relationships: Walk Score versus Level of Service, Level of Service versus Average Nodal Degree, and Walk Score against Average Nodal Degree. The results, shown in scatter plot format with a trend line indicating overall relationship and a R-square value, are documented below as

Figure 7, Figure 8, and Figure 9.

4.2.1 Relationships using Raw Scores

Figure 7 shows the coefficient of determination between Ped LOS and Walk Score by score to be pretty low at 0.144. This means only 14% of Walk Score results can be explained by Ped LOS results, which is not a strong relationship. It is also worth noting that the trendline in

Figure 7 is heading downwards. The direction of the trendline reflects the negative coefficient of correlation that was previously discussed.

Figure 8 shows the coefficient of determination between Average Nodal Degree and Ped LOS by score to also be low at 0.133. This means only 13% of Ped LOS results can be explained by Average Nodal Degree results. Similar to

Figure 7, the trendline in Figure 8 is heading downwards. This is because the coefficient of correlation in this relationship is also a negative number.

Figure 9 shows the coefficient of determination between Walk Score and Average Nodal Degree by score to be 0.32, which is the highest among the three comparisons. Up to 32% of Average Nodal Degree results can be explained by Walk Score results. This is the only relationship where the trendline is heading upwards, as its coefficient of correlation is a positive number.

Figure 10, Figure 11, and Figure 12 display the coefficient of determination between Intersection density and Walk Score (R^2=0.299), Ped LOS (R^2=0.1), and Average Nodal Degree (R^2=0.14)respectively. The strongest relationship is between Intersection Density and Walk Score, which is likely due to the fact that block length is one of components in calculating Walk Score.

