EXPLORING THE RELATIONSHIP BETWEEN URBAN FORESTS AND ETHNICITY IN WEST COVINA USING GIS AND OBJECT-BASED IMAGE ANALYSIS

by

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DEDICATION

This work is dedicated with thanks and love to Ismael, Eliana, Leonardo, parents and entire family.

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AL	Alabama
ATH	Average Tree Height
CBG	Census Block Group
DC	District of Columbia
FTCP	Fruit Tree Candidates per Person
GIS	Geographic Information System(s)
IL	Illinois
INS	Immigration and Naturalization Service
LA	Los Angeles
LAC	Los Angeles County
LAI	Leaf Area Index
LARIAC	Los Angeles Region Imagery Acquisition Consortium
LiDAR	Light Detection and Ranging
NIR	Near Infrared
NY	New York
NYC	New York City
OLS	Ordinary Least Squared
PPAP	Potential Planting Area per Parcel
PPPAP	Percent Potential Planting Area per Parcel
PUTCC	Percent Urban Tree Canopy Cover per Parcels
OBIA	Object-Based Image Analysis
SFHP	Single-family Home Parcels

TD	Tree Density
TH	Tree Height
TPP	Trees per Person
US	United States
UTC	Urban Tree Canopy
VA	Virginia

ABSTRACT

The relationship between culture and urban forests is explored by analyzing residential urban trees within the privately owned residential lots of City of West Covina residents in Los Angeles County, CA. Because the largest percentage of Hispanic immigrants in Los Angeles have historically come from rural, often agriculturally fertile areas in Mexico, urban forest structure was studied to identify possible differences in the management practices of privately owned residential trees in Hispanic neighborhoods; looking for the possibility of increased private urban agriculture. The second largest minority group in the city, Asians, were incorporated into the analysis as the second largest minority group and to compare two sets of results. Object-based image analysis was applied to extract urban forest structure data and OLS regression was employed to explore these relationships. When controlling for several factors like parcel size, property values, and income levels, a statistically significant relationship at the 90% confidence level was found between Hispanic and/or Asian populations and all three dependent variables describing urban forest structure. An inverse relationship between higher tree densities and the height of trees and Hispanic populations was found, however, the coefficients were small. Asian populations were found to have positive associations between all forest structure metrics: a statistically significant and positive relationship was found between large Asian populations, tree density, tree height and urban tree canopy cover. Although results showed some connection between culture and urban forest structure variables, further research and additional methods are needed to explore the validity, strength and complexity of any relationships found.

CHAPTER ONE: INTRODUCTION

According to the US State Department's Special Representative for Global Intergovernmental Affairs, "… fifty-two percent of the earth's population now live in cities and every week one million new people move to one" (Lewis 2013). She contends that continued rapid urbanization will lead to three billion new urban dwellers, and that cities, rather than states, are becoming the focus of governance in the new world order. Landscapes undergo significant land use and land cover changes under urbanization and concern is growing over how these changes are impacting the health and life quality of urban residents (McPherson et al. 2011). These landscape alterations can have enormous costs. One 2006 study found that health costs connected with the contamination of beaches in southern California totaled $21 to $51 million per year (Given, Pendleton, and Boehm 2006). As cities expand and population density grows, local governments are increasingly having to address these issues and are continually being challenged to find solutions to these problems. Trends, such as the revitalization of downtown areas that can bring a new influx of people back to the center of a city, are creating new challenges as well as new opportunities to improve urban environments.

1.1 Urban Ecosystems

There are vast differences between highly disturbed urban ecosystems and those less subjugated by humans. Human-dominated landscapes have unique biophysical characteristics caused by the human redistribution of organisms, materials and energy fluxes, and these changes can be obvious or subtle as well as immediate or long-term (Alberti et al. 2006). Cities are visibly transformed from their original state and dominated by buildings, roads and other built structures. But these collaged landscapes also hold a rich array of green spaces in the form of yards, parks, and commercial landscaping; all playing an integral role in an urban environment.

Native vegetation is scarce and is replaced in part by the non-native plants, weeds and trees growing within the gardens of urban dwellers. Open spaces where native vegetation does have an opportunity to grow, are often dominated by invasive species of flora and fauna. These landscapes are not only highly disturbed, they are also highly unstable, only adding to their ecological complexity.

1.2 Humans in the System

The body of work examining the relationship between urbanization and ecosystems continues to grow and garner attention as environmental and social challenges in most cities mount. However, little research has focused on questions surrounding the human and ecological patterns that emerge from interactions between socioeconomic and physical processes (Alberti et al. 2003; Wu 2010) or between sociocultural ones and the latter. According to Alberti et al. (2003), ecological scholars who study urban areas have found themselves challenging ecological theory to explain the ecology of cities and some have even argued that important theoretical revisions are needed in order to include human action.

1.2.1 Landscape Ecology

Landscape ecology has brought a broad interdisciplinary and transdisciplinary approach some would argue is necessary to understand an especially complex urban environment. Evolving out of an integrative ecosystem approach (Figure 1), it incorporates both bio- and socio-ecological perspectives to study as well as to influence the relationship between spatial pattern and ecological processes; at multiple scales including time (Wu 2008; Turner 2001). Landscape ecology explicitly addresses spatial configuration, composition and form as it approaches process (Wu 2008) and understandably, many advancements in the field have largely been fueled directly and/or indirectly by the increased adoption of GIS (Geographic Information Systems), remote

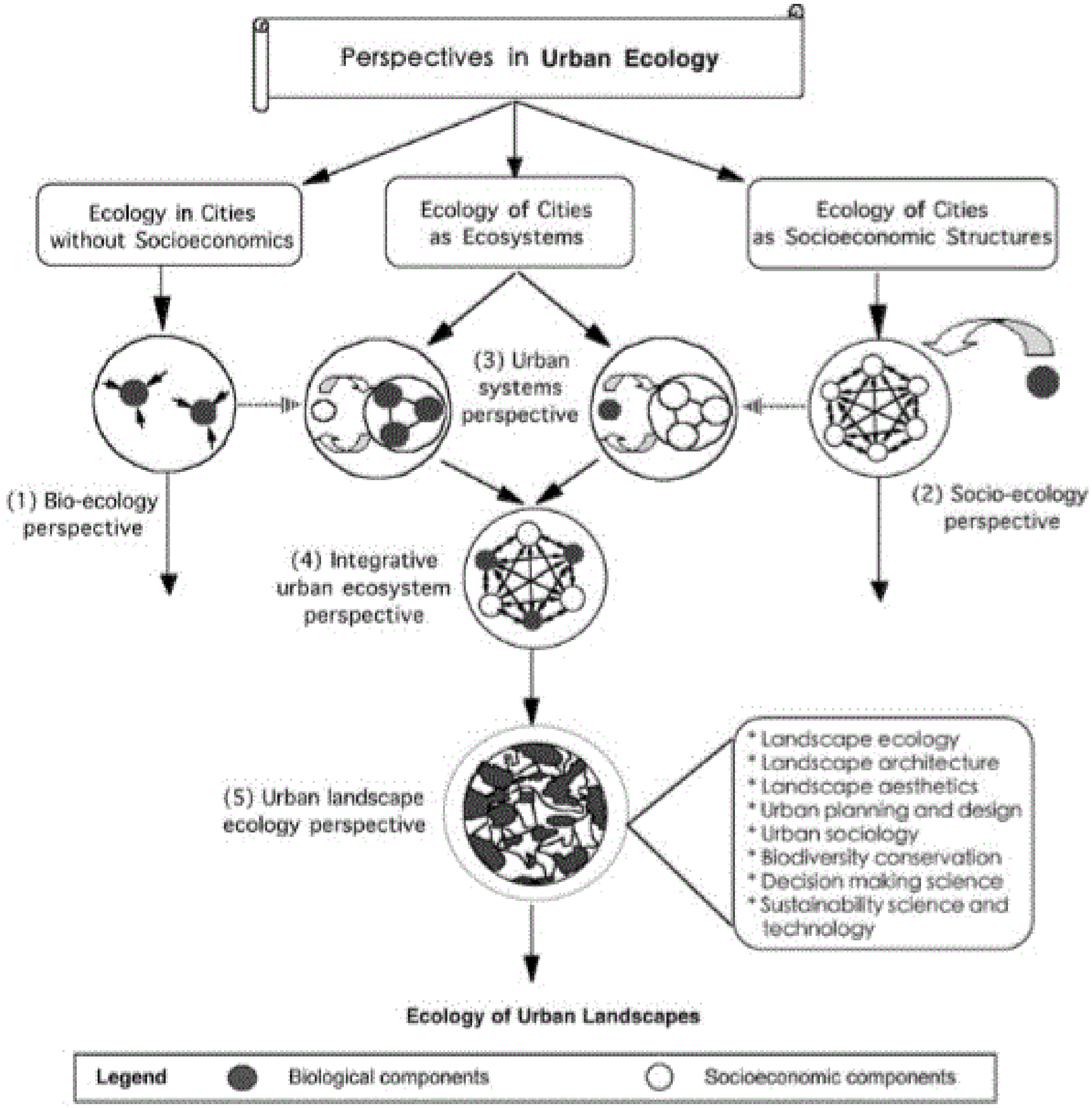

Figure 1 Schematic showing evolution of urban ecology
Source: Wu (2010)

sensing and other spatial technologies and techniques, as well as the ever-greater availability of spatial data including remotely sensed imagery captured at higher and higher resolutions, with greater coverage and in different spectral ranges. Highly relevant to urban sustainability, landscape ecology's contributions have become essential for land use planning and management (Turner 2001). However, despite the discipline's explicit humanistic and holistic approach, most research has not focused on the human element. Instead, it has tended to place humans in the context Turner (2001, p. 7) would suggest: as “but one of many factors creating and responding to the spatial heterogeneity in an ecosystem”, and not as major active agents of change that are complex and sometimes unpredictable.

1.2.2 Incorporating Culture: Exploiting the Spatial Component

To restrain human impacts we must learn to understand them. Urban landscapes are both affected by and developed by culture. In her introduction to “Placing Nature: Culture and Landscape Ecology”, a collection of essays by researchers of diverse disciplines like philosophy, ecology, geography, history and landscape architecture, Joan Iverson Nassauer states that in a world dominated by humans, “we cannot stand apart from nature and now nature as we know it cannot stand apart from us” (Nassauer 1997, p. 3-4). In order to advance ecological health, she states, “we must use culture, or we risk removing ourselves altogether from the ecosystems we know” (Nassauer 1997, p. 3-4). But how do we best conceptualize the relationship between culture and ecosystem in order to use culture to our ecological advantage? Nassauer (1997) suggests that “we must formulate ecological questions by considering cultural possibilities and we must formulate cultural questions by considering ecological processes.”

1.2.2.1 Conceptualizing Human Impact on an Ecosystem

Culture drives the socioeconomic phenomena that integrative disciplines like landscape ecology and sustainability science study, but these relationships are often difficult to conceptualize. Other researchers in similar fields have also turned their attention to the human element. Some conservation biologists have recognized the need for better and more complex representations of human impact when implementing key concepts like habitat fragmentation in the landscape matrix (McIntyre and Hobbs 1999). Geography has a long history of studying human-environmental relationships. The term “cultural landscape” for example, has been a fundamental concept in geography for over a century. Here, the landscape is viewed as one being formed from a natural landscape by a particular culture, wherein culture is the agent and the natural is the medium. Wu (2010) argues that the concept of cultural landscape can be useful and effective in landscape ecology, especially when used in the context of a landscape modification gradient. However he also notes that “no single perspective is sufficient to understanding human-environmental relationships and pluralistic approaches are needed to effectively bridge research cores of different perspectives” (Wu 2010, p. 1148). The spatial sciences play an integral role in bridging these gaps.

1.2.2.2 Increasing our Understanding by Using the Spatial Dimension

The cultural dimension has largely been ignored in mainstream contemporary landscape ecology research despite its centrality to the theory (Wu 2010; Alberti et al. 2001; Nassauer 1997). However, the subject has gained in popularity in recent years, resulting in a surge in research. This in part can be attributed to the increased manifestation of the ecological pressures our world faces (Wu 2010), but the surge may also be attributed to an increased integration with the spatial sciences, largely in the form of an increased adoption of GIS, remote sensing and other geospatial tools and techniques by researchers. This coupled with an enormous amount of spatial socioeconomic, demographic and even behavioral data increasingly becoming available offers great potential. Spatial science theory, methods and tools offer a unique opportunity to support interdisciplinary and transdisciplinary approaches that can facilitate meaningful new insights informing the development of these new concepts. The culturally diverse demographics of a city, for example, may be viewed as just another added layer of variability as we attempt to study an already complex urban environment, but by incorporating and exploring the spatial dimension, it can afford an opportunity to garner new insights. This study aimed to explore such insights.

1.3 Thesis Goals

The overarching goal of this research was to explore the relationship between culture and urban trees by analyzing the relationship between Hispanics and urban forests in the City of West Covina, CA. With the use of high resolution multi-spectral imagery and LiDAR (Light Detection and Ranging) point cloud data, an Object-Based Image Analysis (OBIA) approach and regression analysis within a GIS environment that incorporates census and cadastral data, this study aimed to answer the following questions:

1. Are there quantifiable differences in urban forest structure within predominantly Hispanic and non-Hispanic neighborhoods in West Covina?
2. If so, what do these structural differences suggest about urban tree management practices taking place in Hispanic neighborhoods?
3. How does urban forest structure in Hispanic neighborhoods compare with that in neighborhoods of a different makeup?
4. Are there other socioeconomic, demographic or physical influences affecting urban forest structure in West Covina?

