GEOGRAPHIC ASSESSMENT OF URBAN QUALITY OF LIFE USING SOCIO-ECONOMIC AND ENVIRONMENTAL FACTORS ACROSS MEXICO CITY

By

GUSTAVO ALBERTO OVANDO MONTEJO

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Thesis Approved:

Amy E. Frazier

Thesis Adviser

Jonathan Comer

Thomas A. Wikle

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Abstract: Urban areas are places of economic and social development characterized by progress and improved standards of living, especially in the developing world where some areas have become places of convergence, resembling many affluent cities in the developed world. However, cities are also areas of great social, economic and environmental impairment where a multitude of issues can spatially combine to produce places of hardship and depravation. This economic disparity coupled with spatial segregation between the rich and the poor has led to the argument in Latin America that inequality in terms of income and socio-economic status is the most characteristic trait of the social structure of cities, even more so than poverty. In recent years urban quality of life studies have been developed that incorporate socio-economic as well as environmental data. Their results suggest geographic distribution of inequality might not only be restricted to pockets of socio-economic factors but that they might also be representative of environmental inequality. Yet very few studies have explored how the socio-economic information relates to the environmental factors or how to significantly describe the spatial patterns of quality of life as they relate to the socio-economic and environmental structure of the city. This paper evaluates a quality of life index for Mexico City that takes into account social as well as environmental factors and further analyzes the spatial characteristics of quality of life by applying geographic clustering techniques. Furthermore, it explores the relation between environmental and social factors through a regression model.

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CHAPTER I

INTRODUCTION

Urban areas around the world are places of economic and social development where people have a wide range of options from which to make a living. In many cases urban areas are symbols of progress and improved standard of living, especially in the developing world where some areas of major cities become places of convergence, resembling any affluent city in the developed world (Aguilar and Ward 2003). However, cities are also areas of great social, economic and environmental impairment where a multitude of issues can combine to produce places of hardships and deprivation. This is especially true in developing nations, where urbanization rates are among the highest in the world and where urbanization can be a vague idea rather than a factual description of a place (Cohen 2006). In many developing cities there are zones or neighborhoods that lack the basic infrastructure to facilitate amenities that most persons would identify as an integral part of an urban place, such as paved roads, electricity, or running water (Brugmann 2009). Furthermore, cities can also be places of extreme socio-economic polarization and stratification which often spatially divide the “haves” from the “have-nots”. These characteristics make developing cities places of high contrasts and create a diversity of problems that must be studied geographically to better understand their distribution, patterns, and general characteristics to mitigate their negative effects on the communities.

Indices of urban environmental quality and urban quality of life have been developed in order to measure the conditions under which people live, work, and carry on with life. These measures have become important tools that serve as summaries of complex social conditions that guide the creation of new policies aiming at reducing urban struggles and promoting smart and sustainable growth (Hagerty et al. 2001; Shen et al. 2011). Many indices incorporate a variety of socio-economic variables through quantitative techniques in order to produce numerical summaries of what constitutes a satisfactory urban life (Kamp et al. 2003; Fan and Qi 2009; Kropp and Lein 2012). Yet, defining what is satisfactory or suitable introduces a great deal of ambiguity surrounding the terms 'quality of life' and 'environmental quality', and hence there is some ambiguity in indices attempting to quantify these characteristics. To manage this complexity, indices can be broadly divided into objective and subjective indicators. Objective indices utilize numerical measures to describe the environment, amenities, and benefits that living in certain areas of a city provide, such as crime rate, access to health care, education, and areas of leisure and recreation, to name a few. On the other hand, subjective indicators attempt to describe the ways in which people perceive and rate the urban landscape around them (Pacione 2003). In many cases, both types of indices have been merged, providing depth and dimensionality to the concept of describing human well-being (Diener and Suh 1997; Somarriba and Pena 2009; Rezvani at al. 2012; Feneri et al. 2014)

Furthermore it has been argued that the quality of life or livability of a place is a direct result of the interaction not only between social and economic characteristics of a city but also the physical domain (Shafer et al. 2000). The physical domain refers to the natural elements and processes that constitute the natural landscape such as weather conditions and climate, air, relative location, water, vegetation patterns, etc. The physical domain is often overlooked in urban studies given that cities are often thought of as the pinnacle of synthetic processes and man-made alterations to the natural landscape; however the physical factors representing the environment are always present even in subtle ways (Diener and Suh 1997; Hagerty et al. 2001; Pacione 2003; Felix and Garcia-Vega 2012).