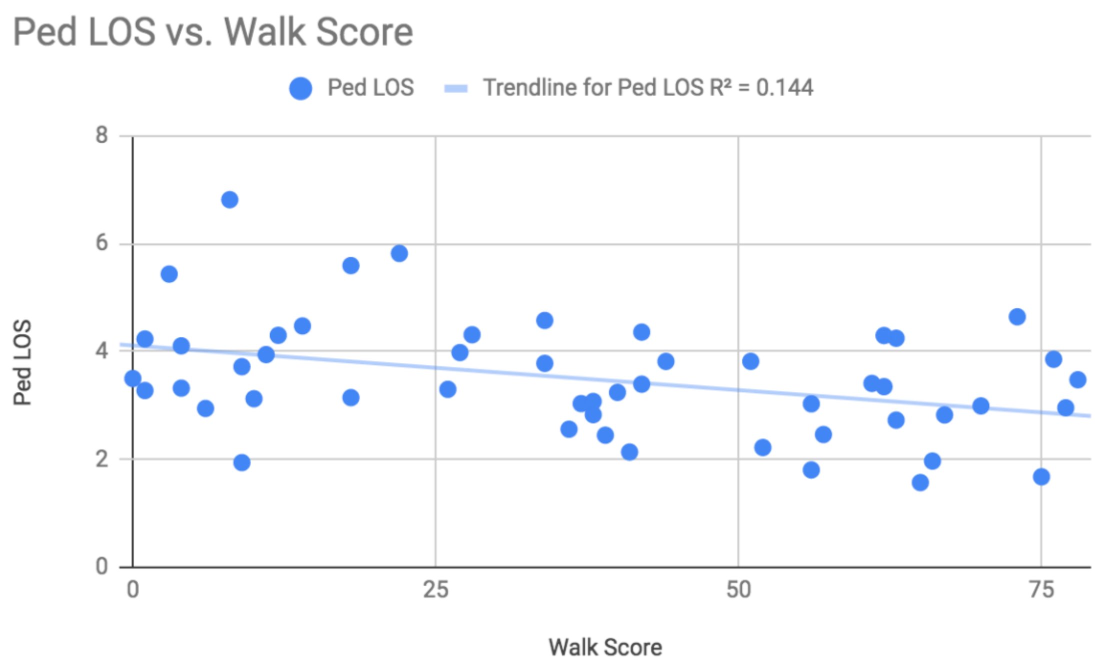

Figure 7: Correlation between Ped LOS and Walk Score by Score

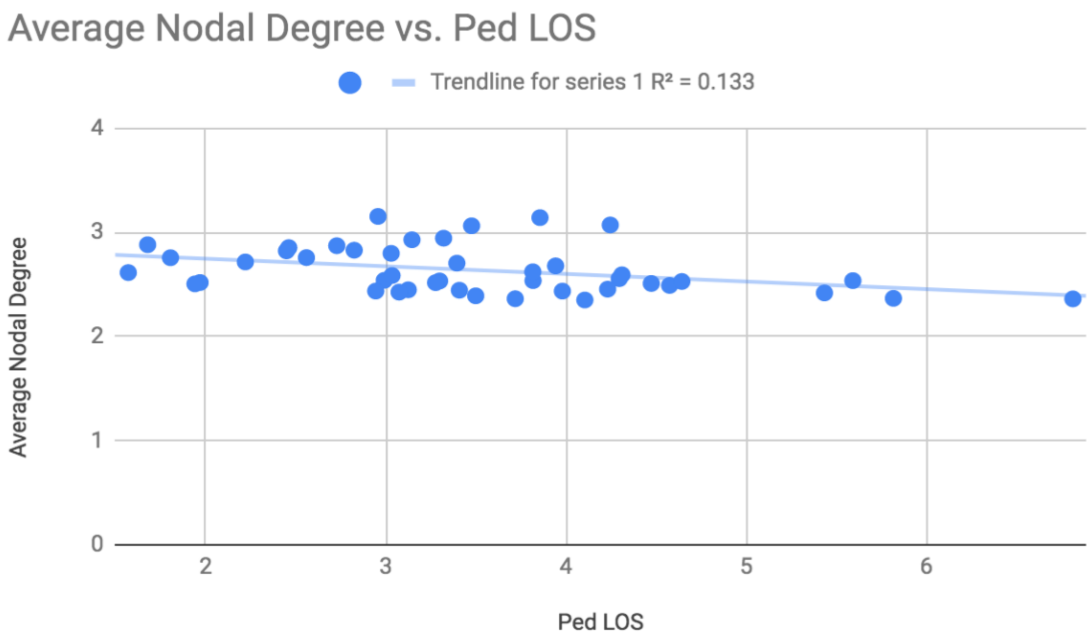

Figure 8: Correlation between Average Nodal Degree and Ped LOS by Score

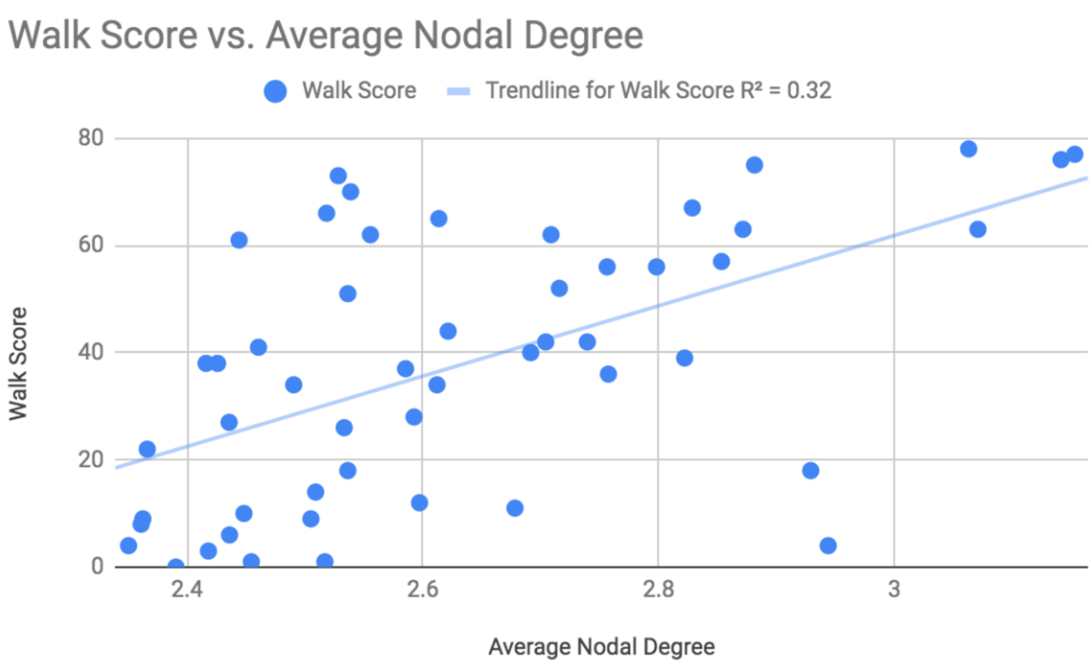

Figure 9: Correlation between Walk Score and Average Nodal Degree by Score

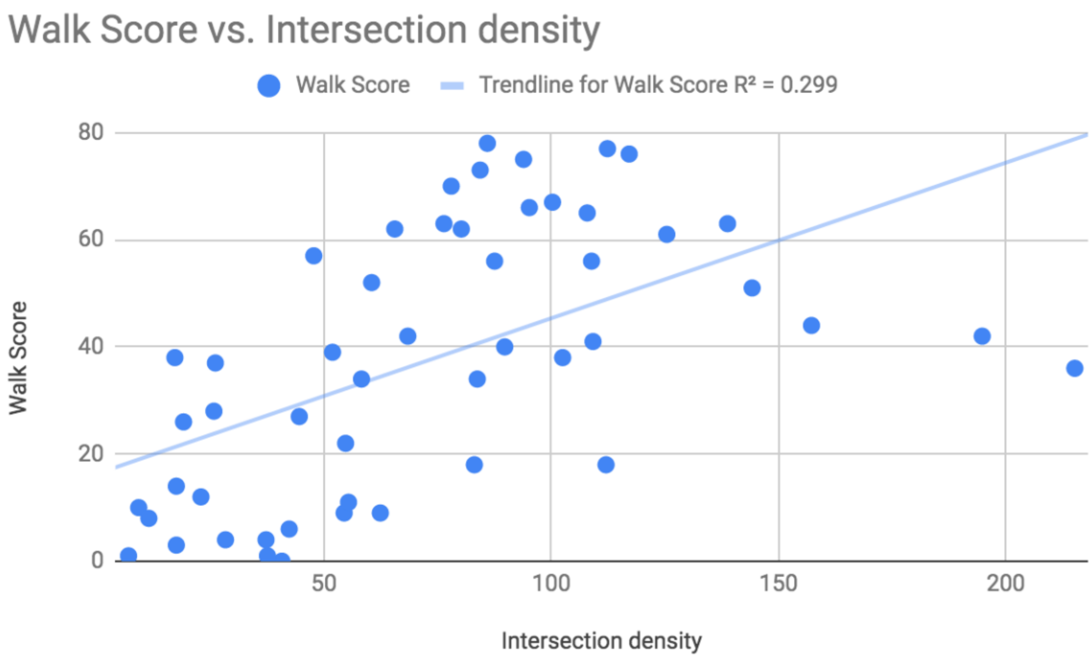

Figure 10: Correlation between Walk Score and Intersection Density by Score

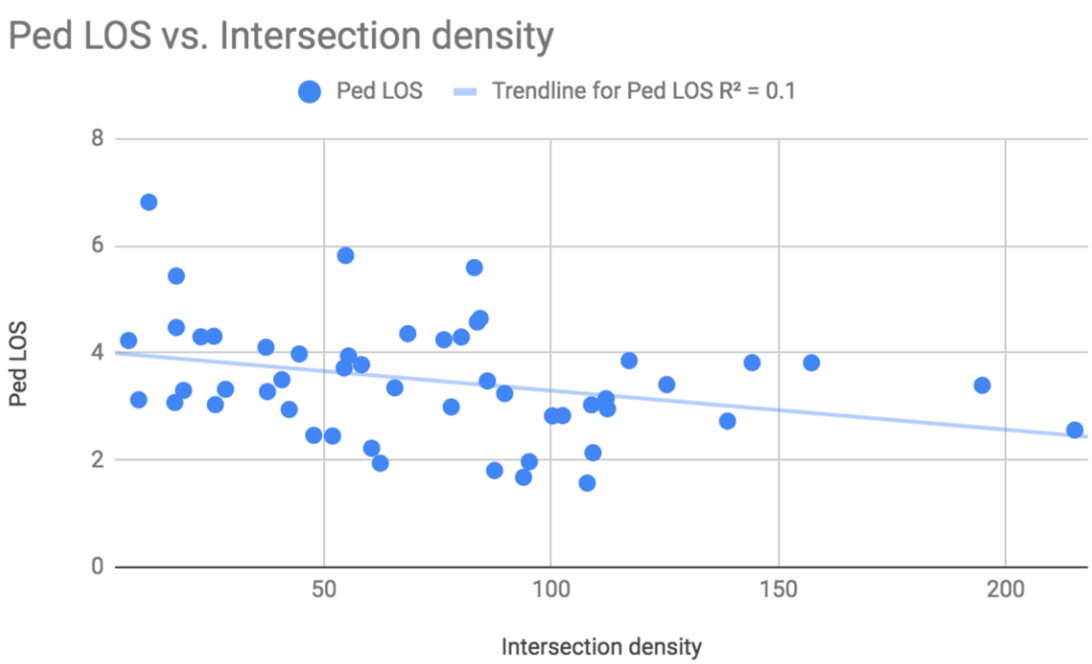

Figure 11: Correlation between Ped LOS and Intersection Density by Score

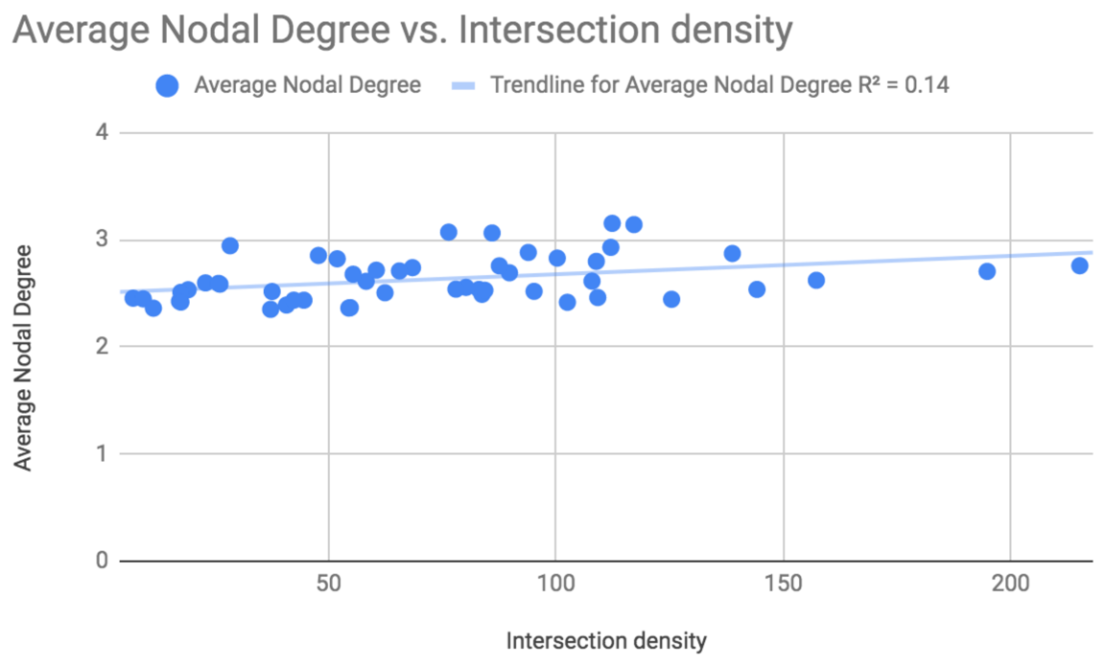

Figure 12: Correlation between Average Nodal Degree and Intersection Density by Score

4.2.2 Relationships using Rankings

The following scatter plots are created using adjusted rankings instead of calculated scores. The reason for this adjustment is due to the nature of the Pedestrian Level of Service metric that favors a lower score.

Figure 13 below shows the coefficient of determination between Pedestrian LOS and Walk Score by ranking. The R-squared value of 0.115 suggests only 11.5% of Walk Score results can be explained by Ped LOS results, which makes the relationship relatively weak. Compared to

Figure 7, the direction of the trendline changed from heading downwards to upwards. This is because the coefficient of correlation is no longer negative due to the adjusted ranking.

Figure 14 below shows the coefficient of determination between Average Nodal Degree and Pedestrian LOS by ranking. The R-squared value of 0.107 suggests that only 10.7% of Pedestrian LOS results can be explained by Average Nodal Degree results, which indicates a weak association between the two metrics. Compared to Figure 8, the direction of the trendline changed from heading downwards to upwards. This is because the coefficient of correlation is no longer negative due to the use of the adjusted ranking for this analysis.

Figure 15 below presents the results of the comparison of Walk Score and Average Nodal Degree by ranking. The R-squared value of 0.356 suggests that up to 35.6% of Average Nodal Degree results can be explained by Walk Score results, which make this comparison the strongest relationship out of the three possibilities. The coefficient of determination using ranking is similar to that of using calculated score in Figure 9.