The City of West Covina was chosen as the study area because it is representative of many of the cities and neighborhoods in Los Angeles County in terms of its large and increasing Hispanic population. It was also chosen because of its wide-ranging income levels and the varied educational attainment of its residents. With declining urban tree canopy cover, West Covina faces many of the same challenges that other urban areas face (Lee 2012). By studying its urban forest, this study aims to further our understanding of the dynamics behind urban tree canopy changes and how GIS and remote sensing technologies can be used to unravel and help to explain them.

1.4 Thesis Organization

The next chapter summarizes related work and starts by exploring the relationship between Hispanic immigrant populations and urban forests in the Los Angeles metropolitan area. The chapter provides a brief background on the history of Mexican immigration into the US and explores questions surrounding how culture may affect the way Mexican and other Hispanic immigrants view and thereby modify and manage private green spaces, and more specifically, urban trees. The chapter also discusses the state of our urban forests and why this issue is critical for the health and well-being of our cities. Examples of other urban forest research are discussed in the chapter, as well as some of the most common tools and techniques currently being employed to evaluate the state of our urban forests. Chapter 3 describes the GIS and remote sensing methodologies used in this study as well as the data used to explore these relationships. Chapter 4 details the results for this study and the final chapter offers a discussion of the broader significance of these results and some suggestions for future research as well as the central role GIS and remote sensing technologies will likely take as we carry our attempts to decipher human–ecosystem relationships forward.

CHAPTER TWO: BACKGROUND AND RELATED WORK

In 1986, the US Immigration Reform and Control Act (IRCA) granted amnesty to nearly three million illegal immigrants; 2.3 million of which were Mexican-born. Waves of Mexican immigration had been taking place for decades, and though for many the move had been temporary, others had chosen to stay, setting roots in their reluctant host-country. During the first part of the 20th Century, Mexican migrants enjoyed somewhat preferential treatment under US immigration law. At a time when the US was implementing strict quotas limiting immigration from even some western European countries like Spain and Italy, labor recruiters were seeking out workers in western Mexico for the rail and agricultural industries (Fussell 2004). Quotas for Mexican immigrants were not put in place until the end of the 1920s, and by then, the demand and recruitment for low-skilled labor and higher wages had given rise to a population of approximately 1 million Mexicans living in the US; a population that mixed freely between the two countries at the time (Anon. 1928; Library of Congress 2015; Borjas 2007).

Things would soon change. The rise in unemployment that began just before and was accelerated by the Stock Market crash of 1929 led, in part, to changes in the law that restricted the once steady influx of Mexican low-skilled laborers into the country (Anon. 1928). Anti-immigrant sentiment grew with job losses and initiatives were put in place by the US government to encourage, and some would argue push, Mexican migrants to return to their country of origin (Borjas 2007); mostly men, but some with their American-born families. It is estimated that hundreds of thousands of Mexicans migrated back to their country of origin during the 1930s (Library of Congress 2015), but by then, enduring cultural linkages had been formed, knowledge and treasure had already been gained, and connections had already been established, and this social, cultural and economic capital would inevitably have a lasting impact on the futures of both countries.

2.1 Social Capital in Mexico to US Migration Patterns

Subsequent waves of Mexico to US migration would largely follow the historical migration patterns already established in the 1910s and 1920s, patterns that remain strong even today and that exemplify an interpretation of cumulative causation theory: past migration creates social ties to the destination and these ties facilitate further migration (Fussell 2004). When in 1942 the US government began implementing a guest worker program in response to labor shortages occurring mainly in the agricultural sector, most of the migrants would largely originate from the same places: predominantly from rural agricultural areas in the high plateau region of "Mesa Central" in west central Mexico. Many from this new generation of migrants profited from the social capital gained by prior ones. Often this meant having an upper hand when obtaining the necessary documentation from farm owners that would allow them to enter and work legally in the US. The guest worker program came to a halt in 1967, but both legal and illegal immigration by Mexicans continued to rise (Figure 2), accelerating in the 1980s when the economic restructuring and ensuing crisis in Mexico made the US labor market more attractive for rural Mexicans (Figure 3). Most were migrating to urban centers in California and Texas as well as to an enclave in Chicago where a Mexican population had been established since the early 20th century. By 2010, approximately 50 million Hispanics were living in the US, 32 million of them were of Mexican origin and many of them would track their origins back to these historical migration patterns (US Census Bureau 2010).

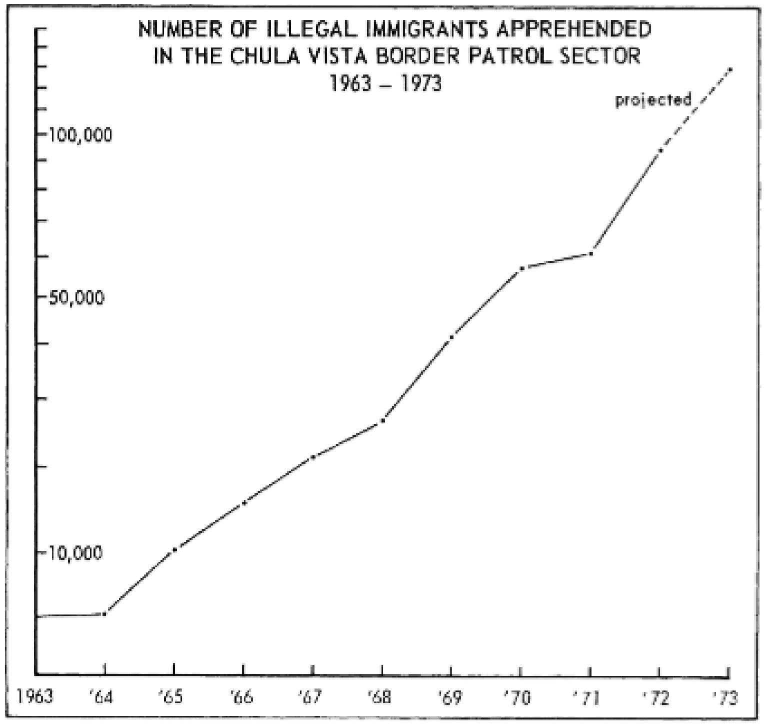

Figure 2: Illegal Mexican immigration to California from 1963 to 1973
Source: Dagodag (1975)

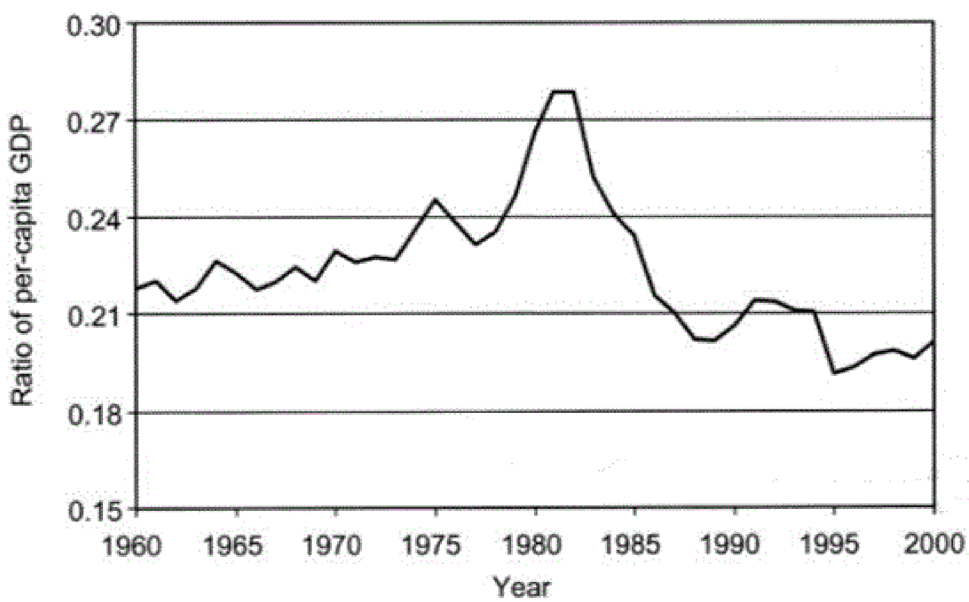

Figure 3: Per capita income in Mexico relative to US from 1960 to 2000
Source: Borjas (2007)

2.2 Agro-related Cultural Capital in Rural to Urban Migration

Given the rapidly shifting demographics occurring in the US, largely due to the growing Hispanic and especially Mexican population, identifying and understanding the cultural capital Mexican and other rural immigrants are transferring to many US urban centers can help us better identify challenges and opportunities for improving urban environments. Considering what we know about Mexico-US migration patterns, what can we assert about the role of rurality and/or agro-related cultural capital in the way Mexican immigrant's value, manage and modify private urban green spaces? Do patterns portray challenges or opportunities? The highly concentrated Hispanic communities that largely exist in urban areas in the US have inadvertently inhibited and delayed assimilation by even legal Mexican residents and sometimes their American-born children (Valdez 2005; Telles and Ortiz 2011). This can prolong cultural effects on urban ecosystems in positive as well as negative ways.

2.2.1 The Mesa Central Migration Route

Although changes in Mexico-US migration patterns have taken place especially since the mid-1990s, with more skilled, educated, metropolitan Mexican individuals migrating to the US in recent years, and although large numbers of immigrants from differing states, demographics and socioeconomic backgrounds have come to the US throughout history, the single largest historical Mexico-US migration pattern of the 20th century still remains that of rural Mexicans from west central Mexico migrating to the southwestern US (Fussell 2004; Dagodag 1975). The states of Jalisco, Michoacán and Zacatecas have historically contributed the largest numbers of Mexican immigrants into the US (Figure 4), with one 1975 study finding that 48 percent of illegal immigrants apprehended by the INS at the time had originated from the states of Jalisco and Michoacán alone (Fussell 2004; Dagodag 1975), (Figure 5). Most of these first-time migrants were mestizo and not native-Mexican (Dagodag 1975), and this meant that among rural communities, they tended to have more social, economic and cultural capital than indigenous peoples.

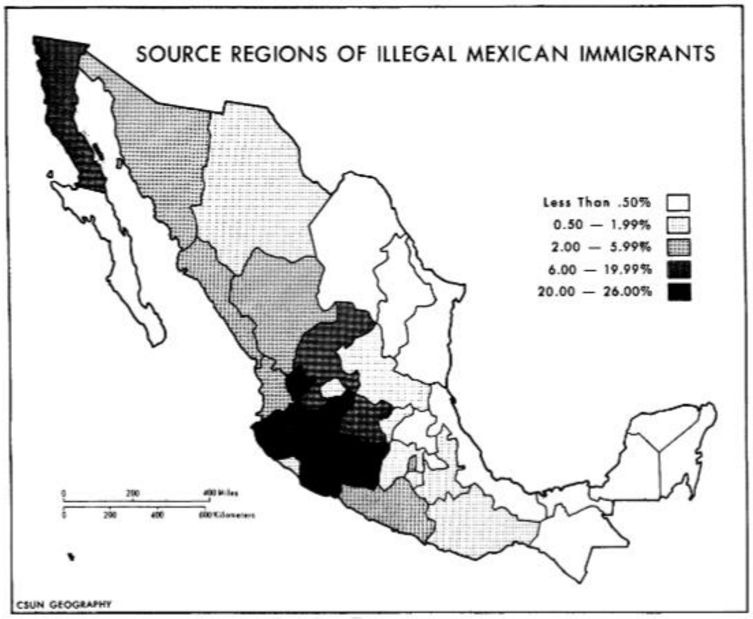

Figure 4: Source regions of illegal Mexican immigrants in 1973
Source: Dagodag (1975)

2.2.1.1 The "Mesa Central" Region

The "Mesa Central" is a high plateau region in west central Mexico that has high volcanic activity, a temperate climate and abundant rainfall. The rich alluvial and volcanic soils create fertile agricultural areas where even the manufacturing and service sectors of the economy are strongly tied to agriculture (Fussell 2004). Most of the mestizo rural residents of this area live in small colonial-style villages surrounded by the ranches and farmland they tend. Cattle grazing is extensive and the land lends itself to wide-ranging agriculture with major crop production in corn, sugar cane, avocados, berries and others (Encyclopedia Britannica 2015).

2.2.2 Private Urban Agriculture: Mexican Immigrants and Residential Green Spaces

If we consider the strong agro-related cultural and even agro-related social capital that a large

Figure 5: The Mesa Central region and major source states of Mexican immigrants into the US

number of Mexican immigrants bring to our urban centers, then we may expect that for many Mexicans, the sustainability practices strongly associated with a rural agricultural way of life may resonate in their new urban environment thereby affecting the way Mexican immigrants view, value, and therefore modify and manage private urban green spaces, and in particular, urban trees. Furthermore, for Mexican immigrants, who are often afforded the ability to require a lesser degree of assimilation in many urban places, there may be a further intensification and prolongation of such effects when compared to immigrants from differing cultures. Strong urban gardening practices in Hispanic neighborhoods predate most recent urban agriculture trends. Fruit trees and vegetable gardens have lined the front and back yards of Hispanic neighborhoods for decades and the European and now American practice of maintaining green lawns can be a completely new experience for the rural Hispanic immigrant. Urban trees are some of the most vital and highly influential flora in urban ecosystems and urban fruit trees tend to be some of the most common plants of consumption in residential green spaces; can we find differences in how rural Mexican and other Hispanic immigrants manage them? Are Hispanics more likely to plant and maintain fruit bearing trees given cultural influences, and inversely, are they more likely to dispose of trees with no consumption value because of the same reasons? Our urban forests are on the decline, and for reasons that are poorly understood. Understanding the dynamics behind urban forest changes and the possible socioeconomic and sociocultural influences affecting them is important.