Therefore, the interactions between socio-economic and environmental factors must be studied together in space in order to achieve a holistic measure of the quality of a place. An issue with this type of approach is that environmental data are often obtained directly from field measurements where sampling is conducted in an aspatial manner, which obfuscates interpretations and the accuracy of the results obtained (Weng 2010). In recent years, however, the use of geospatial technologies has improved the spatial integration of biophysical and socio-economic data so that these data can be spatially displayed and analyzed with ease in a digital environment (Bian 2007; Weng 2010). More specifically, remote sensing offers the ability to collect spectral data of large geographic areas that can be reliably converted into valuable environmental information in an efficient manner. Geographic information systems (GIS) offer a flexible computational environment where environmental data, retrieved from remote sensing, can be merged and analyzed with socio-economic information retrieved from census datasets. The integration of these technologies is well developed and has been used extensively to create holistic measures of socio-environmental systems at urban and regional scales (Mesev 1997; Bian 2007; Weng 2010).

A pioneering study in the incorporation of remotely sensed data into quality of life studies was carried out by Green (1952) in which two scales were developed to measure quality of life in Birmingham, Alabama. The first was termed residential livability scale. The livability was based on the incorporation of physical data extracted from aerial photography and included variables such as land use within and adjacent to residential areas, distance to the central business district, number of single family homes, and housing density. The second scale was termed the socio-economic status scale and was based on an agglomeration of census and crime data. Green (1952) ultimately concluded that both physical and socio-economic scales were highly correlated. Similarly, Forster

(1983) realized the value of using multispectral satellite imagery to extract physical-domain data for quality of life studies. Using a combination of Landsat Multi Spectral Scanner (MSS) and census data for Sydney Australia, the author concluded that housing values can be accurately predicted based on the conjunction of both data types.

Following a similar line of research, Lo (1997) develop a quality of life index for Athens, Georgia where a fusion of census and environmental data was also incorporated using Landsat data, specifically information captured with the Thematic Mapper (TM) sensor. More specifically, this study derived three environmental variables from Landsat imagery: surface temperatures, percent urban, and vegetation vigor or greenness. The pixel values in their original raster formats were then aggregated to census block groups. Using principal component analysis (PCA), the environmental variables were incorporated with select socio-economic variables including population density, per capita income, median house value, education etc. The index values from the principal factor obtained from PCA were used as summaries of the quality of life for Athens. However, the first factor could only explain half the variability of all socio-economic and environmental variables, hence limiting the amplitude of the description of the quality of life index.

More recently and based on this issue, Li and Weng (2007) developed a method to create a composite quality of life index that combines all significant factors derived from PCA. This method weights each factor based on the percentage of variability it can explain from the original socio-economic and environmental data, resulting in a more comprehensive representation of urban quality of life. In this study, the principal environmental variables derived from Landsat Enhanced Thematic Mapper (ETM+) were surface temperature, vegetation vigor, and the percentage of impervious surfaces. These variables have been widely adopted to represent major physical variables of the urban environment due to the dimensions that they can contribute to quality of life studies and the relative ease with which can they can be derived from Landsat imagery (Liang and Weng 2011).

In the case of surface temperatures, research has demonstrated that high temperatures are perceived as undesirable for people, especially in urban areas where the heat island effect is a negative byproduct of the human alteration of the environment (Lo and Quattrochi 2003; Nichol and Wong 2005; Liang and Weng 2011). This variable is a good indicator of the level of change and destruction of the natural environment by human activities. Percentage of impervious surfaces refers to the amount of concretization that the natural landscape has experienced (Arnold and Gibbons 1996). High percentages of impervious surfaces are considered the result of unnatural processes that negatively affect the natural well-being of any geographic area.

Research has also demonstrated that urban vegetation is essential for an optimal quality of life since it works as a natural counter solution to the urban heat island, ameliorates urban pollution by improving air quality, and provides shelter and recreational areas for urban dwellers (Nichol and Wong 2005; Heynen 2006; Shen et al. 2013). Although there is not one definitive metric to establish what constitutes healthy vegetation in the urban landscape, research has demonstrated that the amount of green areas, especially parks, have a direct correlation with healthy lifestyles (Gómez et al. 2011). For example, people living within close proximity to green areas and parks have less risk of adult and childhood obesity, better immune respiratory systems, and are more likely to exercise on a daily basis (Wolch et al. 2011). Current research in urban planning has identified that European countries with a centralized general plan that includes green infrastructure such as high amounts of parkland, protected wetlands, and scenic views have very high sustainability ratings and quality of life standards (Tzoulas et al. 2007).