Figure 16, Figure 17, and Figure 18 display the coefficient of determination between Intersection density and Walk Score (R^2=0.438), Ped LOS (R^2=0.113), and Average Nodal Degree (R^2=0.217) respectively. Again, the strongest relationship among these three pairs is between Intersection Density and Walk Score, which is likely due to the fact that block length is one of components in calculating Walk Score.

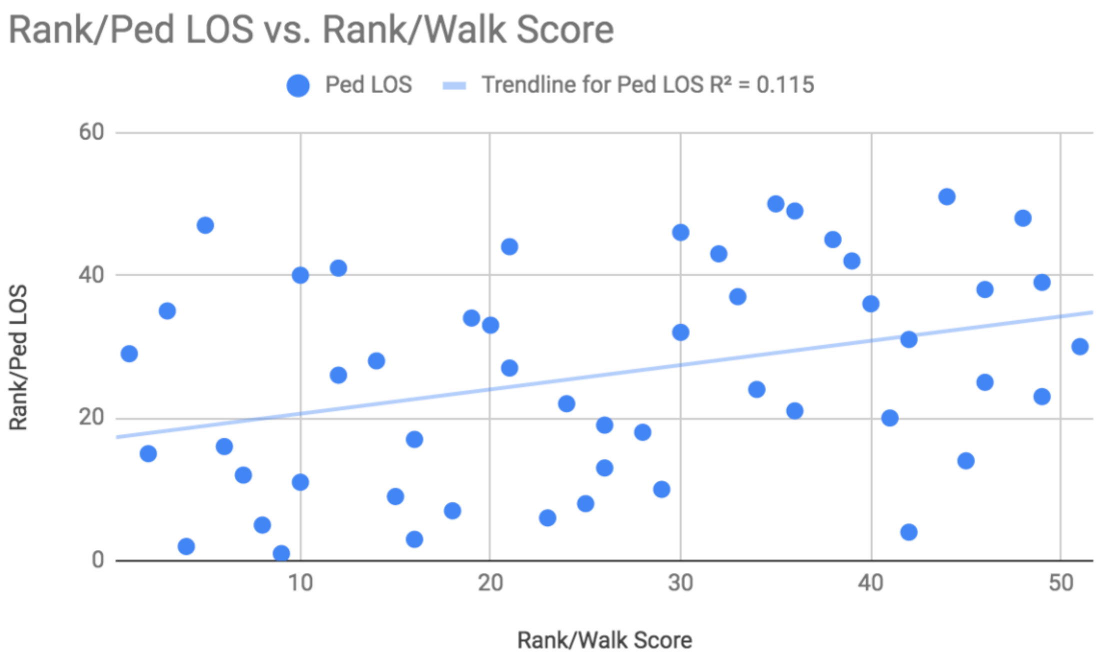

Figure 13: Correlation between Ped LOS and Walk Score by Ranking

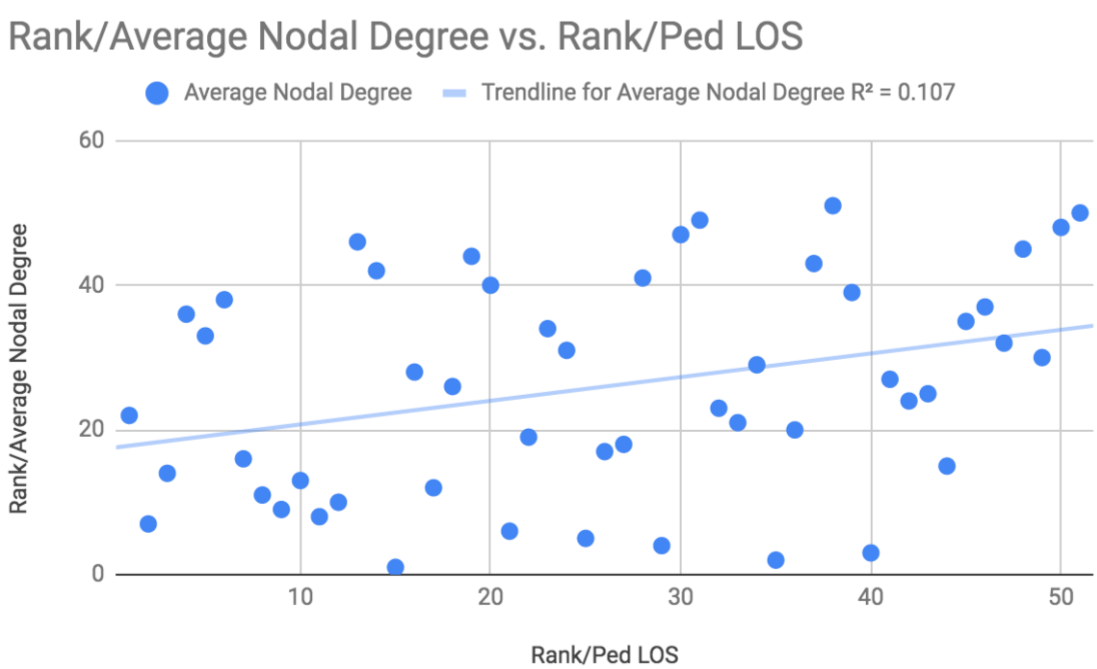

Figure 14: Correlation between Average Nodal Degree and Ped LOS by Ranking

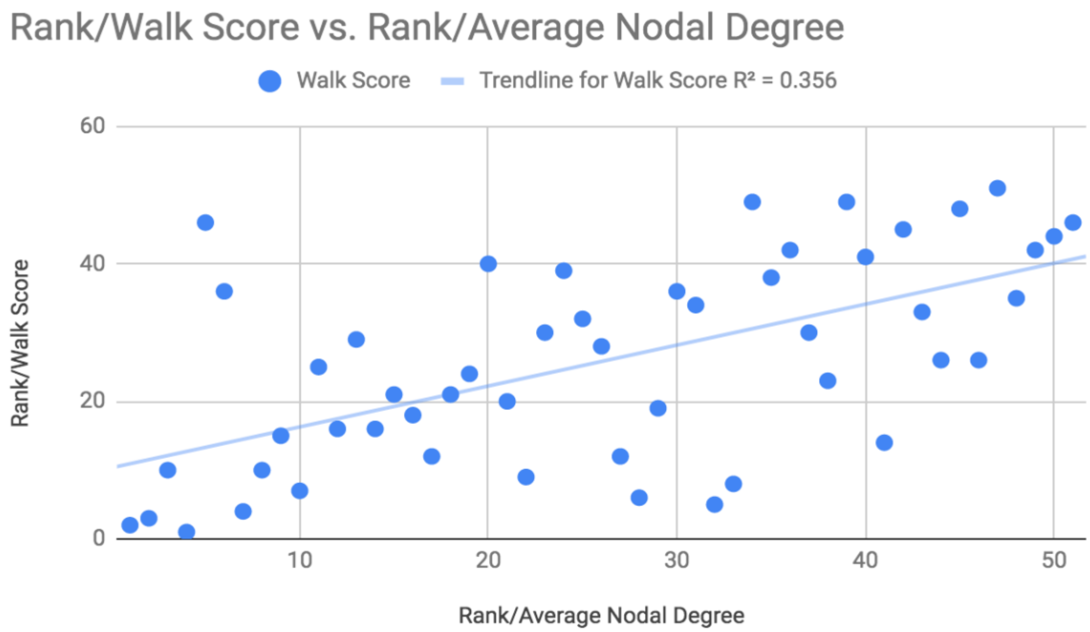

Figure 15: Correlation between Walk Score and Average Nodal Degree by Ranking

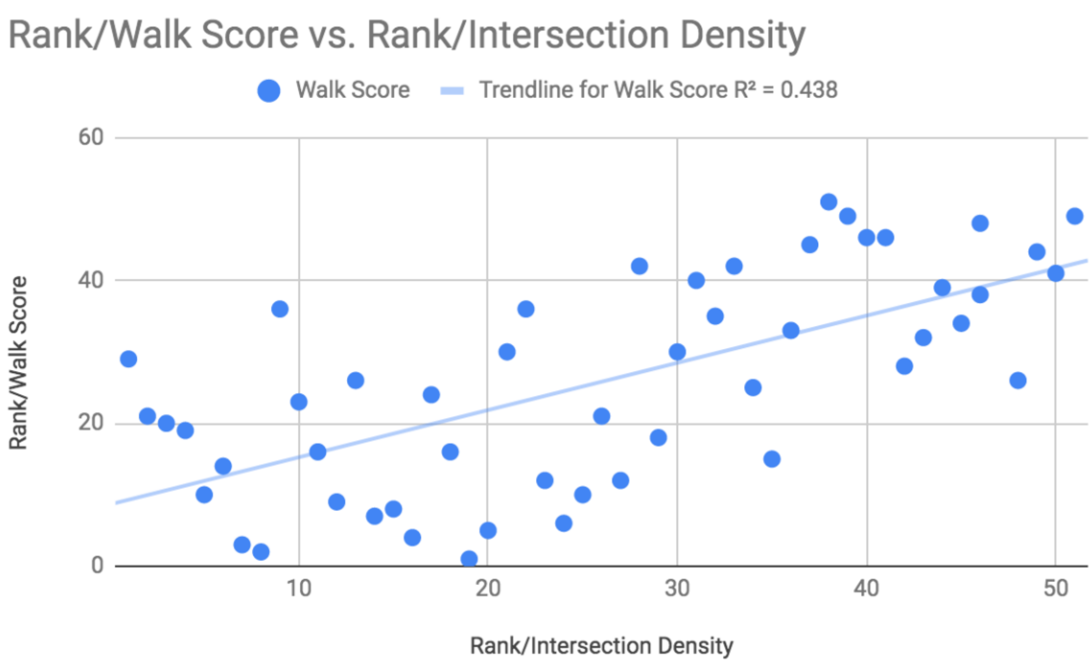

Figure 16: Correlation between Walk Score and Intersection Density by Ranking

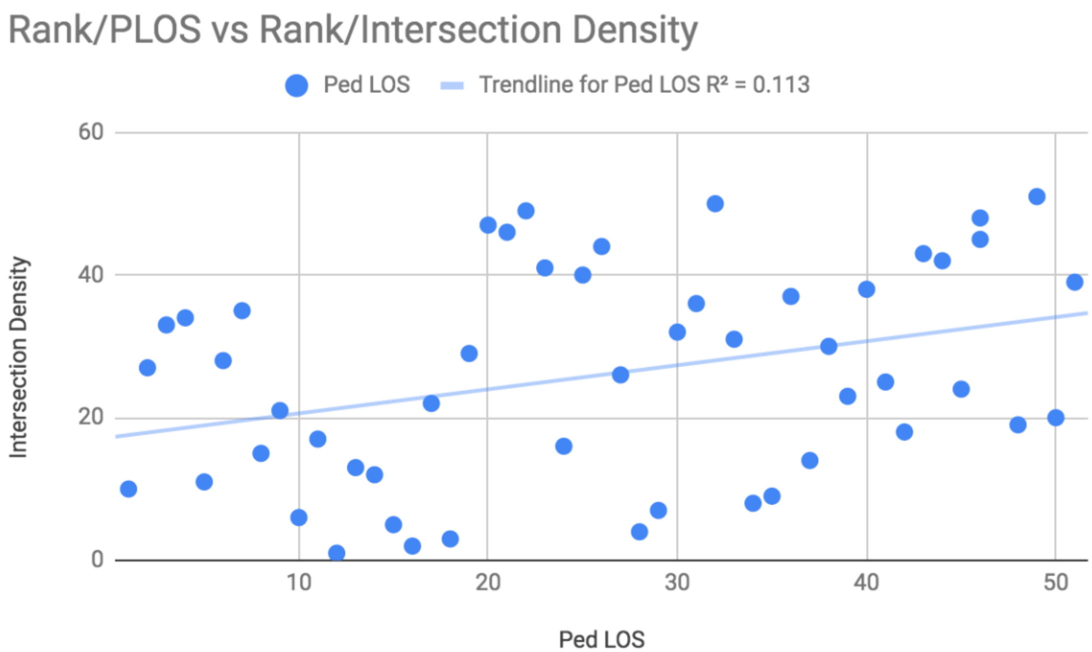

Figure 17: Correlation between Ped LOS and Intersection Density by Ranking

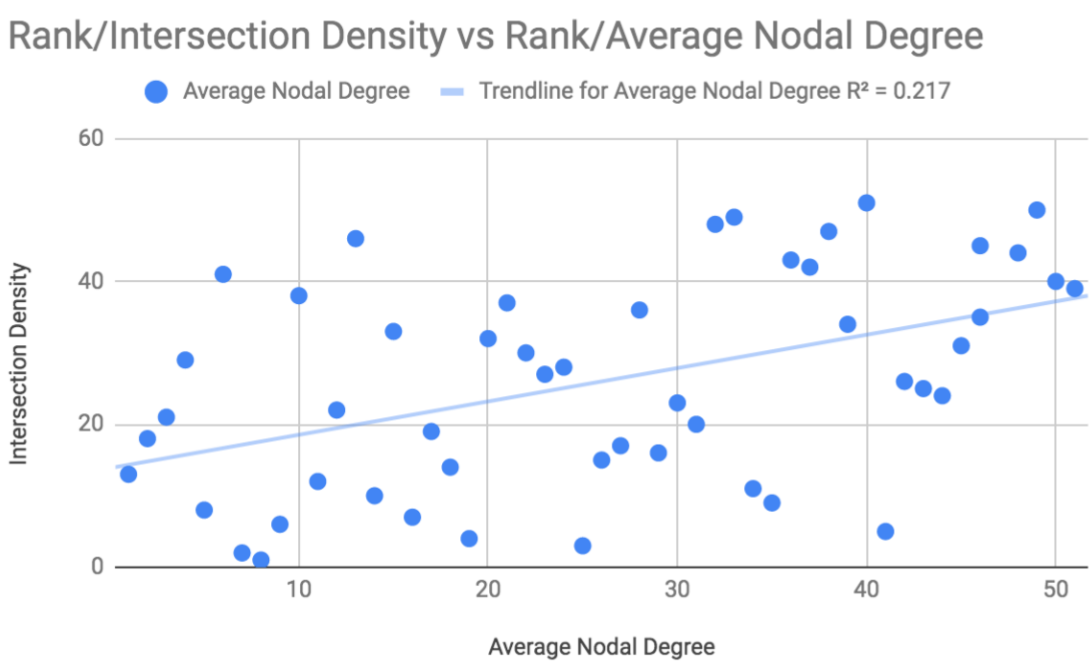

Figure 18: Correlation between Average Nodal Degree and Intersection Density by Ranking

4.3 Multivariate Regression Analysis

The following section shows results from conducting regression. The R^2 value indicates the goodness of fit of the data in this regression model. The estimated value for each variable are the parameter values to multiply by the predictor values and describes the relationship between independent variables and the dependent variable (PLOS). The p-value is an indicator of statistical significance.

Table 5: Results of Regression Analysis

R^2	0.30	
n	51	
Independent variable	**Estimate**	**p-value**
Intercept	3.28	< 0.001
Population	0.11	0.479
Walk Score	0.03	0.911
Average Nodal Degree	-0.15	0.381
Intersection Density	-0.12	0.515
Commercial	-0.25	0.468
Residential (base)	-	-
Other	0.99	0.019

Table 5 presents the results from the multivariate regression analysis of normalized data. The intercept value of 3.28 suggests that a street segment adjacent to residential land uses with an average population, average WalkScore™, and average of the average nodal degree would have a PLOS raw score of 3.28, which corresponds to LOS C. As for the p-value