2.3 Urban Forests in Los Angeles

The Los Angeles metropolitan area has one of the largest concentrations of Hispanics in the nation with approximately 48% of the population in the county being Hispanic, and approximately 34% of Mexican origin. Like other urban areas, Los Angeles faces its own set of environmental challenges: air and water quality, storm runoff, local flooding, and water shortages, among others. Urban forests play an integral role in mitigating many of these and other environmental problems. However, data show that loss of urban tree canopy (UTC), and the consequent decline of urban green cover is a widespread problem across the US, and the Los Angeles metropolitan area is no exception. Between the years 2000 and 2010, one study found that approximately 305,000 trees (and 12% in general green cover) were lost from single-family neighborhoods in 20 of the largest cities in Los Angeles County (Lee 2012). In an already stressed environment, losing the ecosystem services provided by established urban trees can be of great negative impact.

2.3.1 Environmental Benefits of Urban Trees

Urban trees provide invaluable benefits to urban residents as well as to the urban ecosystem as a whole, and by consequence, to those ecosystems that surround it. Increasing UTC, for example, is one of the most effective ways of reducing temperature; especially important in the "heat islands" that many urban areas have become. Trees serve as a natural air conditioner; the evaporation from a single tree can produce the cooling effect of 10 room-sized air conditioners operating 20 hours a day (Evans 2014). This reduction in local air temperatures can result in less need for residential cooling, lowering fossil fuel and water consumption at power plants (McPherson et al. 2011; Shashua-Bar and Hoffman 2000). Trees can also produce a significant positive effect on storm water runoff rates and volume, helping to prevent local flooding (Dwyer and Miller 1999): As urbanization increases, so do the impermeable surfaces covering the landscape. Rainfall will tend to flow quicker to storm water drains and sewers, resulting in more frequent and severe floods (Dwyer and Miller 1999). An urban tree canopy intercepts this rain water, slowing its flow. Trees also provide shade, reduce noise, and trap dust and other pollution with their leaves essentially serving as air filters in a polluted urban environment.

2.3.2 Social Benefits of Urban Trees

Urban trees play a significant role in the social and ecological welfare of cities and their residents. Increased tree cover has been associated with an increase in respiratory health for example, despite some tree species being allergic triggers (McPherson et al. 2011). More urban trees are associated with higher property values, reduced stress and improved general well-being (McPherson et al. 2011). Troy, Grove, and O'Neil-Dunne (2012) found a strong and inverse relationship between urban tree canopy and crime rates: a 10% increase in tree canopy cover was linked to a 12% decrease in crime. Trees define space, provide privacy and prompt significant emotional responses that can be beneficial.

2.3.3 Managing Urban Forests

The environmental and social benefits of urban trees have been well documented and municipal governments are beginning to take notice. Over the last few years, several tree-planting campaigns have been launched in cities across the US in an attempt to increase tree canopy. "MillionTreesNYC" is one such initiative where government agencies, in their efforts to increase the number of trees in the city of New York are even digging up road surfaces in some cases (Vermont Monitoring Cooperative 2014). Similarly, the City of Los Angeles launched the "MillionTreesLA" campaign in 2006 after a UTC assessment determined LA's tree canopy cover of 21% was below the national average (Los Angeles Department of Water and Power 2015). However, a large percentage and in some cases the larger percentage of trees in a city are managed not by local governing agencies, but by residential property owners, and efforts to preserve and promote the growth and vitality of urban forests should also focus there. In 2010, "MillionTreesLA" became "City Plants", refocusing efforts from a campaign that in large part concentrated on planting trees on public land, to a more focused effort to increase tree canopy in low canopy residential neighborhoods. The program provides LA residents with up to seven free shade trees to plant on their residential properties, holds "adopt a fruit tree" events monthly, and plants parkway trees (the area between sidewalk and street) at the request of City residents at no charge (Los Angeles Department of Water and Power 2015). The evolution of this Los Angeles municipal program highlights both the importance of increasing and preserving urban tree canopy in residential neighborhoods, including on private property, but also the importance of identifying and understanding the cultural and socioeconomic dynamics behind differing management practices of urban green spaces. Understanding these dynamics can help better shape conservation efforts, policy and lead to more informed and effective urban design.

2.4 Similar Work – Studying Urban Forests

A substantial body of work has developed around the quantification of the ecosystem services urban trees can provide, and in many cases, actual monetary values are being assigned to some of these benefits. This level of information coupled with an increased adoption of geospatial technologies by local governments has led to an increased allocation of resources towards spatial scientific studies of urban forests, in most cases, in the form of urban tree canopy (UTC) assessments that map and measure urban tree canopy area, and that when repeated, can facilitate monitoring. Researchers are also making great strides in being able to map individual trees and delineate individual tree crowns more accurately, as well as in differentiating between specific tree species, difficult in highly altered and variable urban environments. Some researchers have taken advantage of the many advancements and increased derivation of urban forest data by focusing on questions that surround the socio-ecological relationships and processes involving urban forests; however, this research still remains limited in scope. The three most frequently pursued research areas are discussed in more detail below.

2.4.1 Urban Tree Canopy Assessments

UTC, the percentage of a site covered by trees, has become a commonly used metric for assessing the size and structure of urban forests. One of its advantages is the concept's simplicity so that it can be more easily understood by the general public (McPherson et al. 2011). During the past two decades, dozens of UTC assessments have been performed in metropolitan areas across the US including in major cities like Atlanta, GA, Washington, DC, Baltimore, MD, New York, NY, and Los Angeles, CA (e.g. McPherson et al. 2011; Troy, et al. 2007; McGee et al.

2012). Within the framework of urban landscape ecology, these assessments analyze urban trees from a landscape level by employing high-resolution aerial or satellite imagery, and in more recent years, LiDAR, and some form of semi-automated classification technique to extract and map areas of urban tree canopy in order to quantify and analyze it spatially (McPherson et al. 2011; Walton, Nowak, and Greenfield 2008). Because local governments interested in assessing their urban forests are usually interested in improving them, being able to identify and then prioritize land suitable to plant new trees has become a common part of these assessments, providing local governments with a fairly accurate and cost-effective way to evaluate, monitor and improve the health and management of urban forests.

2.4.1.1 Image Analysis Methods and Classification Techniques

A large percentage of scholarly urban forest research revolves around the image analysis and classification techniques used to extract and quantify urban trees and urban tree canopy. Pixel-based classification methods have traditionally been implemented by researchers to differentiate between different land use and land cover types, as well as to extract urban tree canopy cover. McPherson et al. (2011) used a moving masks method in conjunction with a supervised and unsupervised pixel-based classification technique to map trees and shrubs in the City of Los Angeles, and found that it had a UTC of 21%, below the national average. Irani and Galvin (2003) and Nowak, Kuroda, and Crane (2004) also applied pixel-based remote sensing techniques to assess tree canopy cover over Baltimore, MD by utilizing the near infrared (NIR) and red bands to discern tree canopy from other green areas and estimating that between 1999 and 2001, Baltimore's urban forest experienced a 4.2% annual net loss in tree cover. More recently, McGee and colleagues chose a pixel-based approach to perform a UTC assessment of the City of Winchester, VA over other approaches "due to the fact that the processing is more easily understood and would be more easily implemented in the future by local jurisdictions" (McGee et al. 2012, p. 277).

The advancements in the quantity, quality and availability of remotely sensed data, however, offer a greater capacity for analysis and require more advanced methods to better exploit these opportunities. The reduction in data acquisition costs has led to more repeatability and therefore more opportunities for richer information extraction. Many researchers are beginning to look to other methods because pixel-based image analysis techniques are falling short of expectations in terms of consistency and efficiency (Chubey, Franklin, and Wulder 2006) and because significant advances in classification techniques are greatly limited by the fact that they are pixel-based (Blaschke 2010). Unlike humans, the ultimate image interpreters, these methods are incapable of using photo-interpretative elements such as shape, texture, or spatial relationships and instead place groups of pixels into classes that are primarily based on their spectral values (Gao and Mas 2008). In order to extract the spectral characteristics of geographic features, these methods treat each pixel individually, and assume every pixel to cover an area relevant to the landscape scale (Gronemeyer 2013). When we consider that there could be hundreds of millions of pixels to process in a single image, the limitations of pixel-based methods become increasingly apparent (Blaschke 2010).

OBIA (Object-based Image Analysis) methods, which work differently and more closely resemble the way humans perform image interpretation, have increasingly gained popularity among researchers. In this approach humans are the expert system, offering, in theory, endless potential due to their intuitive nature. Instead of considering the spectral characteristic of each individual pixel, OBIA begins by creating relatively homogeneous and meaningful objects that are made up of groups of pixels by considering one or more characteristics explicitly defined by the user; characteristics that can be simple or highly complex. These characteristics can include spectral value but also, shape, pattern, context, and other cognitive information, placing this technology at the interface between remote sensing and geographic information science (Blaschke 2010). OBIA methods are increasingly gaining popularity in urban forest research as expectations quickly shift toward greater accuracy and finer-scale inventorying of urban forests: Grove et al. (2006) measured tree canopy over the city of New York using object-oriented classification methods that included the use of LiDAR data; Moskal and Zeng (2011) measured tree canopy over Seattle, WA using the RGB and NIR bands in publicly available remote sensing data and achieved accuracies of over 80%; and Lehrbass and Wang (2010) presented a semi-automatic, object-based method for urban tree cover extraction that was applied to London, Ontario, Canada with user's and producer's accuracies for trees of 76% and 86%, respectively.

There are further advantages to OBIA, because the spatial relationship information contained in image objects, for example, allows for more than one level of analysis, it is useful when making landscape level observations that require multiple scales (Gronemeyer 2013). OBIA methods also facilitate the integration of different data types, including vector data, and can create layers to incorporate into the analysis virtually on the fly. OBIA techniques have been shown to be more accurate at higher resolutions than pixel-based ones (Gao and Mas 2008). However, despite these advantages, many researchers have been dissuaded from utilizing OBIA methods since their inception in the 1970s, largely because of their level of difficulty as well as their dependence on user knowledge and experience (Gao and Mas 2008). Other challenges include intensive processing that often requires enterprise software, higher software costs, and limited choices in both software and freeware, and because OBIA methods have only recently gained traction among researchers, knowledge and resources on which to build new applications are still limited. Despite these limitations, their popularity has grown in recent years and many of the advancements in image vegetation classification and feature extraction techniques including those for urban trees can be attributed to the use of these methods.

2.4.2 Individual Urban Tree Detection, Crown Delineation and Species Differentiation

Researchers are developing more accurate methods to collect more specific information about trees besides general tree canopy cover, and many have tackled individual tree detection, individual tree crown delineation and even tree species differentiation with a wide variety of techniques, data and platforms, with good results. However, research in urban tree detection specifically remains very limited: Bacher and Mayer (2000) performed an automatic extraction of leafless deciduous trees from 4 cm high resolution aerial imagery taken in spring in Tamm, Germany. They made use of the dark shadow of the tree as well as the fact that the vertical trunk is imaged as a straight line and they were able to determine the trunk base, height, and width of trees with the results showing good potential for their method. Tiede, Hochleitner, and Blaschke (2005) presented a methodology to extract and delineate single trees in an urban environment from small footprint high intensity laser scanning point data (LiDAR) in a GIS environment, employing any additional image data for visualization and accuracy assessment purposes only (a commonly seen method in current forest research). Dominant trees were detected with an accuracy of 72%; however, the overall tree detection rate was 51% due to suboptimal scan sampling distribution that hindered tree crown delineation (Tiede, Hochleitner, and Blaschke 2005). Zhang and Qiu (2012) developed a neural network-based approach to identify urban tree species at the individual tree level from LiDAR and hyperspectral imagery. Their method was able to detect individual trees, estimate their tree metrics, and also identified species types with an accuracy of 96% in detecting individual urban trees and 68% in tree species identification.

Shrestha and Wynne (2012) developed prediction models to estimate biophysical parameters such as height, crown area and biomass for over 2,000 individual trees in central Oklahoma with the use of a multiple linear regression model. Using LiDAR, they were able to achieve a high level of accuracy for estimating individual tree height (R^2 = 0.89), crown diameter (R^2 = 0.90), and biomass (R^2 = 0.67).

2.4.3 Studying Urban Forests from a Socio-ecological or Urban Landscape Ecology Perspective

Despite the recent surge in interest in studying the sociological components of ecological phenomena occurring in urban environments, urban social science and landscape ecology research related to urban forests remains very limited in scope: Zhang et al. (2007) studied the attitudes surrounding urban forests among Montgomery, AL residents and found that higher income, more educated individuals were more likely to financially support tree planting programs. They also found that characteristics such as race, gender, and residence were not statistically significant factors in explaining attitudes toward urban forestry programs. Troy et al. (2007) used geocoded point crime data and high resolution UTC data with ordinary least squares and spatially adjusted regression, and found a strong and inverse relationship between tree canopy and crime: a 10% increase in tree canopy was associated with roughly a 12% decrease in crime. Iverson and Cook (2000) found a strong correlation between household income and population density and UTC in Chicago, IL. Flocks et al. (2011) applied a random sampling approach to study urban forest cover structural inequities and found that white areas had greater tree density, cover, and species diversity while African American areas had the lowest tree density and LAI (Leaf Area Index). Interestingly, Hispanic areas were found to have more trees per hectare than African Americans, the greatest individual tree LAI, and more trees in excellent condition than either of the two aforementioned groups.