Many quality of life studies have been conducted for cities and even entire regions around the world using a similar methodology developed by Li and Weng (2007) along with the environmental variables described above. More specifically, they have been developed for Massachusetts, U.S. (Ogneva-Himmelberger et al. 2013), Addis Abbaba, Ethiopia (Tesfazghi et al. 2010), Dhaka City, Bangladesh (Dewan et al. 2013), Casa Blanca, Morocco (Berrada et al. 2013), Karachi City, Pakistan (Afsar et al. 2013), and Uttarakhand, India (Rao et al. 2011). Many of these studies have shown that high income areas usually have greener spaces, lower surface temperatures and hence lower percentages of impervious surfaces. This hints that the geographic distribution of inequality might not only be restricted to socio-economic conditions but might be also representative of environmental inequality. The studies noted previously have successfully implemented the method developed by Li and Weng (2007) using PCA as a way to pragmatically merge environmental and socio-economic data in order to develop overall quality of life indices. Yet very few studies have explored how the socio-economic information relates to the environmental factors or how to significantly describe the spatial patterns of quality of life as they relate to the socio-economic and environmental structure of the city.

Understanding the relationship between the socio-economic and environmental factors and describing the spatial patterns of quality of life is especially important for cities in the developing world since they are characterized by very high levels of economic disparity coupled with spatial segregation between the rich and the poor. It has been argued for example, that in Latin America, inequality in terms of income and socio-economic status is the most characteristic trait of the social structure of the cities, even more so than poverty (Aguilar and Mateos 2011). More specifically for Mexico City, a quality of life study has never been carried out that can incorporate socio-economic and environmental variables at very high levels of disaggregation.

The overall objective of this research is two-fold. First, this research evaluates a quality of life for Mexico City that takes into account social as well as environmental factors to assist policy makers, persons in non-profit organizations and researchers identify and allocate resources in areas that more urgently need social and environmental corrective action. This objective is achieved by deriving remotely-sensed variables and combining them with census data through PCA to create three indices: one for socio-economic conditions, one for environmental conditions, and a combined quality of life index. The second objective is to further analyze the spatial characteristics of the resulting indices and explore the relation between environmental and social factors from which the indices were derived, in order to determine whether areas of low socio-economic characteristics also correspond with areas of negative environmental factors. This paper hypothesizes that for a global city in the developing world such as Mexico City, a significant amount of the environmental variability can be explained by socio-economic factors. The second objective was achieved through these specific aims: (1) analyze the spatial distribution of the quality of life, socio-economic and environmental indices using a geographic clustering technique, and (2) regress the environmental index against census socio-economic variables.

CHAPTER II

STUDY AREA AND DATA

2.1 Mexico City as an exemplar

Mexico City's official name is the Federal District. It comprises an area of roughly 1,500 km^2 and sits on the high plateaus of the Valley of Mexico at an average elevation of 2,220 meters above sea level. The combination of high elevation coupled with a tropical location gives Mexico City a subtropical highland climate where annual average temperatures range from 12°C to 20°C (Tamayo 2012). The city is made up of sixteen boroughs with a total population that exceeds 8.8 million according to the 2010 General Census (INEGI 2010). The metropolitan area, also known as the Greater Mexico City, extends beyond the boundaries of the Federal District (Figure 1) to include sixty municipalities of the Estado de Mexico and 29 municipalities from the adjacent state of Hidalgo, reaching a combined population of over 21 million people (Fernandez-Alvarez 2012). Greater Mexico City area ranks as the most populous urban area in the western hemisphere and has the highest population density in the country and one of the highest in the world (United Nations Economic and Social Affairs 2014).

Mexico City's prominent position in terms of population derives from the fact that it has been historically the political capital of Mexico as an independent state and the political as well as economic center of New Spain during colonial times (Stein and Stein 2003). Historical records show that the importance of Mexico City extended even during pre-Columbian times as

Tenochtitlan, the former name of the city and capital of the Aztec empire supported a population of over 250,000 people at its highest peak, making it one of the largest and most populous cities at the time (Smith 2005; Levy 2008). This evidence supports the claim that Mexico City has been globally one of the most important urban centers during the past 700 years.