results, the only independent variable with statistical significance is land use type. Street segments adjacent to land uses of neither residential nor commercial has a PLOS of 0.99 higher than those adjacent to residential land. The difference in PLOS of street segments adjacent to residential or commercial uses is not statistically significant. The three positive regression coefficients, which are population, intersection density, and other land uses, demonstrates a positive correlation between PLOS and the two variables respectively. All of the other input independent variables in this model yielded a negative regression coefficient, which suggest a negative correlation with PLOS. The model fit for this scenario is $R^2 = 0.3$, which means 30 percent of the variation in actual PLOS can be explain by the independent variables. Although and R-squared value of 0.30 is not an indication of a strong fit of the model, it is not the main purpose of this research. The goal is to suggest an appropriate level of service in pedestrian infrastructure that would attain the full walkability potential of a specific street segment.

Therefore, the model also predicted PLOS values based on the variables that reflects the surrounding environment of each sample location, besides conducting regression analysis to estimate R^2 and regression coefficients. The predicted PLOS scores are compared with calculated PLOS to determine the difference in street segments' current and potential walkability. Since the predicted PLOS score indicates the appropriate level of service based on the given independent variables, street segments with the largest difference between raw PLOS value versus a better predicted PLOS are likely to be the places where improvements to pedestrian infrastructure may have the biggest impact on increasing walking activity.

4.4 Case Studies

This following section includes eight case studies selected from the results. The five sample points are worth an in-depth discussion either because of interesting patterns in their rankings or big difference between actual and predicted PLOS scores. The primary purpose for selecting these cases is indicated in the numbers highlighted in red.