CHAPTER THREE: METHODS

To explore the relationship between Hispanics and urban forest structure in the City of West Covina, data was extracted with image analysis software and subsequently analyzed together with census and cadastral data within a GIS environment. Eight explanatory variables were derived at the census block group level including: Average Parcel Size, Average Building Age, and Average Property Value. In addition, other demographic and socioeconomic variables including Percent Hispanic, Percent Asian and Median Household income were also analyzed. This chapter provides a description of the study area chosen, the data and the data sources employed, the OBIA techniques implemented to extract urban forest structure information, and the geostatistical methods used to explore possible connections between culture and privately owned trees.

3.1 Study Area

The city of West Covina is located approximately 20 miles northeast of downtown Los Angeles (Figures 6 and 7), and had a population of 106,000 as of the 2010 Census. With 54% of the residents being Hispanic, the City was ranked 25th by the US Census Bureau among cities with the highest percentage of Hispanics in 2010. In addition, 34% of West Covina's residents reported that they were foreign born during the last decennial census. The second largest minority group, Asians, accounted for approximately 26% of its population and was therefore included in the analysis. The city was chosen as a study area because of the varying demographic nature of its different neighborhoods, its large and growing Hispanic population, and because in an earlier study, it was found to have higher than usual UTC losses despite having some of the largest average residential lot sizes in the county (Lee 2012).

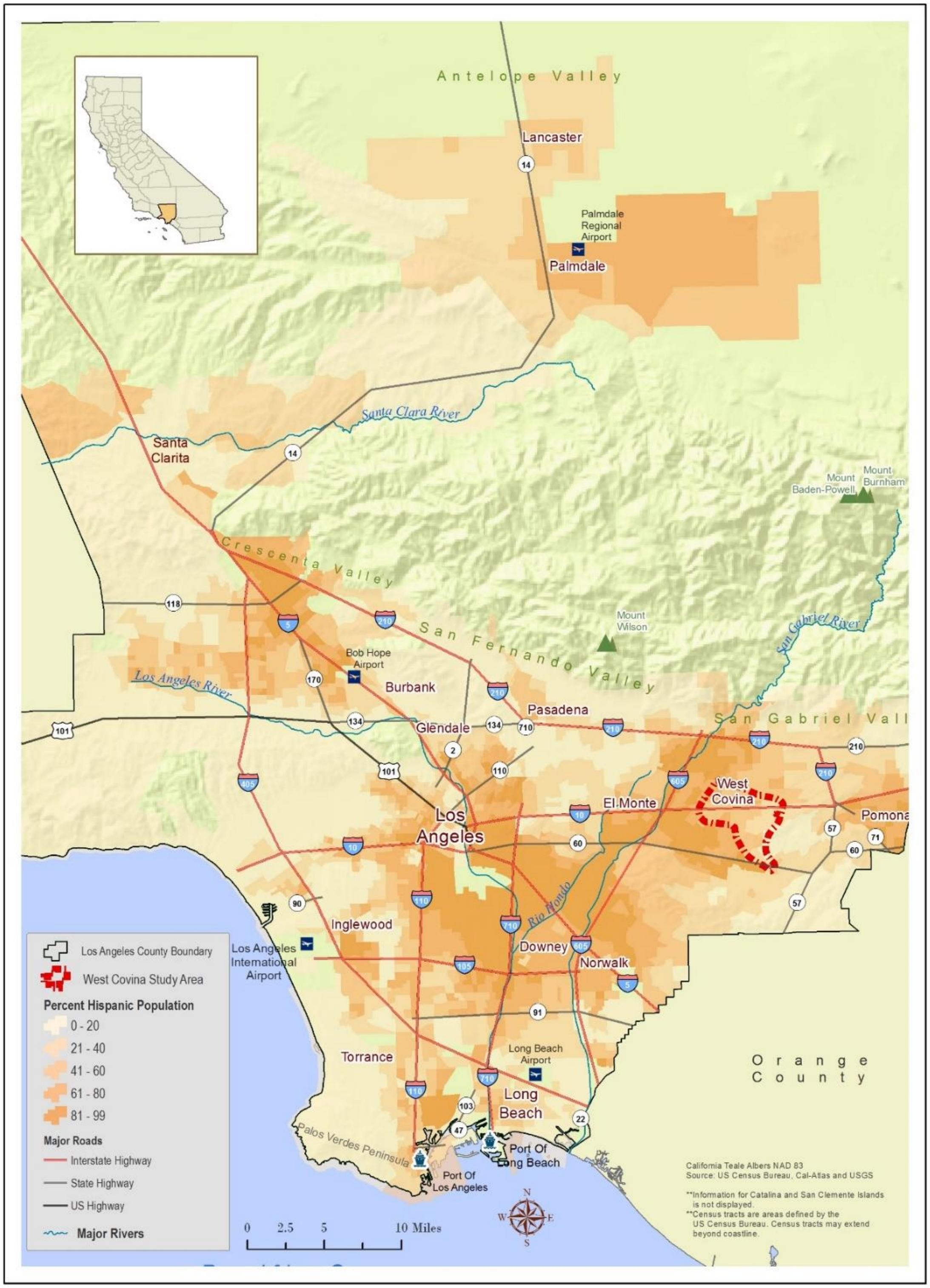

Figure 6: Map of Los Angeles County, Hispanic populations and West Covina study area location

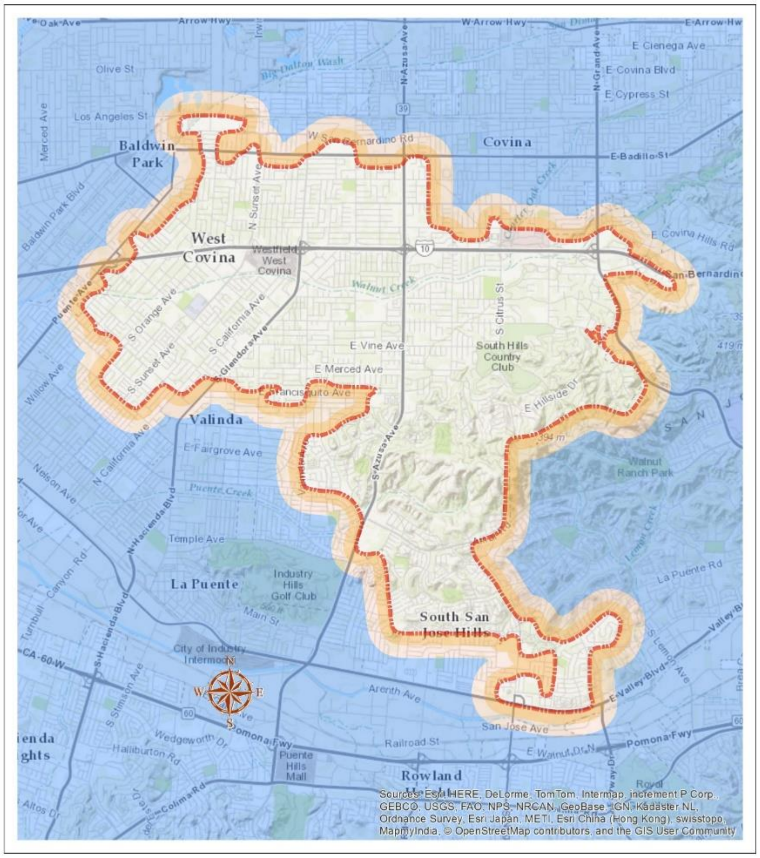

Figure 7: Map of the City of West Covina and major points of interest

3.2 Data and Sources

All of the data used in the image analysis and feature extraction originated from the LAC Department of Regional Planning and the Los Angeles Region Imagery Acquisition Consortium (LARIAC) Program. The LARIAC Program involves multiple organizations, county departments and various public agencies in a multi-beneficiary, cost-sharing spatial data acquisition program. The program launched its first acquisition project in 2006 and accomplished its fourth (LARIAC 4) in 2014. Most of the LARIAC data employed in this study originated from the original 2006 acquisition, executed by Infotech Enterprises America using a single-pass DMC (Digital Mapping Camera) system. The RGB and CIR data were delivered as two separate products with a 1.5 ft horizontal accuracy at a 95% confidence level. For this study, a 2006 leaf-off 12 in RGB orthogonal image originally acquired at a 4 in resolution was used in the extraction, as well as a readily available 5-foot NDVI (Normalized Difference Vegetation Index) raster layer derived from the 2006 RGB and Color Infrared (CIR) orthophotos. A 5-foot Normalized Digital Surface Model (nDSM) derived from LARIAC's 2006 LiDAR data was also used in the feature extraction as height information. Typically, an nDSM is derived by normalizing a Digital Surface Model (DSM) with a gridded Digital Terrain Model (DTM):

$$nDSM = DSM - DTM \tag{1}$$

However, the DSM used for this work was normalized by subtracting a Digital Elevation Model (DEM) from the DSM instead. Although many of these terms are often used interchangeably, a DEM represents the bare earth surface, whereas a DTM usually attempts to incorporate more geographic elements and natural features such as rivers and other break lines (Hashemi 2008; Li et al. 2010). In an urban setting, a DTM is usually based on height points of streets (Hashemi 2008; Li et al. 2010). Because the DTM was not available in the necessary gridded format, the readily available LAC "Height" file or DEM-normalized nDSM was utilized for height information. Vertical accuracy for the LiDAR used to derive all of the aforementioned terrain datasets was tested with 0.82 ft accuracy at a 95% confidence level (LARIAC Product Guide 2006). Lastly for the high-resolution feature extraction, a "Building Outlines" vector layer captured from stereo imagery during the 2008 LARIAC 2 acquisition was employed as a mask to aid in the classification and to reduce processing times. For the GIS analysis, the aforementioned building layer, an LAC Assessor's 2013 cadastral layer and a 2010 US Census Bureau census block group data layer and corresponding Topologically Integrated Geographic Encoding and Referencing (TIGER) vector reference layer downloaded from the US Census Bureau website were also incorporated into the analysis. All of the data was preprocessed to match a single geographic projection (NAD 1983, State Plane, Zone V) and clipped to the extent of the city boundary of West Covina.

3.3 Remote Sensing Methods

An OBIA approach was used to extract both the general UTC area as well as individual trees and tree heights. Trimble® eCognition Developer was chosen as the image analysis software. The first of its kind, the software was founded by Nobel laureate and OBIA pioneer Gerd Binning and his team of researchers and was first launched in 2000 by Munich, Germany-based Company Definiens® (and acquired by Trimble® in 2010) (Nassbaum 2008; Esch et al. 2008). Arguably, much of the software's success can be attributed to their software implementation of multi-resolution segmentation for the purposes of remote sensing, allowing for multi-source, multi-region, multi-method and multi-scale image analysis, that is well suited to landscape ecology and other urban forest research. Multi-resolution segmentation was the main segmentation algorithm used in this study and Esch et al. (2008, p. 2) describes the segmentation in the following manner: the segmentation is controlled by heterogeneity criteria color and shape. Color h_c is calculated:

$$h_c = \sum_b w_b \; * \; \sigma_b \tag{2}$$

where b = the band, w_b = the weight, and σ_b = the standard deviation of the band. The shape is composed of both smoothness h_{ss} and compactness h_{sc} which are calculated as follows:

$$h_{ss} = 1/k \tag{3}$$

$$h_{sc} = l/\sqrt{n} \tag{4}$$

where l = the length of the object's outline, k = the shortest length of the bounding box, and n = the number of pixels of the object. After each merge process, the change of heterogeneity, which flows into the fusion value S_f, was calculated in the following manner:

$$S_f = w_s h_c + (1 - w_s) h_s \tag{5}$$

where, w_s represents a user-defined weighting factor of the shape criterion.

The fusion value was then compared with a user-defined scale parameter which defines the maximum allowable heterogeneity of the image objects. By varying the scale parameter, arbitrary object levels with scale-specific segment sizes can be generated. An example of multi-resolution segmentation can be seen in Figure 8.

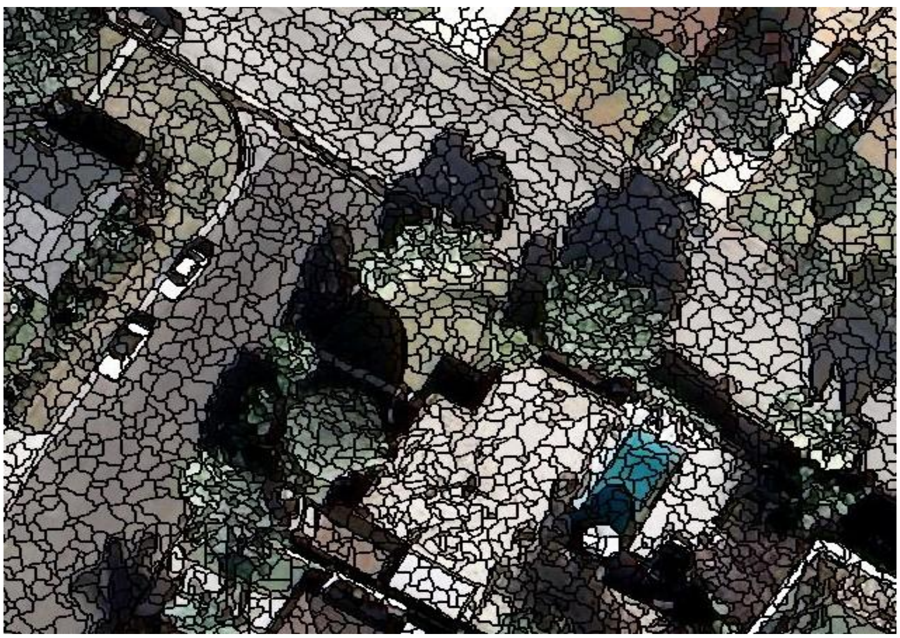

Figure 8 Example of multi-resolution segmentation

3.3.1 Extracting UTC

To extract the general UTC area, a multi-resolution segmentation was first applied to the RGB bands of the 1 ft orthoimage, taking advantage of the highest resolution of the dataset in this first segmentation to create the first primitive or sub-objects. Because the red band is known to provide the most vegetation information of the three bands, a higher weight could have potentially been assigned to it; however, weighting each of the three bands equally for the segmentation provided the best results for this particular extraction process. The smallest possible scale parameter or highest possible spatial resolution was chosen, allowing for the edges of even small trees to be properly segmented. The shape and compactness were set to 0.9 and 0.1, respectively. Setting the highest shape value possible (0.9) meant that less weight was given to color, providing good discrimination between grass and tree canopy cover. The compactness value (0.1) was chosen by testing several parameter combinations. Higher compactness values would have resulted in more bounded objects. Although some research has focused on the optimization of these parameters, this process still remains largely an iterative one for researchers, highly dependent on the dataset as well as the information being extracted.