Currently, Mexico City produces over 22 percent of the country's GDP and ranks as the fifth largest stand-alone economy in Latin America (Brookings Institute 2012; Forbes 2013). Furthermore, it generates an average of $450 million USD annually, making it one of the wealthiest urban areas in the world (Brookings Institute 2012). Yet empirical observations of the urban landscape as well as documented studies suggest that this wealth is extremely polarized. Studies over the past seven years have estimated that in the Federal District alone over 32.7 percent of the population lives in high levels of poverty where cases of extreme residential segregation are the main trait of the socio-economic structure of the city (Ward 2009; Mier y Teran et al. 2012).

Figure 1: Map of the Federal District showing boroughs, surrounding municipalities of the Estado de Mexico (Edo.Mexico) and basic geo-statistical area units (AGEB).

Historically, the spatial arrangements of poverty and social well-being have been very unevenly distributed. Major cases of spatial segregation were first observed when most of the native inhabitants of then Tenochtitlan were displaced to the peripheries of the city and beyond as the Spanish conquistadors settled in the city center after the conquest (Lockhart 1994). For centuries, the city center and its adjacent neighborhoods accumulated most of the wealth of the city and hence had the highest quality of life standards, while areas outside this area, and especially the periphery, were occupied by people of lower socio-economic status (Ward 2009). By the 1970's, the city center started to depopulate rapidly creating issues of urban deterioration fueled by the redistribution of the population towards peripheral residential locations (Aguilar and Ward 2003). Currently, patches of wealth can be found along urban corridors characterized by concentrated corporate developments, and exclusive residential areas which have been created within former peripheral areas (Aguilar and Ward 2003).

In terms of the physical domain, little has been done to advance the combined study of environmental and socio-economic factors in Mexico City. Most environmental studies focus solely on physical issues such as air pollution, water quality, or soil degradation. One recent study, however, suggested that the poorest areas of the city correlate visually with the less green areas, hence adding to the argument that Mexico City exhibits a clear case not only of socio-economic and residential segregation but also of environmental injustice (Fernandez-Alvarez 2012). The magnitude of the population size as well as its overall global economic and political prominence makes Mexico City a logical study area to evaluate a quality of life index and explore its spatial patterns. Due to the fact that there is very little literature with similar research objectives specifically for Mexico City, this study will contribute to an understanding of the socio-economic and environmental structure of this important global city. It is expected that the results will help urban planners and policy makers identify areas and neighborhoods that more urgently need measures and policies to address quality of life issues. Application of corrective plans and policies is sometimes difficult in large metropolitan areas such as the Grater Mexico City due to the fact that they often have a multijurisdictional administrative structure and lack a single metropolitan tier of planning authority (Aguilar and Ward 2003). As a result, this study will focus exclusively on the Federal District, which as a united political entity implies that corrective measures and policy can be applied without the adversity of having multi-state jurisdictional authority.

2.2 Selection of socio-economic variables

All socio-economic variables used in this study were collected by the National Institute of Statistics and Geography (INEGI) during the 2010 General Census of Population and Housing. A dataset containing over one hundred socio-economic variables was retrieved directly from an official INEGI information center located in Mexico City. All variables are aggregated to the basic geo-statistical area or AGEB, which represents the smallest unit with statistical information made available through the INEGI (Aguilar 2008). AGEB units can be compared in size and purpose to the census block groups used by the U.S. Census. Furthermore, the nature of these variables is comprehensive and encompasses all major socio-economic characteristics of Mexico City's population, including demographics such as age groups and gender ratios, and economic indicators including percent of people unemployed and economically active population. It also includes migration information, religious diversity, and Native American dialects spoken at home as well as other indicators useful to quality of life studies such as education, access to healthcare, type of employment, and housing conditions.

An initial selection of thirteen socio-economic variables (Table 1) was done following patterns of variables used in other quality of life studies corresponding to developed and developing cities as well as patterns of variables used in socio-demographic studies done specifically for Mexico City (Li and Weng 2007; Aguilar and Mateos 2011; Rao et al. 2011; Shen et al. 2013; Afsar et al. 2013; Berrada et al. 2013). One inherit limitation of the INEGI dataset is that income information is not made available at highly disaggregated levels such as the AGEB unit. Income-related variables are key in most quality of life studies to determine patterns of wellbeing as they relate to environmental conditions (Lo 1997; Li and Weng 2007; Ogneva-Himmelberger et al. 2009; Liang and Weng 2011; Ogneva-Himmelberger et al. 2013). The census does however, collect dwelling descriptors and counts of amenities available per household that can be used as proxies for income. A similar issue was encountered by a quality of life study performed in Pakistan where income data were not available, yet housing characteristics were able to successfully replace these data (Afsar et al. 2013).