For disparities in ranking patterns, if all walkability metrics perfectly relate to each other, every location would yield the same ranking across all three metrics. Since it is demonstrated above that, no matter by score or by ranking, none of the three metrics' comparison have a strong correlation, there were some instances where one location would produce a high ranking with one metric but a low ranking with another. As a result, upon review of the results list (Appendix B), five of these cases were chosen because their rankings across three metrics are significant.

As discussed in the previous section, disparities in actual and predicted PLOS scores, where predicted PLOS scores are substantially lower in value compared to calculated PLOS scores, are locations where improvements to pedestrian infrastructure would have the greater potential to increase walking. Three of such cases will be discussed in the following section. Although street segments where the predicted PLOS scores is worse than the actual PLOS scores are also worth discussing, it is not logical to suggest the reality to worsen its level of service to match the model results. Therefore, the discussion will be limited.

4.4.1 Cases with interesting disparities in rankings

4.4.1.1 Case #1: Quintana Road @ W South Bay Boulevard in Morro Bay, CA

For case 1, all three metrics scored the location very differently. Walk Score scored this location to be one of the worst with it being the 47th out of 51, Ped LOS regarded it as middle of the pact at 25th, and Average Nodal Degree ranked it to be one of the best at 5th place (Table 6). This is certainly an interesting case to evaluate because of its large disparity in rankings. As shown in Figure 20, the point of interest is not located within a short walking distance of destinations that are heavily favored in the Walk Score methodology, hence the low ranking is generated. On the other hand, the average nodal degree is very high even though most of the buffered area is not connected. This is because the number of nodes is limited and not enough to lower the calculation. Case 1 is an instance where the predicted PLOS score is worse than actual PLOS score. It is possibly due to the remote location, the adjacent land use of "other" (vacant or agricultural), and the low WalkScore™. This suggests that this location would not necessarily benefit from pedestrian infrastructure improvements, unless the land use and streets network connectivity were to change so that there are more destinations for walking.

Table 6: Comparison across metrics for location #1

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	4	3.2	2.9	28.33	4.12
Rank	**47**	25	**5**	**41**	-

Figure 19: Location #1

Figure 20: 1-mile buffer of Location #1

4.4.1.2 Case #2: Grand Avenue @ W 4th Avenue in Grover Beach, CA

The location of case #2 is very different from case #1. Walk Score scored this location to be the best out of 51 and Average Nodal Degree ranked it to be also the best at 1st place, while Ped LOS regarded it as above average at 15th (Table 7)

This place in Grover Beach is located at one of the city's major arterials in its downtown area, which features plenty of destinations for a high Walk Score and a connected grid system for a high Average Nodal Degree (Figure 21).

The Pedestrian Level of Service is not bad either, as there are parking, bike lanes, and well-constructed sidewalks to provide a high level of comfort for pedestrians (Figure 21).

In this case, the predicted PLOS score is lower (better) than the actual PLOS score. This suggests that given the independent variables, the level of service on this street segment should be better, and that improving pedestrian infrastructure here would increase potential to more walking. To make the PLOS score improve from 2.95 to 2.62, the values of a majority of variables in PLOS score have to be adjusted given the available elements of good pedestrian amenities at this location. For example, increased on-street parking provides protection for pedestrian by increasing physical separation. One way to achieve increased on-street parking would be to reduce the availability of off-street parking. Also, utilizing traffic calming measures such as reducing speeds by narrowing travel lanes or replacing road space for vehicles with bike lanes. I found that simply incorporating a 0.5 proportion of on street parking and lowering the speed limit from 35 mph to 30 mph can bring the PLOS score down to 2.3, which improves PLOS from C to B.

Table 7: Comparison across metrics for location #2

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	77	2.95	3.15	112.36	**2.62**
Rank	**1**	**15**	**1**	**8**	**-**

Figure 21: Location #2

Figure 22: 1-mile buffer of Location #2

4.4.1.3 Case #3: Florence Street @ W Old Country Road in Templeton, CA

In case #3, two of the three metrics scored the location very well but the other metric did not. Walk Score scored this location to be one of the best at 8th out of 51, Ped LOS regarded it as even better at 5th, yet Average Nodal Degree only ranked it to be 33rdplace (Table 8). As shown in

Figure 24, this location is near the core of Templeton's downtown, making it close in proximity to attractive destinations that would increase Walk Score. In addition, the pedestrian infrastructure is well constructed with a proper sidewalk and a bike lane to provide buffer from vehicle traffic (Figure 23). The predicted PLOS score for case #3 is worse than the actual PLOS score, similar to case #1, so improvements are likely to have a low impact on walking unless land use or street networks also change. Therefore, it may be worth considering the potential of growth at this location, since there is adequate pedestrian infrastructure to support added activity.

Table 8: Comparison across metrics for location #3

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	66	1.97	2.52	80.21	3.30
Rank	8	**5**	**33**	23	-

Figure 23: Location #3

Figure 24: 1-mile buffer of Location #3

4.4.1.4 Case #4: Sandydale Drive @ W Frontage Road in Nipomo, CA

The rankings for this location in Nipomo are the opposite of Case #2. While Case #2 has Walk Score and Average Nodal Degree ranked at the top and Pedestrian LOS near the bottom (Table 7), Case #4 features an inverse scenario. Where Walk Score scored this location to be one of the worse with it being the 37^{th} out of 51^{h} and Average Nodal Degree ranked it to also be one of the worse at 36^{th} place , Ped LOS regarded it as one of the best for 4^{th} place (Table 9). This is also an interesting case to investigate because of its large disparity in rankings. In Figure 25, a complete sidewalk with parked cars as a buffer is available, which makes for a pleasant walking environment that contributes to a higher Ped LOS score. However, by examining Figure 26,it can be concluded that the location is not well-connected within the one-mile buffer due to being separated by the freeway, which lowers the average nodal degree score as well as the Walk Score. Similar to cases #1 and #3, the predicted PLOS score here in case #4 is also worse than the actual PLOS score. The scenario is due to the poor WS and AND performance that negatively impacted the predicted PLOS score. Therefore, this is not a place that would benefit from simply pedestrian infrastructure improvements, unless land use and street networks are changed.

Table 9: Comparison across metrics for location #4

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	15	1.94	2.5	62.39	3.15
Rank	**37**	**4**	**36**	28	-

Figure 25: Location #4

Figure 26: 1-mile buffer of Location #4

4.4.1.5 Case #5: Madonna Road @ Pereira Street in San Luis Obispo, CA

For case 5, its Walk Score and Pedestrian Level of Service rankings are on opposite spectrums. Walk Score scored this location to be near the top at 4th place, while Ped LOS regarded it as one of the worst at 47th (Table 10). The average nodal degree for this location is average at 32nd place, which is explainable by looking at Figure 29 where the area is largely made up of residential pockets that are well-connected. As for the high Walk Score, this location is in the middle of three large shopping centers, which provides a lot of amenities that are desirable for the Walk Score methodology. On the other hand, the low Pedestrian Level of Service is due to the high vehicle speed limit (40 mph) in addition to the lack of any sidewalk infrastructure on this road (Figure 27).

In this case, the predicted PLOS score is worse than the actual PLOS score. This suggests that given the independent variables, especially the high walk score, the level of service on this street segment should be better, and improving pedestrian infrastructure would potentially contribute to more walking. However, there are interesting elements about this location that could change the calculation of its existing PLOS score. As seen in Figure 28, there are over 3 ft. tall, continuous, barriers that separates the main vehicle arterial from frontage roads on both sides, which are for lower traffic volume and speed, and access to homes. In addition, the frontage roads both have on street parking, sidewalk, and sidewalk buffer. Adjusting for street components, lowering speeds to 25 mph, and reduced volumes contribute to an improved PLOS score of 1.03. This changes the PLOS for this location from E to A.

Table 10: Comparison across metrics for location #5

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	75	4.64	2.5	84.35	**3.41**
Rank	**4**	**47**	32	20	-

Figure 27: Location #5

Figure 28: Location #5 - on the other side of the continuous barrier

Figure 29: 1-mile buffer of Location #5

4.4.2 Cases where predicted PLOS performs better than existing PLOS

4.4.2.1 Case #6: Main Street @ S Radcliff Avenue in Morro Bay, CA

In this location, there is a big difference between PLOS and Average Nodal Degree. While PLOS is regarded as one of the worst at 40^{th} (Table 11), the Average Nodal Degree is ranked one of the best at 3^{rd} place. This high ranking in average nodal degree is illustrated by looking at Figure 30 where streets in the southern portion resembles a grid-like network. However, the PLOS for this location is not great because of a combination of the narrow sidewalk, high vehicle speeds and high traffic volumes.