In the next step, classification, the NDVI layer was used to differentiate between vegetation and non-vegetation sub-objects. Using a threshold condition of $\geq$ -0.045, lower than the more common > 0.1 NDVI threshold used to classify vegetation, leaf-off and sparsely leaved trees were clearly identified as such. Figure 9 shows a leaf-off tree in a parking lot (marked with an X) on the left, and is identified as a tree object in green on the right along with other green canopy. Within residential lots, lowering this threshold resulted in small misclassifications mainly over portions of light colored roofs, walkways, and driveways. These misclassifications were largely addressed during subsequent steps in the analysis. More prominent errors occurred over commercial areas where light colored surfaces tend to be more common. Here, larger areas of parking lots and commercial building roofs were confused with vegetation. These larger errors, however, were not relevant to the scope of this study and were later filtered out when

Figure 9 Example of leaf-off tree being identified as a tree in image analysis

single-family home residential lots were isolated for the analysis. For the purposes of this study, the benefit of more accurate leaf-off tree detection greatly outweighed the remaining degree of error.

Next, the LiDAR was used to discriminate between vegetation of different heights. Common thresholds for tree heights range between 5 and 8 ft, largely dependent on the tree type. For this study, a height threshold of 5 ft was chosen to classify trees, allowing for more flexibility in the data post-extraction where lower height values could easily be filtered out. More importantly, due to the coarseness of the NDVI and nDSM as well as the natural structure of most tree tops, tree heights tended to be underestimated. Setting this minimum height allowed for better identification of smaller trees and also of the edges of trees. This step also largely addressed any misclassifications over walkways and driveways. Finally, the vector building outline from LAC Assessor's 2013 cadastral data was used to mask out buildings, largely addressing the misclassifications over roofs. A merging operation was applied to tree canopy objects before extracting UTC objects and exporting them as vector polygon data. Figure 10 summarizes the aforementioned workflow.

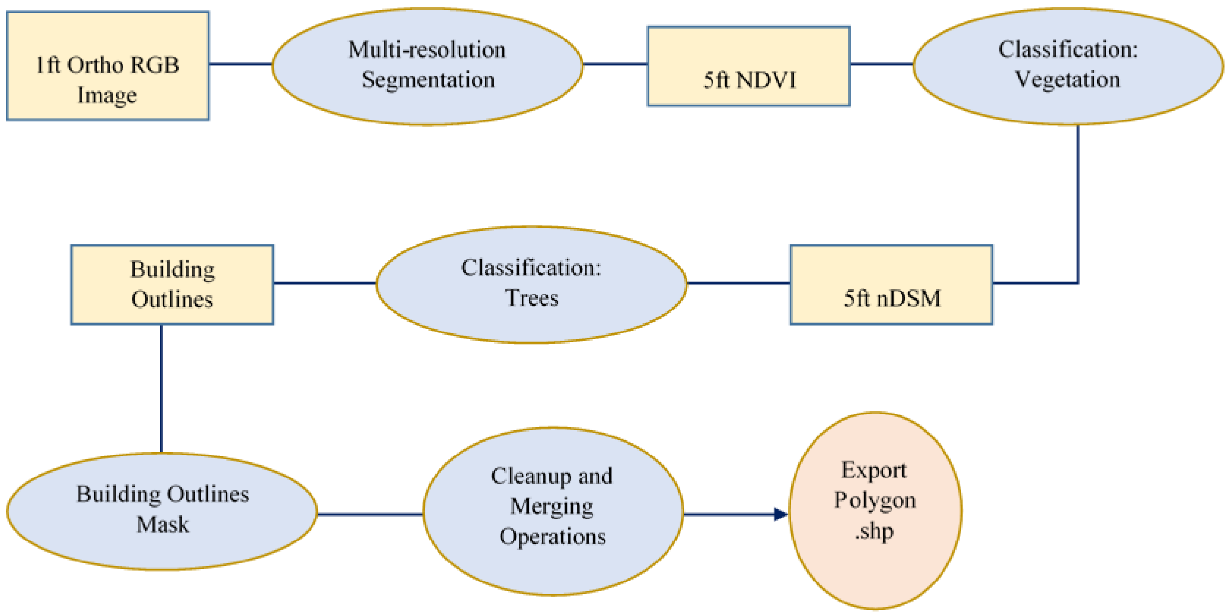

Figure 10 UTC extraction workflow

The resulting UTC extraction can be seen in Figures 11 and 12. Because of the coarseness in the LiDAR data, the UTC was slightly overestimated. This can clearly be seen in Figure 11, where the UTC is overlaid on a 4 inch RGB orthoimage. Figure 13 illustrates this problem more clearly. The coarseness of the nDSM in violet juxtaposed with the 1 ft orthoimage seen in green. The lightest violet colors show the highest points in the image. Figure 12 shows the resulting UTC extraction in vector format with and without a base image layer.

Figure 11 Resulting UTC extraction

Figure 12 Resulting UTC vector layer

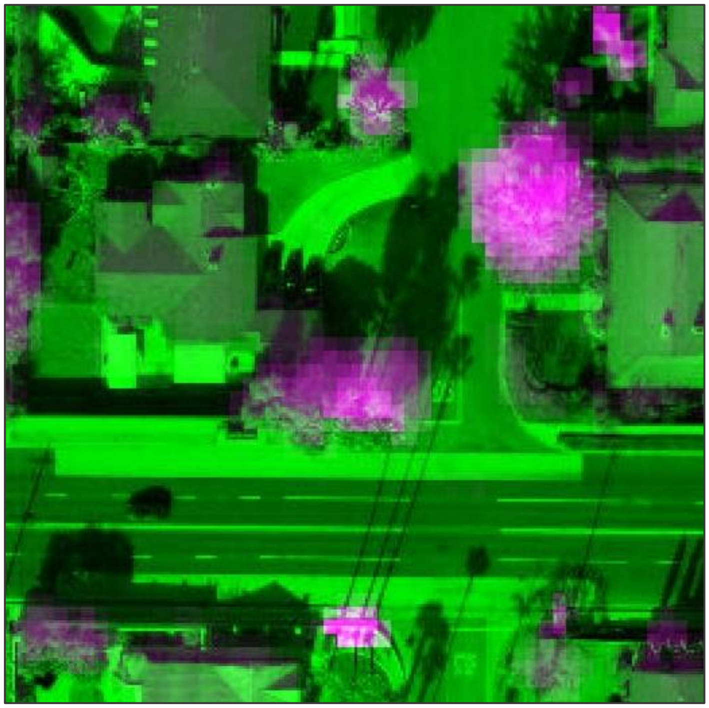

Figure 13 LiDAR data overlaid over a 1 ft orthoimage

3.3.2 Individual Tree Identification

In order to identify individual tree tops, the NDVI and nDSM layers were again utilized. A multi-resolution segmentation was applied with the lowest possible scale parameter, with a weight of 2 for the nDSM height layer and a weight of 1 for the NDVI layer. A lower emphasis on shape (0.3) and a higher compactness value (0.7) that would create more bounded objects was chosen because of the coarseness of the data (Figure 9). Using only these two layers of information provided better individual tree detection than when a sharper image was incorporated into the analysis. The same classification criteria for UTC was then applied, ≥ 0.045 for the NDVI and ≥ 5 ft for the nDSM. Here, a chessboard segmentation that divides the image into a predefined grid would commonly be applied to the areas classified as tree canopy before applying a local maxima algorithm to identify potential individual tree tops. Instead, a spectral difference segmentation that merges neighboring objects according to their mean layer intensity values was first applied, using both the nDSM and NDVI layers as equally valued weights. This method provided better results in this particular case with the particular set of parameters. The assigned search range value in the find local maxima algorithm is predefined normally depending on the forest type. The spectral difference segmentation provided more meaningful objects for the search range. In this highly heterogeneous urban forest, this method provided more accurate local maxima designation. After some clean-up operations, the resulting local maxima points or individual tree crown points were exported as vector data with height and NDVI attribute information. Figure 14 below describes the workflow and Figure 15 shows the individual tree identification results.

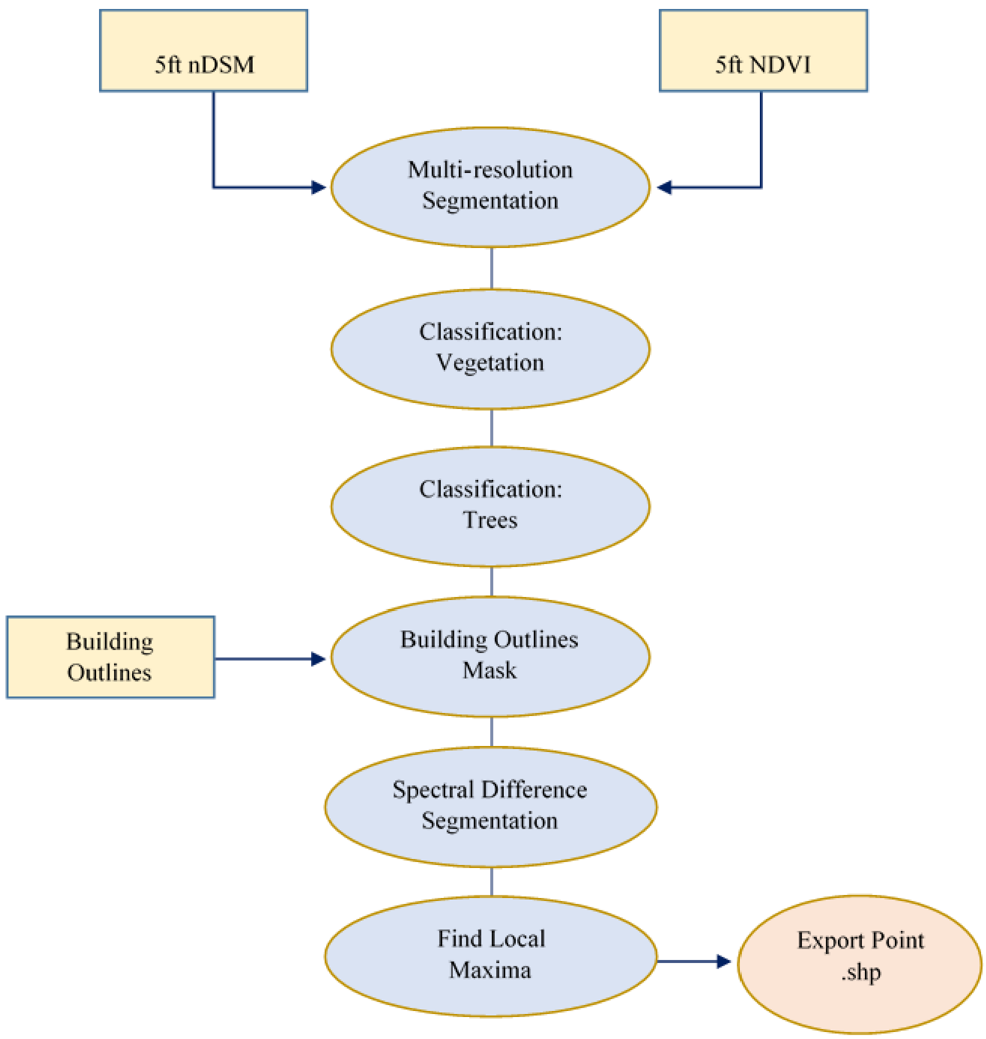

Figure 14 Individual tree extraction workflow

Figure 15 Extracted individual tree locations

3.4 GIS Methods

In traditional statistics, observations are assumed to exist in a world that is abstract and void of any external influences, in spatial statistics, the observations are real world phenomena with a location, and almost always exhibit regional and local trends. Post feature extraction, the remotely sensed data was imported into ArcGIS 10.2 for geostatistical analysis. An Ordinary Least Squared (OLS) global regression was applied to model the relationship between forest structure and several socioeconomic, demographic and cadastral variables. A Global Morans I was then applied to the residuals to check for spatial autocorrelation that would indicate spatial clustering of residuals and misspecification of the model due to some spatial variables not accounted for in the model but present in the relationship(s).

3.4.1 Dependent Variables

Four dependent variables were derived for the analysis, all with the use of the extracted urban forest data. Two aggregation levels were used to derive these variables: the first at the parcel level, and the second at the census tract level (the coarsest level of granularity and the level used for the regression analysis). Dependent variables at the census block group level included: Average Tree Density per Parcel (TDP); average Percent UTC Canopy Cover (PUTCC) per parcel; Trees per Person (TPP); and Average Tree Height (ATH) per parcel. Table 1 describes each of these variables in more detail.