Table 1: Selected socio-economic variables retrieved from the 2010 general census for Mexico City.

Socio-Economic Variable	**Description**
Percent unemployed	Percent of economically active people who are unemployed
Percent no health insurance	Percent of people without access to state or private health services
Percent illiterate	Percent of people who cannot read nor write
Percent 12 to 15 no school	Percent of children ages 12 to 15 that to not attend school
Percent 25 w/college education	Percent of people 25 and older with at least 1 year of college education
Percent child mortality	Percent of children who die before 1 year
Percent 12 older no school	Percent of people 12 years and older without education that work fulltime
Percent dirt floors	Percent of houses whose floors are made out of dirt
Percent no internet	Percent of households without access to the intern or a computer
Percent no phone	Percent of people without access to a landline phone
Percent no car, washer, refrigerator	Percent of households without a car, a washer and a refrigerator at home
Percent one room	Percent of households with only one room at home
Population density	Number of persons per square kilometer

2.3 Selection of environmental variables

This study incorporated three environmental variables frequently derived from remote sensing imagery, including vegetation vigor, surface temperatures, and percent impervious surfaces. The extraction of these variables is well-documented in quality of life studies and has produced acceptable results (Jimenez-Munoz et al 2014, Weng et al. 2004; Yuan and Bauer 2007; Voogt and Oke 2003; Jensen 2007). Other environmental variables besides the ones to be included in this research might further contribute to a more detailed quality of life assessment. While an ideal model would include air pollution and soil contaminants (containing heavy metals), the extraction of these environmental variables is quite labor-intensive, and results might contain very high margins of error. As research progresses, it will be possible to derive these environmental variables more efficiently and with higher accuracy. For this study only the three variables mentioned above were used to fulfill the environmental requirements of the evaluation of quality of life of Mexico City. All three variables were derived from Landsat 8 imagery. The Landsat program has demonstrated over three decades of data collection to be an excellent source of biophysical information (Lo 1997; Jensen 2007) and has the advantage of offering free satellite products to the public. A single, cloud-free, Landsat 8 image encompassing the majority of the metropolitan area of Mexico City was retrieved from the official USGS data center (www.earthexplorer.org). This image was acquired on August 27, 2014; this late summer date ensures that the vegetation is fully mature so urban vegetation can be accurately measured (Tamayo 2012).

The first variable derived was the level of vegetation vigor in the city using the Normalized Difference of Vegetation Index (NDVI) at the standard Landsat spatial resolution of 30 meters. The NDVI technique is commonly employed to measure the amount vegetated surface areas. It is a ratio that contrasts the energy reflectance from senescent vegetation with that of the healthy vegetation (Lo 1997; Jensen 2007). It is calculated using the following formula:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \tag{1}$$

where VIS represents the spectral reflectance in the visible red region and NIR represents the reflectance from the near infrared region. The resulting NDVI index values range from -1 to 1 where index values close to 1 indicate that the surface is completely vegetated, while values close to -1 indicate that that vegetation is mostly absent. In theory, higher NDVI values are indicative of a healthier urban environment given that they represent urban amenities such as public parks, botanic gardens, large private gardens and urban forests.

The second variable derived was surface temperatures. Surface temperatures are of major concern for urban quality of life due to the fact that high urban temperatures directly affect human comfort levels, increase the energy demand to cool houses and buildings, raise pollution levels, and affect precipitation patterns (Yuan and Bauer 2007). Urban areas are particularly affected by the urban heat island effect, which causes a significant increase in temperatures for the city when compared to its surrounding rural areas (Voogt and Oke 2003). Furthermore, measurements of surface temperatures are not static but change spatially according the predominant land cover for a particular neighborhood. Highly vegetated neighborhoods are likely to experience lower temperatures than neighborhoods with higher population densities and higher percentages of impervious surface. In Landsat 8, spectral bands ten and eleven are the thermal bands from which surface temperatures can be derived. The procedure to extract this variable followed the method described by Weng at al. (2004), which employs three basic steps; first the digital numbers (DN) from band ten in Landsat 8 were converted into spectral radiance; second, the spectral radiance values were transformed to their black body temperatures; finally, the black body temperatures were adjusted to true land surface temperatures by incorporating emissivity biases produced from an unsupervised spectral classification image from the same study area (Weng 2007; Liang and Weng 2011).