This location is ranked 1st among the list of locations where the difference between the predicted PLOS score is much more improved than the existing PLOS score. The fact that the actual PLOS score is worse than the predicted PLOS score in this case suggest that given the higher walk score and average nodal degree of this location, improvements in pedestrian infrastructure has a great potential in increasing walking. I adjusted the speed limit from 25 mph to 20 mph, increased sidewalk and bike lane width, added a buffer, a shoulder, and a parking lane to theoretically simulate what it would take to bring the PLOS score down to 2.98. This suggests much improvement at this location is needed to improve PLOS from its current D to C.

Table 11: Comparison across metrics for location #6

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	63	**4.25**	3.07	76.39	**2.98**
Rank	10	**40**	**3**	25	-

Figure 30: 1-mile buffer of Location #6

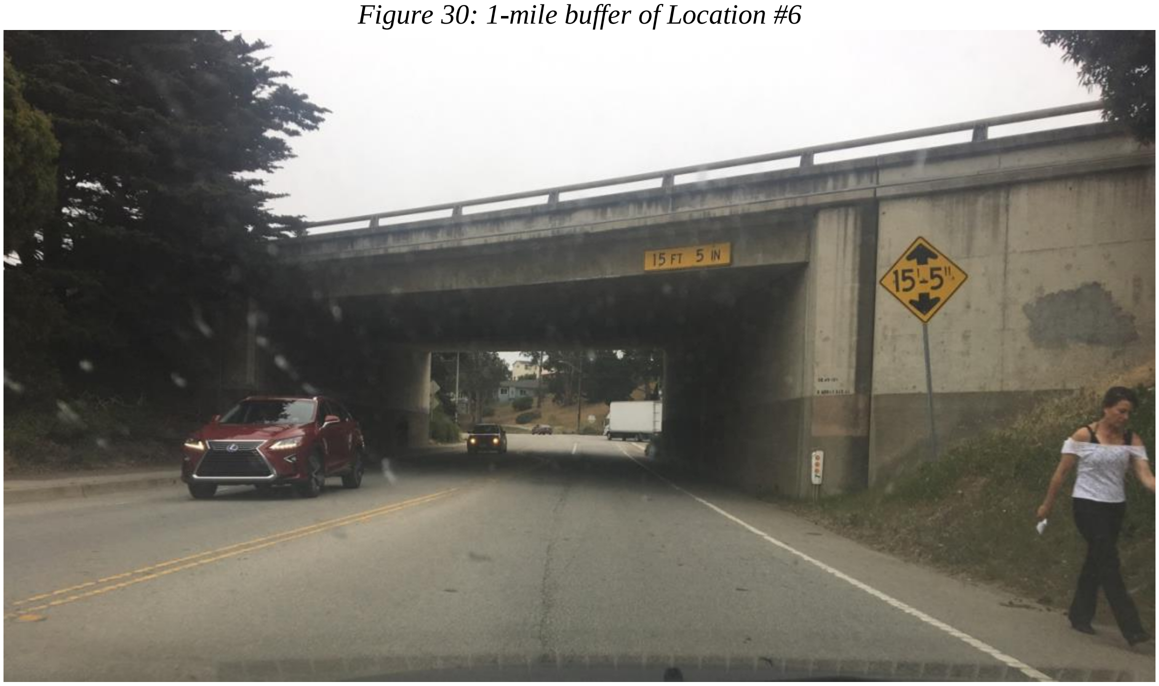

Figure 31: Location #6

4.4.2.2 Case #7: Los Osos Valley Road @ W of Clark Valley Road in Los Osos, CA

This location is worth discussion because of the bad overall performance across all three methodologies used in this study (Table 12). PLOS for this location is on the bottom of the list and AND is ranked second to last. The low WS can be explained by its distance from destinations, the low AND is due to its sparse surrounding street network (Figure 32), and the bad PLOS score is because of the lack of sidewalk, and high vehicle speeds and volumes. As such, even the regression model predicted PLOS to be better than the existing one, the PLOS grade would only improve from F to E.

However, this location is ranked 2nd among locations where the difference between predicted PLOS performs better than existing PLOS. Therefore, improvements such as adding a sidewalk would be the most beneficial in increasing potential for walking in this location. If the vehicle speeds are adjusted from 55 mph to 40 mph, traffic volumes slightly lowered, a sidewalk, buffer, bike lane added, the PLOS score is down to 4.58, which is still a E. This suggests a lot of work needs to be done for this location to make it walkable.

Table 12: Comparison across metrics for location #7

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	8	**6.81**	2.36	11.46	**4.62**
Rank	44	51	50	49	-

Figure 32: 1-mile buffer of Location #7

Figure 33: Location #7

4.4.2.3 Case #8: Avila Beach Drive @ W of San Luis Bay Drive in Avila Beach, CA

The last case selected for discussion has a similar profile to the previous case (#7). Across the three methodologies, the location did not perform well for both PLOS and AND with rankings of 50th and 48th respectively, and is ranked only 35th for WS. According the regression model, the PLOS of this location should be 4.44, which translates to a grade of E versus a grade of F in the existing condition.

However, this location is 3rd on the list of locations with the biggest difference between predicted PLOS and existing PLOS. As such, Case #8 features a place where pedestrian improvements would be beneficial. For example, lowering the speed limit to 35 mph and adding a 12-ft sidewalk are already enough to bring PLOS score down to 4.39. However, given the topography of this location, adding a wide sidewalk may be challenging.

Table 13: Comparison across metrics for location #8

	Walk Score	**PLOS**	**Average Nodal Degree**	**Intersection Density**	**Predicted PLOS**
Score	22	**5.82**	2.37	54.75	**4.40**
Rank	35	50	48	32	-

Figure 34: 1-mile buffer of Location #8

Figure 35: Location #8

4.5 Before and After Regression Comparisons

With the adjustments in PLOS for the four locations in the previous section, their updated PLOS is used to estimate another regression model for comparison. The goal is to find out if improved PLOS scores would increase the R^2 value of this analysis. As the improved PLOS scores belong to locations where existing and predicted PLOS were the most different, updating them to match the predicted score would improve the R^2 value, indicating a better fit of the model. In this case, the R^2 increased from 0.3 to 0.38. Under this scenario, about 38% of the variation in actual PLOS can be explain by the independent variables. The intercept value with the proposed improvements decreased from 3.28 to 3.245, which indicates an overall decrease in PLOS score (better PLOS) under average conditions within the sample. It is to assume that if another regression analysis is performed, after places where PLOS is currently underperforming are improved, the R^2 would be improved even more.

Table 14: Results of Regression Analysis with Proposed Improvements

R^2	0.38	
n	51	
Independent variable	**Estimate**	**p-value**
Intercept	3.245	< 0.001
Population	-0.052	0.686
Walk Score	-0.229	0.224
Average Nodal Degree	-0.014	0.942
Intersection Density	-0.019	0.899
Commercial	-0.415	0.163
Residential (base)	-	-
Other	0.582	0.096

5 CONCLUSION

This research looked at the relationship between different measures of walkability by comparing and correlating Walk Score™, Pedestrian Level of Service, and Average Nodal Degree using 51 sample points selected from the County of San Luis Obispo. A regression model is calibrated to predict a possible PLOS score given independent variables such as WS, AND, land use and population. The locations where the predicted PLOS is significantly better than the existing PLOS are identified as potentially prioritized pedestrian improvement projects to exert the greatest impacts on increasing walking activity. Similarly, locations where the actual PLOS score is already better than the predicted PLOS score given the surrounding built environment factors can be categorized as having potential for more growth, since the existing pedestrian infrastructure is able to support increased activity. This method of analyzing existing roads using walkability metrics and regression is proposed as the framework for agencies to select and prioritize for potential pedestrian upgrades. The conclusions from this study are summarized below, including limitations of this research, future improvements to the workflow, and possible applications that could strengthen the results of this study.

5.1 Discussion of Results

The correlation between walkability metrics is measured using Pearson's R. Among the three relationships, the correlation between Walk Score™ and Average Nodal Degree is the strongest with a R-squared of 0.356, which means 35.6% of Average Nodal Degree results can be explained by Walk Score™ results. The fact that none of the these relationships showed statistical significance indicates the difficulty of measuring walkability using a single metric due to the multi-dimensional nature of walkability.

5.2 Limitations and Future Work

The key limitations of this study include small sample size, limited comparison metrics, limited independent variables, and measurement errors. A common factor that connects all three limitations is limited time and resources to complete this project.

5.2.1.1 Sample Size

Since the sample is limited to 51 street segments in the County of San Luis Obispo, there is a question of how valid the results are due to the small sample. A more complete study could include all or most of the street segments for an entire region.