Table 1 List of dependent variables at the US Census block group level

Variable	Abbreviation	Explanation	Problems
Average Tree Density per Parcel (TDP)	Avg_TDP	Number of individual trees per sq. ft of available planting area within each residential parcel, aggregated to the census block group level	Available planting area does not exclude pools or other hardscape and further image processing would be necessary to address; error in feature data extraction
Average Percent UTC Cover per Parcel (PUTCC_p)	Avg_PUTCC_p	Average percent urban tree canopy cover of available planting area within each residential parcel, aggregated to the census block group level.	Available planting area does not exclude pools or other hardscape; does not include UTC cover over buildings; error in feature data extraction
Average Tree Height (ATH)	ATH	The average tree height in census block group	Error in feature data extraction
Trees per Person (TPP)	TPP	Total number of trees in block normalized by the total census block group population	Error in the data extraction; US Census Bureau estimates

3.4.2 Derivation of Variables

To calculate dependent and explanatory variables, the LAC Assessor's cadastral data was first used to isolate single-family home parcels (SFHP). All other parcels including commercial and multiple family dwellings parcels were filtered out. Next, an erase overlay operation was applied to mask out buildings in SFHP parcels, leaving a theoretical Parcel Potential Planting Area (PPAP) within SFHP Parcels:

$$PPAP = Single\ Family\ Home\ Parcel\ (SFHP) - Building\ Footprint \qquad (6)$$

PPAP did not exclude pools or other impermeable surfaces, and further land-use classification methods or data layers would have to be added to identify them. Next, an overlay operation intersecting parcel features and the extracted individual trees was applied. This assigned a parcel identification number to each individual tree. This information was then summarized to a table by parcel number and was subsequently joined back to the parcel layer. The Tree Density per Parcel (TDP) was then calculated by dividing the total number of trees in each parcel t, by the potential planting area:

$$TDP = \frac{t}{PPA} \tag{7}$$

Next, to calculate the average PUTCC per parcel (the percentage of UTC within the potential planting area of each SFHP), the extracted UTC features were intersected with the SFHP layer, assigning a parcel identifier to each feature. Again a field summary operation was applied to the parcel identifier. A dissolve operation was used, aggregating UTC polygons to the parcel level, then calculating the area for each. Then the total UTC area u of each parcel was calculated and then divided by the PPA:

$$PUTCC = \frac{u}{PPA} \tag{8}$$

Another overlay intersect operation was applied to aggregate data to a second level. The average TDP and PUTCC per parcels for each census block was then calculated. To calculate the average PUTCC in each census block group, the UTC areas in each parcel were summed by census block group to a table, joined back to the analysis and then divided by total PPA in each census block group. The Average Tree Height (ATH) for each census block group was calculated and included as a dependent variable. Trees per Person (TPP) was also calculated by normalizing the total number of trees in each census block group by the total census block group population. Because these variables were measured at different scales, the possibility of introducing issues of MAUP (modifiable areal unit problem) and/or ecological fallacy into the models exists.

3.4.2 Explanatory Variables

Eight explanatory variables were derived at the census block group level including: Average Parcel Size, Average Building Age, and Average Property Value. In addition, single-level census block group level data calculations were performed to obtain: Population Density, Percent Hispanic, and Percent Asian. Two existing Census data fields, Median Age and Median Household Income, were also included as explanatory variables (Table 2). Figure 16 shows variables and data sources used to derive each variable.

Table 2 List of explanatory variables aggregated to the US Census block group level

Variable	Abbreviation	Explanation	Problems/Potential Error
Population Density	Pop_Den	People per square mile	US Census Bureau estimates
Percent Hispanic	Perc_Hisp	Percentage of Hispanics living in the census block group	US Census Bureau estimates (historically thought to be underestimated)
Percent Asian	Perc_Asian	Percentage of Asians living in the census block group	US Census Bureau estimates (historically thought to be underestimated)
Median Age	Med_Age	Median age of census tract population	US Census Bureau estimates
Median Income	Med_Incm	Median income of census tract population	US Census Bureau estimates
Average Parcel Size	Avg_PrclSz	Average parcel size in census block group, sq. ft	Error in cadastral data
Average Building Age	Avg_BldgAg	Average Age of home in the census block group	Error in cadastral data
Average Property Value	Avg_PrpVal	Average single home property value within study are and study parcels	Error in cadastral data

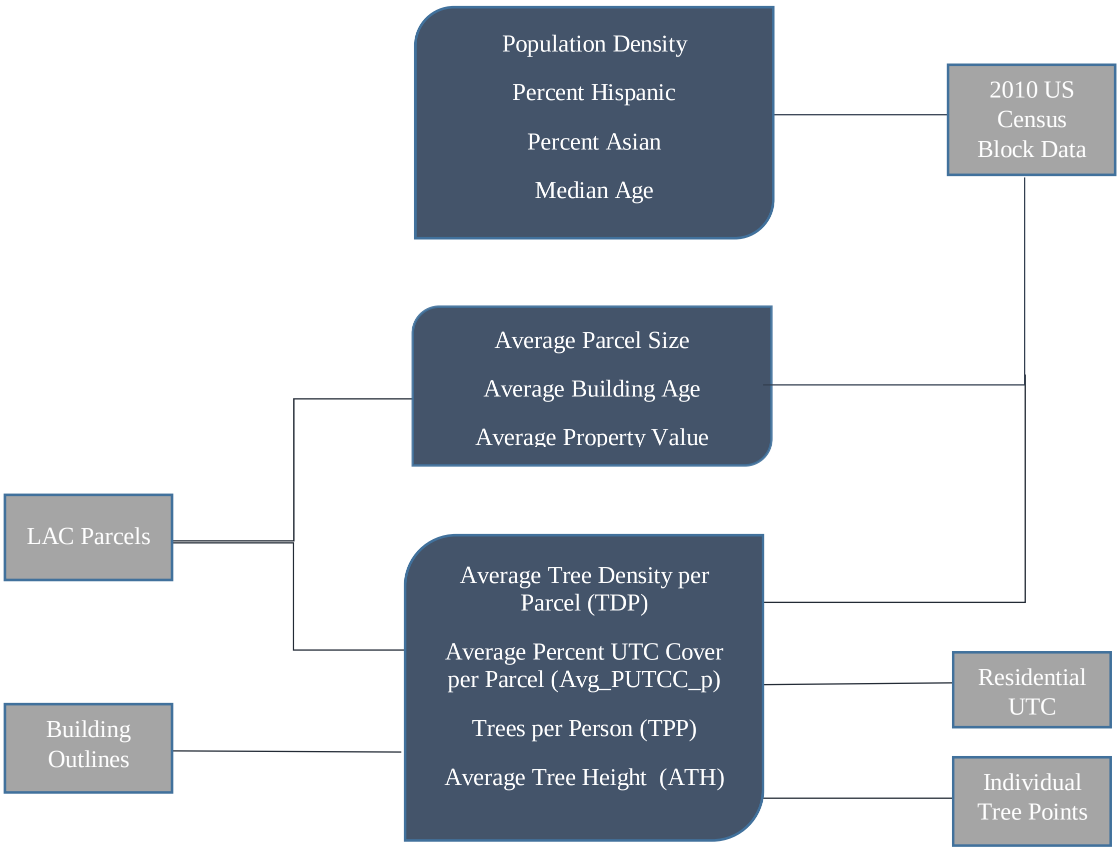

Figure 16 Data layers used to produce each variable

3.4.3 Exploratory Regression and OLS

Next, an exploratory regression was applied to each of the four dependent variables with the eight explanatory variables. The explanatory regression was used to explore variable significance when choosing explanatory variables for OLS models. All variables with no significance were removed. The suggested regression model(s) with the largest number of variables and consisting of only statistically significant p-values < .10 and highest R^2 values, were used as the starting point for fitting the OLS models for each of the dependent variables. A series of OLS models were tested for each variable. Results and models are discussed in the next chapter.

CHAPTER FOUR: RESULTS

Six of the 79 census block groups (CBGs) spanning the City of West Covina in 2010 were excluded from the analysis because they did not contain parcels classified as single-home residential, leaving 73 remaining census block groups in the analysis. With most of its land contained in the north, the results portrayed two distinct sides of West Covina: the northeast and the northwest. The northeast had higher Asian populations, higher incomes, larger lot sizes and newer homes. The northwest had higher concentrations of Hispanic populations and portrayed a more checkered and complex picture. While some links were found between urban forest structure and Hispanics, the more significant relationships were found between forest structure variables and Asian populations.

4.1 Spatial Patterns

Spatial patterns were detected in the demographic, socioeconomic, housing stock and urban forest structure data used in the analysis. The denser northwest was found to have larger numbers of CBGs with higher population densities (Figure 17a). Other CBGs with high population densities are located sporadically over the remainder of the city. Many of the least densely populated groups tended to be the ones with higher median ages (Figure 17b). Many census block groups did not follow this pattern, however. Higher concentrations of Hispanics tended to be located in the northeast portion of the City, while Asian populations tended to concentrate in the southwest (Figures 18a and 18b). The least densely populated CBGs tended to have some of the highest incomes with central West Covina having among the highest. Many census block groups with higher median incomes also occurred in the eastern portion of the city (Figure 19a). Some higher income neighborhoods were found in the northwest part of the city where Hispanic populations also tended to concentrate (Figure 19a), despite the higher property values

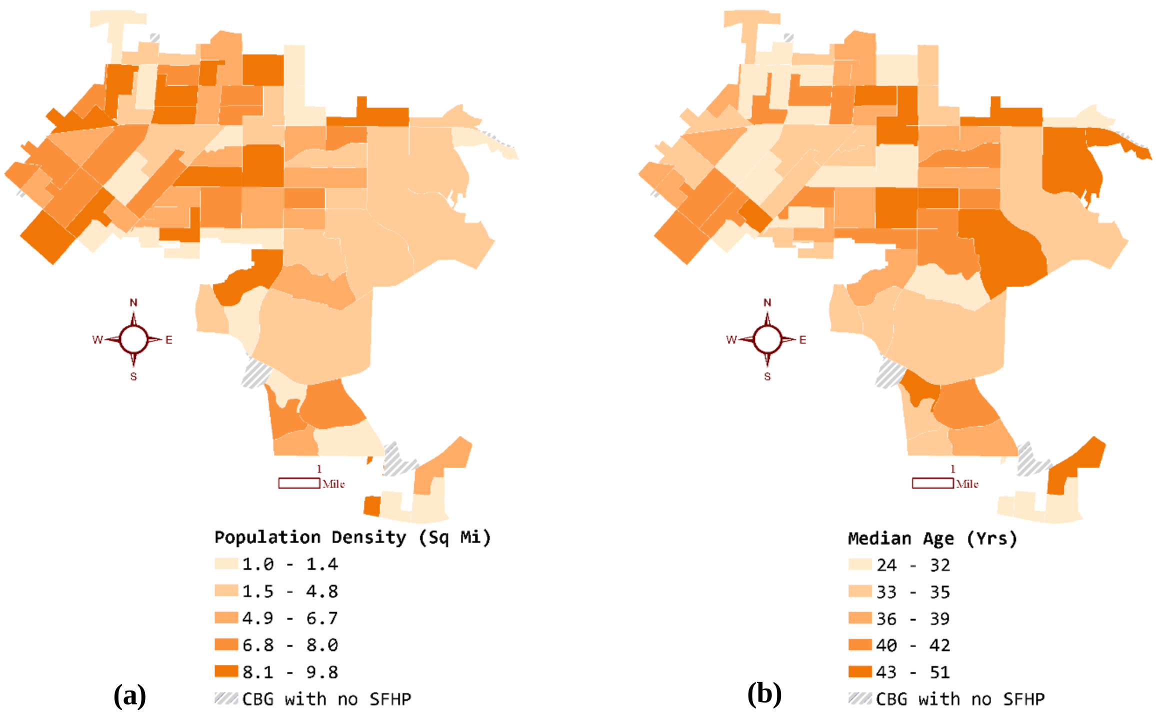

Figure 17 Maps of Population Density (a) and Median Age (b) by census block group

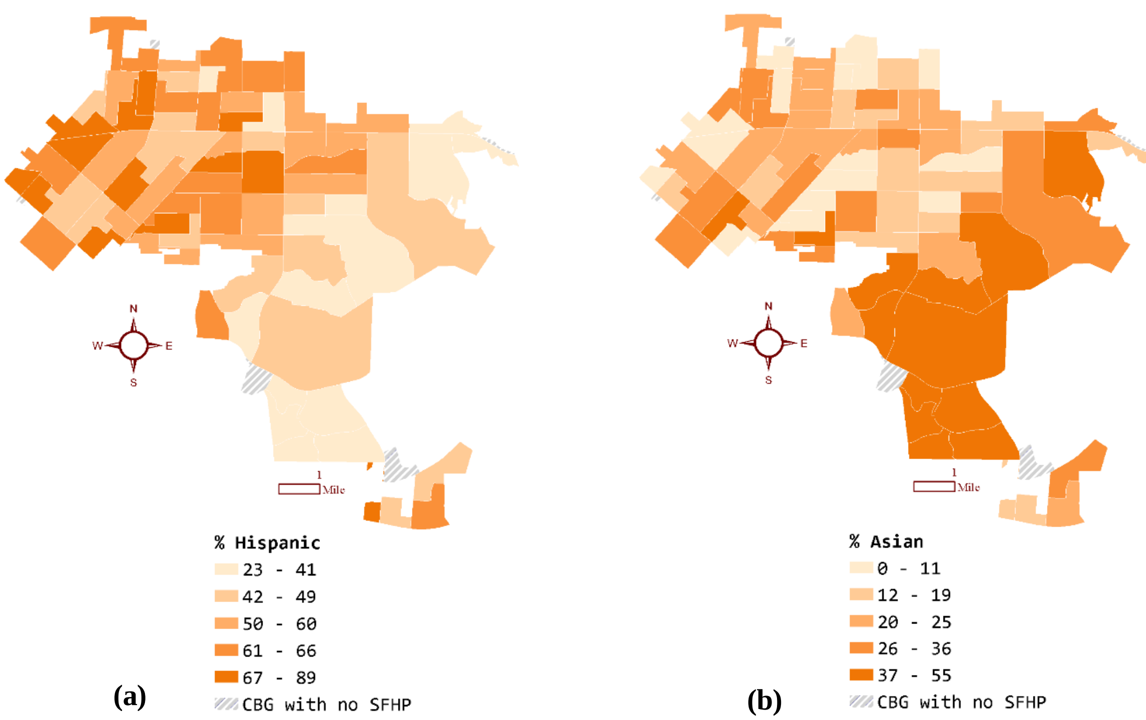

Figure 18 Maps of Percent Hispanic (a) and Percent Asian (b) by census block group