The third variable derived was the amount of impervious surfaces. The amount of impervious surfaces has been recognized as one of the most important environmental indicators due to the fact that it is a direct measure of anthropogenic activities that adversely alters the natural environment (Arnold and Gibbons 1996). High amounts of impervious surfaces are particularly negative to urban areas due to the fact that they increase surface temperatures, increase the intensity of downstream run-off, and significantly decrease water quality (Yang et al. 2003). Mexico has been categorized as one of the top ten countries in the world in terms of constructed impervious surfaces, with the largest portion located in the Valley of Mexico where Mexico City is located

(Elvidge et al. 2007). Very few studies have incorporated this variable to understand urban sustainability, climate change, and other environmental phenomena within Mexico City. Impervious surfaces were extracted by using the method of decision tree classification where the amount of impervious surfaces was estimated by separating vegetation and shadows from all other urban land cover types, mainly building roofs, highways, and commercial/industrial uses (Figure 2). Finally, these environmental variables were aggregated to their respective AGEB units based on their mean values. This was done using the 'zonal statistics' tool in ArcMap 10.2.2 (ESRI 2014), which calculates descriptive statistics for each individual spatial feature, in this case AGEB units, based on the environmental variables in raster format (Ogneva- Himmelberger et al. 2009).

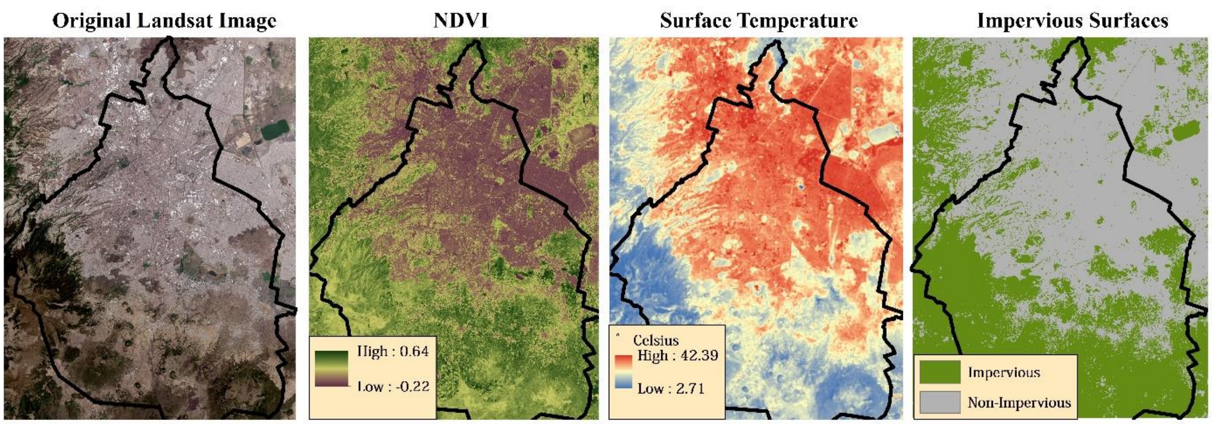

Figure 2: Landsat image and derived environmental variables.

CHAPTER III

METHODOLOGY

One of the main issues with the creation of objective quality of life indices is organizing a large number of variables into succinct and comprehensive summaries that can effectively combine and reflect divergent human and environment conditions of a city. The most important consideration in geography is the fact that most socio-economic data are usually distributed in vector format such as the TIGER files provided by the U.S Census, while environmental data is captured and maintained as raster format as is the case with impervious surfaces included in the National Land Cover Dataset or NLCD. While the conversion of both data types to carry out conjunct analysis imposes some limitations, they should not discourage their combined analysis (Huby et al. 2007).

Moreover, a number of techniques have been developed that are especially suited to handle spatial data such as spatial multiple criteria analysis and simple GIS overlay methods (Jankowski 1995). Both of these techniques can effectively combine socio-economic and environmental data and output geographically-referenced indices. However, they require some degree of subjectivity on the part of the analyst, given that some variables can be weighted more heavily than others in the final product. In the case of urban quality of life studies, there is no definitive theory that confirms what socio-economic or environmental variables are more important than others. Therefore a practical approach to this issue must be implemented.