5.2.1.2 Criterion for Sample Selection

In addition, both low volume rural roads and highly trafficked vehicle arterials that may not be best used for walking purposes are included in the selection using average daily traffic (ADT) as the criteria. This is in an attempt to sample a broad range of street segments with various traffic patterns and location characteristics. Future research should explore different sample selection methods or criteria, such as random sampling of all street segments, using a map with grids and selecting the centroid location of each grid, using development density in the form of population and jobs. One future study could be using the location of bus stops to evaluate the walkability and accessibility to transit.

5.2.1.3 Comparison Metrics and Variables

As previously discussed in the literature review chapter, the term *Walkability* has many definitions and associated metrics to measure the different aspects of walkability. It is, therefore, worth noting that the three walkability metrics selected for this study are not all encompassing. For example, none among WS, PLOS, and AND explicitly measures aesthetics, block length, or topography, which are all factors that affect the desire and ability to walk.

In the regression step of the analysis, additional external factors such as population and adjacent land uses are added in to the model as independent variables to provide more data for a more accurate prediction of PLOS. While other demographic factors like income can raise concerns of bias and prejudice, community population and land uses are more neutral factors that also associate with the amount of walking. In the future, researchers might consider controlling for factors like car ownership per household within a one-mile radius.

5.2.1.4 Assumptions and Measurement Errors

Briefly mentioned in the Methodology chapter are assumptions made while calculating the existing PLOS and AND. For PLOS, only the link portion of the whole methodology is calculated due to limited data and a tight timeframe. Also, assumptions were made about on-street parking proportions, if any, and mid-segment demand flow rates are assumed to be ADT divided by 10 as well. These are factors that can be measured more precisely given more time and resources. As for AND, certain types of roads are filtered out in GIS prior to calculating AND based on the assumption of low pedestrian utilization. However, filtering a roadway from the street network potentially decreases the number of nodes present even though the particular type of roadways are unsuitable for pedestrians. A potential refinement for AND could also be measured in the form of intersection density per unit area.

5.3 Conclusions from Findings

Walk Score™, which measures proximity to destinations, and Average Nodal Degree, which measures street network connectivity, focuses on more permanent urban forms that are harder to change by pedestrian planners. On the other hand, Pedestrian Level of Service, which measures pedestrian infrastructure and design characteristics such as the presence of a sidewalk, can be improved easily and of which elements like adding sidewalks or increasing buffer space between vehicles and pedestrians are within the control of pedestrian planners. Between WS, PLOS, and AND, these three metrics encapsulates the different definitions of walkability. In practice, if a street segment performs well across these three metrics, it can be demonstrated that the location is highly walkable. It is asserted, therefore, that locations where WS and AND scores are high but PLOS score are low are prime for upgrading pedestrian infrastructure.

This thesis provides two approaches to selecting and prioritizing pedestrian infrastructure. The first being using analyzing a group of street segments using a given number of walkability metrics, and then identifying sample locations where a wide gap between rankings across the metrics. A simple coefficient of correlation analysis should also be used to determine the least relatable measurement. The second approach is a regression model based on work done in the first step that predicts a new score of the dependent variable, which is the new PLOS score. It is important to note that further research needs to be done on this topic, especially regarding sample and metric selection. With appropriate and necessary adjustments, the improved regression model should be an inclusive and easily measurable measure of walkability that encompasses the numerous dimensions of walkability.

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Appendix A - R Code Inputs

```
setwd("/Users/junelai/Documents/Cal Poly/Thesis")

walk_normdata <- read.csv("For_R_Normalized.csv")

colnames(walk_normdata) <- c("POP","WS","PLOS","AND",
“Int.D” ,"COM","VAC","ID")

model <- lm(PLOS ~ POP + WS + AND + Int.D + COM + VAC,
data=walk_normdata)

summary(model)

walk_normdata$pred_PLOS <- predict(model)

walk_normdata$dif <- walk_normdata$pred_PLOS -
walk_normdata$PLOS

summary(walk_normdata$dif)

write.csv(walk_normdata,file="results_norm.csv")
```

Appendix B – **Walkability Metric Results**

Community	Selection	Road Name	Nearest Cross Street	LAT	LONG	A D T	Population	Walk Score	Ped LOS	Average Nodal Degree
Arroyo Grande	15th Percentile	Tally Ho Rd	S James Way	35.12981	-120.57452	2,581	17,971	41	2.136	2.461
	50th Percentile	Thompson Ave	NB US 101	35.07189	-120.51360	5,401	17,971	12	4.300	2.597
	85th Percentile	Huasna Rd	E Branch St/ SR 227	35.12755	-120.56804	8,137	17,971	38	2.830	2.42
Atascadero	15th Percentile	Atascadero Ave	S Santa Rosa Rd	35.46388	-120.65597	1,722	29,797	34	3.780	2.61
	50th Percentile	Curbaril Ave	W US 101	35.47593	-120.65950	6,608	29,797	42	4.359	2.74
	85th Percentile	Curbaril Ave	E US 101	35.47727	-120.65672	12,981	29,797	62	3.349	2.71
Paso Robles	15th Percentile	S. Vine St	S of 1st St	35.61444	-120.69285	5,109	31,409	40	3.242	2.69
	50th Percentile	Union Rd	E of Golden Hill Rd	35.64175	-120.65600	8,820	31,409	27	3.980	2.44
	85th Percentile	Niblick Rd	E of Melody Dr	35.61576	-120.66581	15,289	31,409	51	3.817	2.54
Morro Bay	15th Percentile	Quintana Rd	W South Bay Blvd	35.36292	-120.82529	2,353	10,568	4	3.321	2.94
	50th Percentile	Morro Bay Blvd	W Quintana Rd	35.36619	-120.84159	11,637	10,568	78	3.476	3.06
	85th Percentile	Main St	S Radcliff Ave	35.37374	-120.85130	11,737	10,568	63	4.246	3.07
Grover Beach	15th Percentile	Farroll Ave	Oak Park Blvd	35.11062	-120.60636	5,116	13,524	36	2.559	2.76
	50th Percentile	4th St	N Grand Ave	35.12248	-120.62645	11,548	13,524	76	3.856	3.14
	85th Percentile	Grand Ave	W 4th St	35.12174	-120.62710	11,968	13,524	77	2.957	3.15
Pismo Beach	15th Percentile	James Way	E 4th St	35.13740	-120.62045	5,325	8,060	56	3.030	2.80
	50th Percentile	Price Canyon Rd	N Solar Way	35.14321	-120.63649	9,460	8,060	62	4.296	2.56
	85th Percentile	Price St	S Hinds Ave	35.14071	-120.63902	16,496	8,060	70	2.991	2.54
Oceano	15th Percentile	Twenty-Third St	N of Paso Robles St	35.10160	-120.60528	951	7,788	44	3.816	2.62
	50th Percentile	Twenty-Second St	S of The Pike	35.10619	-120.60709	3,130	7,788	42	3.394	2.70
	85th Percentile	Halcyon Rd	S of Arroyo Grande Creek	35.09703	-120.59140	9,239	7,788	18	5.592	2.54
Santa Margarita	15th Percentile	I St	W of Highway 58	35.39129	-120.60299	272	1,394	37	3.034	2.59
	50th Percentile	San Antonio Rd	S of Santa Barbara Rd	35.44280	-120.63690	1,565	1,394	9	3.718	2.36
	85th Percentile	El Camino Real	N of SR 58	35.39639	-120.60485	3,850	1,394	28	4.311	2.59
Shandon	15th Percentile	Second St	S of Highway 41	35.65496	-120.37605	229	1,219	26	3.298	2.53
	50th Percentile	Center St	S of Highway 46 (east)	35.66505	-120.35926	745	1,219	1	4.231	2.45
	85th Percentile	Center St	W of El Portal Dr	35.65550	-120.38483	1,810	1,219	14	4.474	2.51
Templeton	15th Percentile	Santa Rita Rd	W of Ridge Road	35.53573	-120.72854	506	7,989	4	4.105	2.35
	50th Percentile	Florence St	W of Old County Rd	35.54998	-120.70906	1,741	7,989	66	1.969	2.52
	85th Percentile	Vineyard Dr	W of US Highway 101	35.54331	-120.71693	7,147	7,989	34	4.575	2.49
Nipomo	15th Percentile	Sandydale Dr	W of Frontage Rd	35.04530	-120.49310	550	16,706	9	1.941	2.51
	50th Percentile	El Campo Rd	S of US Highway 101	35.11047	-120.56372	1,774	16,706	0	3.499	2.39
	85th Percentile	South Frontage Rd	S of Tefft	35.03562	-120.48403	6,962	16,706	61	3.408	2.44
San Miguel	15th Percentile	Wellsona Rd	W of US Highway 101	35.69597	-120.69853	370	2,824	10	3.124	2.45
	50th Percentile	River Rd	N of Paso Robles City Limit	35.65569	-120.69004	1,030	2,824	11	3.942	2.68
	85th Percentile	Mission St	N of Fourteenth St	35.75360	-120.69599	2,861	2,824	57	2.461	2.85
Los Osos	15th Percentile	Palisades Ave	N of Los Osos Valley Rd	35.31215	-120.83654	963	15,714	67	2.824	2.83
	50th Percentile	Tenth St	N of Los Osos Valley Rd	35.31260	-120.83218	3,058	15,714	75	1.678	2.88
	85th Percentile	Los Osos Valley Rd	W of Clark Valley Rd	35.30384	-120.80288	14,731	15,714	8	6.814	2.36
Cayucos	15th Percentile	Montecito Rd	E of Old Creek	35.43874	-120.87191	98	2,847	1	3.276	2.52
	50th Percentile	Pacific Ave	N of Thirteenth St	35.44013	-120.89329	666	2,847	39	2.449	2.82
	85th Percentile	South Ocean Ave	N of Thirteenth St	35.27768	-120.71420	4,009	2,847	38	3.074	2.43
Cambria	15th Percentile	Main St	E of Windsor Blvd	35.55490	-121.08167	759	5,934	18	3.145	2.93
	50th Percentile	Pineridge Dr	E of Burton Dr	35.56315	-121.09168	3,063	5,934	56	1.805	2.76
	85th Percentile	Tamsen St	N of Main St	35.56883	-121.10304	5,245	5,934	52	2.220	2.72
Avila Beach	15th Percentile	Cave Landing Rd	E of Avila Beach Dr	35.18131	-120.72185	859	1,080	6	2.944	2.44
	50th Percentile	San Luis Bay Dr	W of Ontario Rd	35.19594	-120.70124	8,510	1,080	3	5.435	2.42
	85th Percentile	Avila Beach Dr	W of San Luis Bay Drive	35.18849	-120.72167	11,460	1,080	22	5.817	2.37
San Luis Obispo	15th Percentile	Tassajara	Foothill to Ramona	35.29378	-120.67803	1,750	46,997	65	1.570	2.61
	50th Percentile	Grand	101NB to Mill	35.29111	-120.65331	6,644	46,997	63	2.728	2.87
	85th Percentile	Madonna	LOVR to Pereira	35.25688	-120.69002	19,162	46,997	73	4.643	2.53