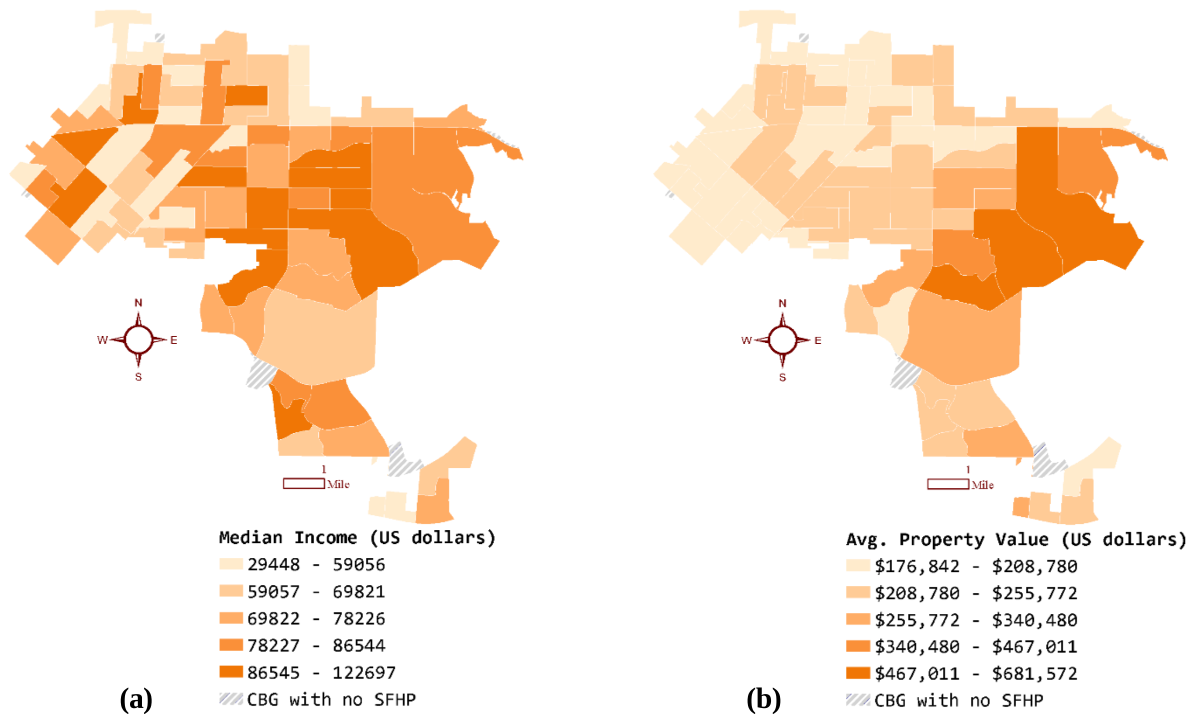

Figure 19 Maps of Median Household Income (a) and Average Parcel Size (b) by CBG

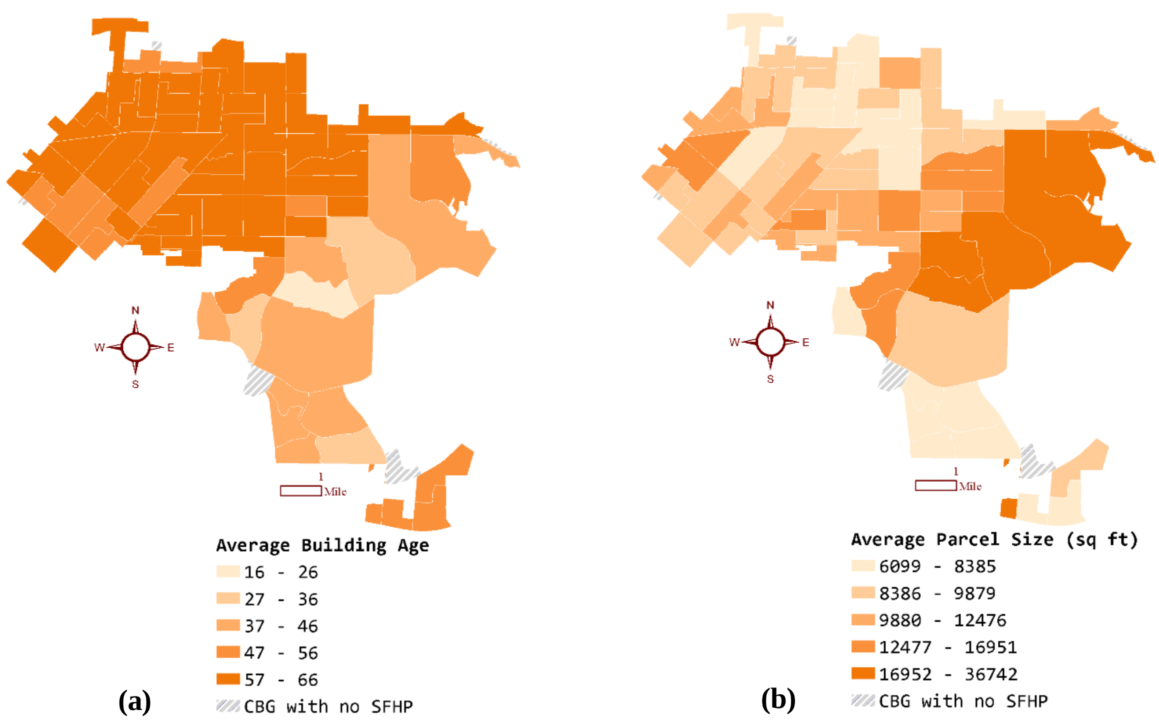

Figure 20 Maps of Average Building Age (a) and Average Parcel Size (b) by census block group

and larger lot sizes found in the eastern areas of the city (Figures 19b and 20b). Some high Hispanic, high income and low property value census block groups were located in the northwestern quadrant. Older homes also tend to be located in the northwest, with most homes in these areas having been built over 50 years ago (Figure 20a).

The urban forest structure data that was derived did not show such clear patterns at the CBG level, with the exception of TDP. The average tree density per parcel (TDP) was found to be higher in the south and eastern portions of the city, as well as in some CBGs located in the northwest part (Figure 21a). A similar but less pronounced pattern can be seen for UTC cover. The average percent UTC cover in these areas seemed to be higher, where higher property values, more people of Asian descent and higher incomes were also found. Some CBGs in the northeast part of the city also showed higher tree densities and percentages of UTC cover. The average height of trees (ATH) and trees per person (TPP) did not show strong patterns (Figure 22), however there were some clusters of CBGs with higher ATH in the eastern, western, and central areas of the city.

4.2 Summary of Regression Results

Three tables are included for each of the modeled relationships: an exploratory summary of variable significance, a table showing OLS regression results including coefficients and p-values, and a table showing other OLS statistical tests. None of the variables in the models were found to have VIF (Variance Inflation Factor) values greater than 7.5 (> 7.5). Values greater than 7.5 would have indicated high multi-collinearity between variables (O'Brian 2007; Esri 2014). With the exception of Average Tree Density in Parcel, all variables used in the models were used were at the > 90% significance level for either probability or robust probability values. The Koenker

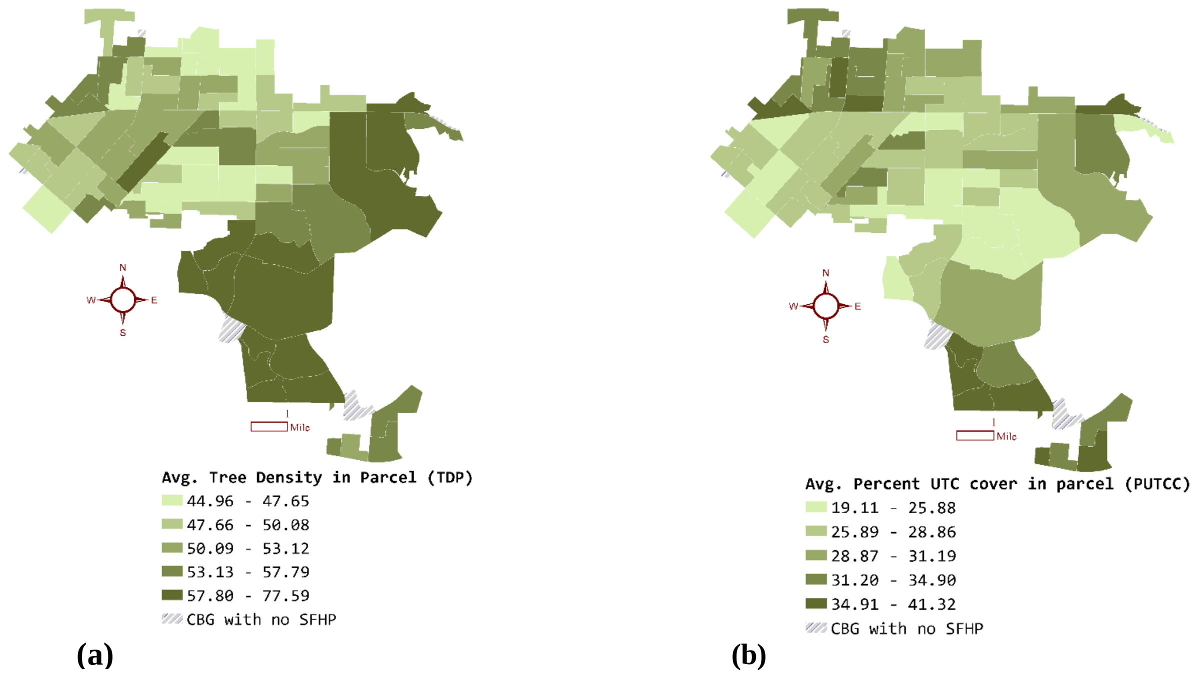

Figure 21 Maps of average TDP (a) and average PUTCC (b) per parcel

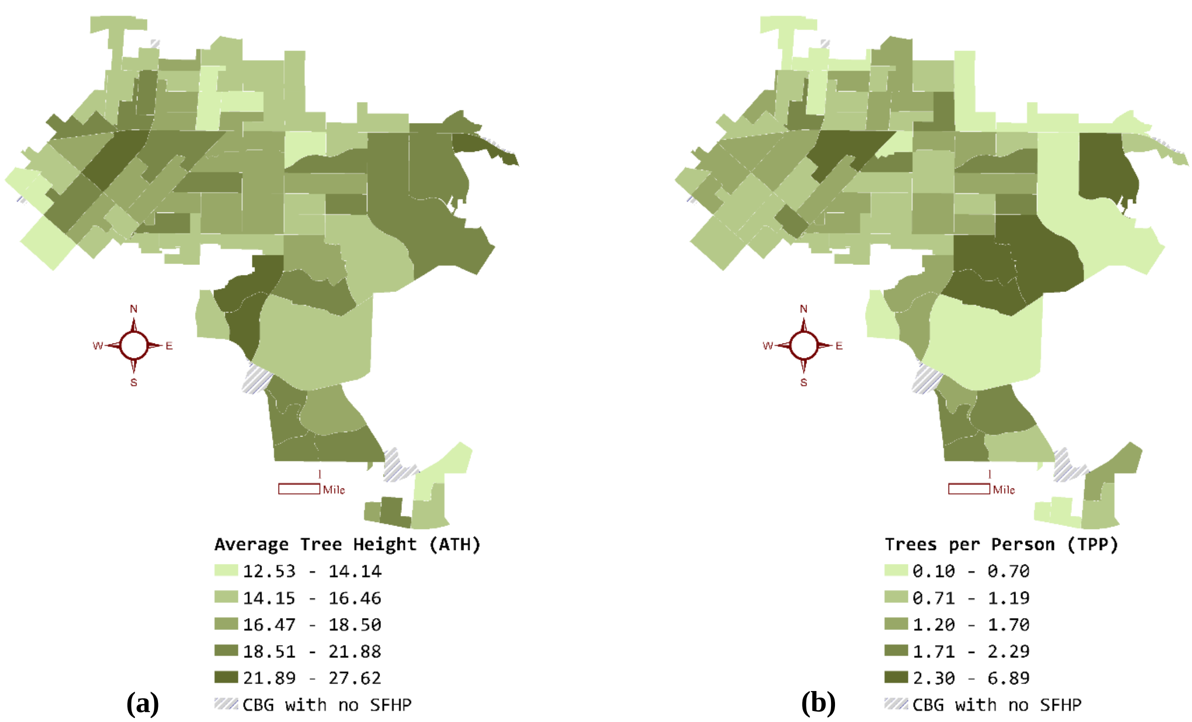

Figure 22 Maps of ATH (a) and TPP (b) by census block group

Breusch-Pagan test was not statistically significant ($p < 0.01$) for any of the models. A statistically significant Koenker (BP) value would have indicated the relationships modeled were not consistent due to non-stationarity or heteroscedasticity (Cai et al. 1998; Esri 2014). Jarque-Bera, one of the most commonly applied tests to evaluate model fit was not found to be statistically significant ($p < 0.01$) for any of the models. (Jarque and Bera 1987; Esri 2014). This indicated that the residuals were not found to be normally distributed and that no significant bias was found in the predictions due to non-linear relationships, data outliers or other problems. (Esri 2014).