3.1 Principal component analysis and composite index

Principal Component Analysis (PCA) is a data reduction technique commonly used in Factor Analysis, which allows an entire dataset to be synthesized into a smaller set of underlying factors or components (Rogerson 2010). The objective of PCA is to extract the significant components that can accurately represent a large proportion of the overall variability in all variables that compose an original dataset. Principal components is the most widely used data reduction method in quality of life studies (Tesfazghi et al. 2010; Liang and Weng 2011; Rao et al. 2011) and is the method used in this research. PCA works by decomposing the original variables into axes that represent the variability of a dataset where individual components are axes that incorporate part of that variability. The longest axes are representative of the majority of the variability, and their lengths are known as *eigenvalues*. There are two key elements in PCA; the first one is to determine the number of significant components that are most representative of the original data. A common rule for this procedure is to select only the factors whose eigenvalues are greater than one (Kaiser 1960; Lo 1997). This is the case since the original variables account for one unit of variance out of the total variance in the dataset. Factors with eigenvalues less than one usually account for less variance than single original variables, thus these factors become less useful for the reduction process since they account for less variability than even the original data. Second, the resulting significant components must be interpreted and related back to their original constituent variables. To do so, the highest *loadings*, or the highest correlations between original variables, and the component are identified and interpreted. The results of this interpretation allows the components to be associated with the real-world information from which they were derived.

Overall, PCA is an appropriate approach to combine socio-economic and environmental data given that the ensuing components are indices that represent linear combinations of the original variables that produced them (Lo 1997). Therefore, each component can be considered a direct element of the overall quality of life of a place (Li and Weng 2007). Furthermore, PCA has the advantage of creating index values or factor scores for all the geographic units involved in the analysis. These are derived by averaging all the variables that defined any given component. Factor or component scores are necessary for mapping and analyzing the spatial distribution of the quality of life. The first component in PCA usually contains the highest percentage of the variability of the original dataset, making it the principal component of the analysis. This however, does not imply that it is the only important component since it does not explain all of the variance in the original dataset. In order to produce a more complete representation of the quality of life, all factors must be integrated into one composite index. This was done by following the formula developed by Li and Weng (2007):

$$Composite\ index = \sum_{1}^{n} F_i . W_i \qquad (2)$$

where *n* is the number of significant components obtained from the PCA based on their eigenvalues. F_i is the factor score for a given geographic unit for any given significant component and W_i is the percentage of variance explained by the same component. This formula allows each significant component to be combined and weighted for the overall quality of life based on the amount of variability that each individual component can explain, making it an accurate technique to summarize proportionally all objective aspects that significantly contribute to the quality of life of a place, thus removing the need for external judging.

For the purpose of this research, PCA was run three times, once for a dataset containing the socio-economic data only, again for the dataset containing the environmental variables, and finally for a dataset containing both socio-economic and environmental data. Subsequently, Equation 2 was implemented for each PCA run except for the dataset of only environmental variables since only one factor was produced (refer to chapter 4). The goal of this procedure was to generate and map three different indices, one of socio-economic conditions, one of environmental conditions, and finally a comprehensive quality of life (QLI) that includes both.

3.2 Cluster analysis with Getis-Ord statistic

Statistical techniques have been developed that are capable of detecting the existence of significant clusters of activities for any given geographic neighborhood. Clusters can be identified as ‘hot spots’ when particular values of a phenomenon are exceptionally high or low (Ord and Getis 1995). The measurement of hot spots can be divided into global and local statistical tests. Global or general tests produce a single value that describes the degree of spatial autocorrelation but are limited because they are unable to provide the size and location of spatial association or clustering for high or low values of specific pockets within the study region (Burt et al. 2009; Rogerson and Yamada 2009). Local statistics measure the spatial association specifically within a geographic neighborhood, detecting the existence of clusters or sub-regions and further indicating the degree of heterogeneity across the study region (Anselin 1995; Ord and Getis 1995). Local clustering techniques are relevant to urban studies since they test the probability of an urban phenomenon such as crime or poverty being distributed randomly or whether significant processes of clustering are at work. In the case of this research, local measures of hot spots analysis can determine if clusters of low or high quality of life values exist within Mexico City, revealing where the pronounced spatial patterns of segregation are across the city.