	POP	WS	PLOS	AND	Int.D	COM	VAC	ID	pred_PLOS	dif
1	0.39584	0.13106	2.13637	-0.81692	0.75954	0	0	1	3.41641127	1.28004127
2	0.39584	-1.04371	4.29973	-0.15635	-1.09644	0	1	2	4.3919569	0.0922269
3	0.39584	0.00953	2.82978	-1.00566	0.61581	0	0	3	3.44951679	0.61973679
4	1.34678	-0.15251	3.77982	-0.10917	-0.33628	0	0	4	3.3909423	-0.3888777
5	1.34678	0.17157	4.35871	0.50422	-0.11703	0	0	5	3.28459388	-1.0741161
6	1.34678	0.98175	3.34854	0.36267	-0.17878	1	0	6	3.11062511	-0.2379149
7	1.4764	0.09055	3.24155	0.2683	0.34169	1	0	7	3.15341148	-0.0881385
8	1.4764	-0.43607	3.98004	-0.91129	-0.63084	1	0	8	3.35623404	-0.623806
9	1.4764	0.53615	3.81727	-0.43945	1.51281	0	0	9	3.44476714	-0.3725029
10	-0.19944	-1.36778	3.32073	1.44789	-0.98004	0	1	10	4.08068453	0.75995453
11	-0.19944	1.6299	3.47606	2.01409	0.25950	1	0	11	2.6888562	-0.7872038
12	-0.19944	1.02226	4.24576	2.06127	0.05402	0	0	12	2.87476457	-1.3709954
13	0.03825	-0.07149	2.55927	0.59858	3.04024	0	0	13	3.15541205	0.59614205
14	0.03825	1.54888	3.85566	2.39155	0.93080	0	0	14	2.83275794	-1.0229021
15	0.03825	1.58939	2.95664	2.43874	0.82796	1	0	15	2.64129765	-0.3153424
16	-0.40111	0.7387	3.02966	0.78732	0.75265	0	0	16	3.0706362	0.0409762
17	-0.40111	0.98175	4.29564	-0.34509	0.13621	1	0	17	3.06922509	-1.2264149
18	-0.40111	1.30583	2.99128	-0.43945	0.08845	0	0	18	3.26203932	0.27075932
19	-0.42299	0.25259	3.81584	-0.06199	1.79381	0	0	19	3.21657066	-0.5992693
20	-0.42299	0.17157	3.39428	0.31548	2.60196	0	0	20	3.1560392	-0.2382408
21	-0.42299	-0.80065	5.59233	-0.43945	0.19797	0	1	21	4.3603501	-1.2319799
22	-0.93713	-0.03098	3.03428	-0.20354	-1.02802	0	1	22	4.26180173	1.22752173
23	-0.93713	-1.16524	3.71844	-1.28876	-0.41847	0	0	23	3.39640492	-0.3220351
24	-0.93713	-0.39556	4.31052	-0.20354	-1.03491	0	1	24	4.26818923	-0.0423308
25	-0.95121	-0.47658	3.29843	-0.48664	-1.17864	0	0	25	3.25142513	-0.0470049
26	-0.95121	-1.48931	4.23123	-0.86411	-1.43898	0	1	26	4.39449647	0.16326647
27	-0.95121	-0.96269	4.47351	-0.581	-1.21285	0	0	27	3.27542837	-1.1980816
28	-0.40682	-1.36778	4.1046	-1.33594	-0.78833	0	0	28	3.45550002	-0.6491
29	-0.40682	1.14379	1.96897	-0.53382	0.45809	0	0	29	3.27985172	1.31088172
30	-0.40682	-0.15251	4.57529	-0.67537	0.21174	0	1	30	4.38917171	-0.1861183
31	0.29412	-1.16524	1.94072	-0.581	-0.24720	1	0	31	3.20822821	1.26750821
32	0.29412	-1.52982	3.49898	-1.14721	-0.71303	0	1	32	4.5539258	1.0549458
33	0.29412	0.94125	3.40836	-0.91129	1.10874	1	0	33	3.22552982	-0.1828302
34	-0.82215	-1.12473	3.12449	-0.86411	-1.39100	1	0	34	3.15335987	0.02886987
35	-0.82215	-1.08422	3.94239	0.22111	-0.39782	0	1	35	4.22092503	0.27853503
36	-0.82215	0.77921	2.46124	1.02323	-0.56220	1	0	36	2.81024942	0.34900942
37	0.21435	1.1843	2.82449	0.92887	0.56783	1	0	37	2.91207107	0.08758107
38	0.21435	1.50838	1.67793	1.16478	0.43077	1	0	38	2.86767523	1.18974523
39	0.21435	-1.20575	6.81354	-1.28876	-1.34302	0	1	39	4.56428879	-2.2492512
40	-0.8203	-1.48931	3.27631	-0.53382	-0.78145	0	1	40	4.35208929	1.07577929
41	-0.8203	0.05004	2.44868	0.88168	-0.47334	0	0	41	3.02942843	0.58074843
42	-0.8203	0.00953	3.07382	-0.95847	-1.21973	0	0	42	3.33214636	0.25832636
43	-0.57207	-0.80065	3.14507	1.4007	0.82129	0	0	43	2.98152633	-0.1635437
44	-0.57207	0.7387	1.80477	0.59858	0.29393	1	0	44	2.90319612	1.09842612
45	-0.57207	0.57666	2.22036	0.40985	-0.28830	1	0	45	2.93700974	0.71664974
46	-0.96238	-1.28677	2.944	-0.91129	-0.67860	0	1	46	4.39768429	1.45368429
47	-0.96238	-1.40829	5.4346	-1.00566	-1.21285	0	1	47	4.41530149	-1.0192985
48	-0.96238	-0.63862	5.81747	-1.24157	-0.41159	0	1	48	4.44053464	-1.3769354
49	2.72985	1.10328	1.57045	-0.10917	0.73221	0	0	49	3.49361361	1.92316361
50	2.72985	1.02226	2.7278	1.1176	1.39641	0	0	50	3.29369376	0.56589376
51	2.72985	1.42736	4.64302	-0.48664	0.22529	1	0	51	3.36688096	-1.276139

Appendix C **– R results**