Tables 3 through 5 show the results for the average tree density (TDP) per parcel model. A statistically positive relationship was found between the percentage of Asians living in the area and tree density in residential parcels. In addition, parcels with older homes tended to have lower tree densities irrespective of parcel size.

Table 3 Exploratory regression results after applying OLS regression to all possible combinations of explanatory variables: average Tree Density per Parcel (TDP)

Variable	Percent Significant	Percent Negative	Percent Positive
PERC_ASIAN	100.00	0.00	100.00
AVG_BLDGAG	100.00	100.00	0.00
AVG_PRPVAL	50.00	50.00	50.00
PERC_HISP	25.00	64.06	35.94
MED_AGE	23.44	99.22	0.78
AVG_PRCLSZ	18.75	48.44	51.56
POP_DEN	0.00	82.03	17.97
MED_INCM	0.00	15.62	84.38

Table 4 OLS regression coefficients and significance levels: average TDP

Variable	Coefficient	P-Value	Robust P-Value	VIF
Intercept	73.536757	0.000000***	0.000000***	--------
PERC_HISP	0.061253	0.199206	0.135847	1.800252
PERC_ASIAN	0.151828	0.007432***	0.013586**	1.920284
AVG_BLDAG	-0.501719	0.000000***	0.000000***	1.557480

*Significant at 90% level **Significant at 95% level ***Significant at 99% level

Table 5 OLS regression diagnostics: average TDP

n	73
Multiple R^2	0.616370
Adjusted R^2	0.599690
Koenker (BP) Statistic	12.571826
Jarque-Bera Statistic	16.699200
Global Morans I	1.604524

Tables 6 through 8 show the results for the percentage of UTC over residential lots OLS model. A positive relationship was also found between higher percentages of UTC on residential lots and Asian populations. In addition, median age and property value were also found to be statistically significant but negatively correlated with UTC.

Table 6 Exploratory regression results after applying OLS regression to all possible combinations of explanatory variables: average Percent UTC Cover (PUTCC) per parcel

Variable	Percent Significant	Percent Negative	Percent Positive
AVG_PRPVAL	97.66	100.00	0.00
PERC_ASIAN	53.12	0.00	100.00
MED_AGE	45.31	100.00	0.00
AVG_PRCLSZ	10.16	50.00	50.00
AVG_BLDGAG	9.38	68.75	31.25
MED_INCM	7.81	100.00	0.00
POP_DEN	0.00	96.88	3.12
PERC_HISP	0.00	39.84	60.16

Table 7 OLS regression coefficients and significance levels: average PUTCC per parcel

Variable	Coefficient	P-Value	Robust P-Value	VIF
Intercept	37.853496	0.000000***	0.000000***	--------
PERC_ASIAN	0.087237	0.025322**	0.027469**	1.143105
MED_AGE	-0.178216	0.030954**	0.045515**	1.076361
AVG_PRPVAL	-0.000014	0.006765***	0.029085**	1.099178

*Significant at 90% level **Significant at 95% level ***Significant at 99% level

Table 8 OLS regression diagnostics: average PUTCC per parcel

n	73
Multiple R^2	0.178507
Adjuster R^2	0.142789
Koenker (BP) Statistic	5.891550
Jarque-Bera Statistic	1.300332
Global Morans I, z-Score	0.708727

A statistically significant negative relationship was found between the number of Hispanics in each census block and the average height of trees (ATH) within SFHP parcels in the study area (Tables 9-11). Higher numbers of Hispanic residents were associated with lower tree heights. In contrast, the relationship between Asian populations and tree heights was positive. Taller trees tended to be correlated with higher Asian population numbers. Median age was negatively correlated: a younger demographic profile in the census block group was associated with taller trees. Higher incomes, higher property values and larger parcel sizes were also associated with taller trees. Properties with older homes tended to have shorter trees in addition to lower concentrations and lower percentages of canopy cover.

Table 9 Exploratory regression results after applying OLS regression to all possible combinations of explanatory variables: Average Tree Height (ATH) per census block group

Variable	Percent Significant	Percent Negative	Percent Positive
AVG_PRCLSZ	100.00	0.00	100.00
MED_AGE	96.88	100.00	0.00
AVG_BLDGAG	57.81	100.00	0.00
MED_INCM	50.00	0.00	100.00
PERC_HISP	46.88	100.00	0.00
AVG_PRPVAL	43.75	50.00	50.00
PERC_ASIAN	29.69	0.00	100.00
POP_DEN	0.00	100.00	0.00

Table 10 OLS regression coefficients and significance levels: ATH per census block group

Variable	Coefficient	P-Value	Robust P-Value	VIF
Intercept	33.266574	0.000000*	7.608690	--------
PERC_HISP	-0.063328	0.005185***	0.010868***	1.660652
MED_AGE	-0.212528	0.000058***	0.000057***	1.386687
MED_INCM	0.000034	0.035142**	0.016711***	1.203189
AVG_PRCLSZ	0.000344	0.000010***	0.000002***	3.362716
AVG_BLDGAG	-0.107541	0.010924***	0.041534**	2.288284
AVG_PRPVAL	0.000021	0.000597***	0.002280***	4.931695

*Significant at 90% level **Significant at 95% level ***Significant at 99% level

Table 11 OLS regression diagnostics: ATH per census block group

n	73
Multiple R^2	0.446353
Adjuster R^2	0.396022
Koenker (BP) Statistic	5.000781
Jarque-Bera Statistic	1.520840
Global Morans I, z-Score	0.319906

The TPP (Trees per Person) dependent variable model found that more trees per person were associated with higher incomes, higher property values and lower median ages (Tables 12-14). Areas with higher percentages of Hispanics tended to have fewer trees per person. Higher Asian populations pointed to more robust urban forest plots, with more trees per person being associated with higher concentrations of Asian residents.

Table 12 Exploratory regression results after applying OLS regression to every possible combination of explanatory variables for Trees per Person (TPP) per census block group

Variable	Percent Significant	Percent Negative	Percent Positive
MED_INCM	100.00	0.00	100.00
PERC_HISP	89.84	100.00	0.00
AVG_PRPVAL	87.50	0.00	100.00
MED_AGE	74.22	0.00	100.00
PERC_ASIAN	29.69	9.38	90.62
AVG_BLDGAG	10.94	48.44	51.56
AVG_PRCLSZ	7.81	50.00	50.00
POP_DEN	0.00	21.09	78.91

Table 13 OLS regression coefficients and significance levels: Trees per Person (TPP) per census block group

Variable	Coefficient	P-Value	Robust P-Value	VIF
Intercept	-0.790664	0.391922	0.446162	--------
PERC_HISP	-0.011530	0.112201	0.050013**	1.330502
MED_AGE	0.027891	0.109947	0.098454*	1.265537
MED_INCM	0.000011	0.066781*	0.003808***	1.197055
AVG_PRPVAL	0.000004	0.000335***	0.066007*	1.233927

*Significant at 90% level **Significant at 95% level ***Significant at 99% level

Table 14 OLS regression diagnostics: Trees per Person (TPP)

n	73
Multiple R^2	0.413886
Adjuster R^2	0.379408
Koenker (BP) Statistic	25.757151
Jarque-Bera Statistic	73.106057
Global Morans I, z-Score	0.577187

4.3 Research Questions

The goal of course, was to use the aforementioned results to answer the four research questions posed in Chapter 1. The following bullets summarize what was learnt about socio-cultural and ecological processes and outcomes in the City of West Covina.

1. **Are there quantifiable differences in urban forest structure within predominantly Hispanic and non-Hispanic neighborhoods in LAC?**

   An inverse relationship between higher tree densities and the height of trees and Hispanic populations was found, however, although the p-values were significant, the coefficients were small. The highest UTC was associated with CBGs with large Asian populations and no significant relationship was found between UTC and percent Hispanic.

2. **If so, what do these structural differences suggest about urban tree management practices taking place in Hispanic neighborhoods?**

   The results support the notion that Hispanic neighborhoods tend to have a higher number of smaller trees with no significant increase or decrease in UTC cover. However, although the relationship was significant it was not found to be particularly strong and extending the study to a larger area may yield clearer and more significant results.

3. **How does urban forest structure in Hispanic neighborhoods compare with that in neighborhoods of a different makeup?**

   Asian populations were found to have positive associations between all forest structure data. A statistically significant and positive relationship was found between large Asian populations, tree density, tree height and UTC cover.

4. **Are there other socioeconomic, demographic or physical influences affecting urban forest structure in LAC?**

   A negative, statistically significant relationship was found between building age and tree density. Older homes tended to have lower tree densities. UTC and median age also had a negative relationship. More UTC was associated with CBGs with younger populations and lower property values. Taller trees were associated with CBGs with younger populations, higher incomes, larger parcels, newer homes and higher property values.

CHAPTER 5: DISCUSSION AND CONCLUSIONS

Are residential green spaces in Hispanic neighborhoods more rural in nature? If there are more urban agricultural practices taking place in certain areas what does that mean for the landscape? Are there more fertilizers and pesticides being used that may be leaching into the soil? What are the implications given the water shortages in California? These are larger questions that should be addressed.

This study set out to analyze the relationship between culture and urban ecosystems by studying the relationship between Hispanic populations and urban forests in Los Angeles. Because the largest percentage of Hispanic immigrants in Los Angeles have historically come from rural, often agriculturally fertile areas in Mexico, urban forest structure was studied to identify possible differences in the management practices of privately owned residential trees in Hispanic neighborhoods. Using remote sensing techniques to extract urban forest structure data and geostatistical tools to map and analyze these relationships, three variables describing urban forest structure within single home residential parcels for the City of West Covina were derived and analyzed: the average density of trees within each parcel, the percentage of UTC cover over each residential lot, and the average height of trees in lots spanning 73 census block groups in the study area. When controlling for several factors including parcel size, property value and income levels, a statistically significant relationship at the 90% confidence level was found between Hispanic and/or Asian populations and all three dependent variables.

The lower tree heights found in Hispanic neighborhoods support the idea that Hispanic immigrants may have larger numbers of fruit trees that tend to be kept at shorter heights. This could also suggest larger percentages of younger trees. Overall, one of the most significant (positive) relationships identified was between Asian populations and tree density within each parcel: the percentage of Asians and average building age in the census block alone explained over 60% of the variation in tree density. There were other positive links between Asians and urban forests: neighborhoods with higher percentages of Asian residents were found to have taller trees as well as higher percentages of UTC cover. Obtaining individual tree point data provided more samples and therefore richer data extraction at multiple level. Delineation of each individual tree crown for measurement, which was not achieved in this study, would have provided additional information on urban forest structure. Finer-scale inputs with individual tree points, refining the study area and applying two levels of aggregation (parcel and parcel census block group) were methods applied in an attempt to yield finer-scale results. In future studies, ownership rates as well as other ethnic and racial backgrounds should be incorporated. In addition to a change detection analysis, extremely useful in studying these relationships, an improved feature extraction, achieving individual tree crown delineation and more accurate delineation of potential planting area per parcel (PPAP) could be useful. Utilizing more cognitive variables during the feature extraction would have improved the image classification and feature data extraction, increasing accuracy. In addition, being able to differentiate between tree species could provide valuable information and clearer answers (see Figure 18 for example).

The interactions studied here, however, remain highly complex, and more work, layered on top the results shown here and using other methods such as random surveys of residents, would be needed to accept or reject the hypothesis that Hispanics and/or Asians have a unique approach to managing urban trees. The self-sustainability practices as well as the cultural, political, economic, and ecological dynamics experienced by an immigrant both in their place of origin as well as their new environment all have the potential to influence the value placed on and the management practices of privately owned urban residential green spaces. The degree of need for assimilation in the host country also plays a role. The term ‘‘ecology of prestige’’, for example, suggests that a household's land management decisions are influenced by its desire to uphold the prestige of its community and outwardly express its membership in a given lifestyle group (Troy et al. 2007). Studying these spatial relationships can shed insight into these dynamics and their significance (Figure 23).

Figure 23 Photo of the front yard of a home in a West Covina Hispanic neighborhood showing a newer avocado tree and full grown orange tree.
Photo by Kathy M. Ulloa

Understanding these relationships can inform us in improving our urban forests as efforts need to reach beyond government agencies. Outreach campaigns can be targeted towards maintaining established trees and not just planting new ones. More education on the importance and care of trees may prove useful in Hispanic neighborhoods. As forest structure spatial data becomes increasingly common in urban centers, exploiting the data to analyze these complex relationships can serve as groundwork for other studies.

Differing management practices can have unexpected implications. Because shorter trees take up more space near the ground, for example, it can mean less open space available for children to play. This could potentially also mean closer and more frequent contact with fertilizers and pesticides used for fruit trees. Although the importance of urban forests has been well studied, understanding the ecological processes taking place and how factors like culture is influential remains underexplored. It is important to understand these dynamics both to mitigate losses and improve urban forest health. As the world increasingly becomes more urban, and complex urban ecosystems grow in size and importance, the spatial sciences will increasingly take a lead role in their study, seizing the opportunity for improvements through better understanding of processes and what they offer.

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