The Getis-Ord local G_i* statistic (Ord and Getis 1995) is frequently used in hot spot analysis and is available in most GIS software packages, including ArcMap. It is derived from the Getis and Ord’s global test. The Getis-Ord local G_i* was run three times, one for each index derived from PCA and Equation 2, and was calculated as:

$$G_i^* = \frac{\sum_j w_{ij}(d)x_j - W_i^*\bar{x}}{s\{[mS_{1i}^* - W_i^{*2}]/(m-1)\}^{1/2}}, for\ all\ j \tag{3}$$

where $\{w_{ij}(d)\}$ is a symmetric one/zero spatial weight matrix with ones for all links defined as being within distance d of a given i. All other links are zero. In the standardized version of the statistic used here (G_i^*), the target region i is included in the computation of the statistic. Therefore, $w_{ij} \neq 0$. The variables $\bar{x}$ and s are the sample mean and standard deviation of the observed set of x_i, respectively. G_i* will produce high positive z-scores where there are dominant patterns of high quality of life values near other high values and will produce negative z-score values where there is clustering of low quality of life values (Rogerson and Yamada 2009).

An important consideration when using local clustering statistics is the selection of the neighborhood search distance. Many studies adopt a default neighborhood search distance from the software without considering the scale of the process generating the data. These types of arbitrary definitions of 'neighborhood' can lead to inaccurate results and can possibly identify significant relationships when no meaningful associations exist (Rogerson and Kedron 2012). In order to avoid the misrepresentation of insignificant clusters and to determine the distance in an empirical manner, the method proposed by Frazier et al. (2013) was used to identify the most appropriate neighborhood search distance at this particular scale of analysis. This method uses z-scores from global G statistic values at incremented distances in order to determine the point at which the significance of global clustering levels off. This distance is then adopted as the neighborhood search distance. These calculations were performed in ArcGIS 10.2.2 (ESRI 2014) at distance thresholds every 150 m starting from 300 m to 2500 m, where the z-scores are plotted against their individual distances (Figure 3). The significance levels off at 1050 m therefore this distance was chosen as the neighborhood search distance for the analysis.

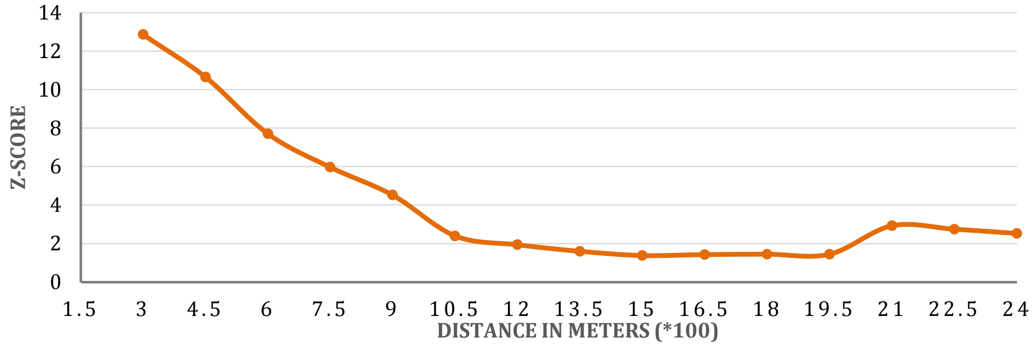

Figure 3: Plot of neighborhood search distance vs z-score for the global *G* statistic (Ord and Getis 1995)

3.3 Determining the relationship between socio-economic and environmental variables

One of the objectives of this study is to determine if there is a relationship between the environmental and socio-economic conditions of Mexico City. More specifically, this paper argues that neighborhoods with high socio-economic conditions will also have more satisfactory environmental conditions than neighborhoods with lower socio-economic status in terms of lower surface temperatures, more green areas, and lower amounts of impervious surfaces. To test this hypothesis, Ordinary Least Square (OLS) regression is implemented to test the statistical strength of the relationship between socio-economic and environmental variables. In this case, the only component derived from the PCA run for the environmental dataset is used as the dependent variable and the census socio-economic variables in Table 1 are used as the independent variables

CHAPTER IV

RESULTS

4.1 Component interpretation

The first step in analyzing the results was to check the suitability of the data used for PCA. This was done by reviewing the results of the Kaiser-Meyer-Olking tests (KMO) and the Bartlett's test of sphericity values. The data are suitable only when the KMO values are greater than .5 and the significance level of the Bartlett's test is less than .01 (Li and Weng 2007). For the PCA run for the socio-economic dataset, values of .911 and a significance of .000 were obtained. For the PCA run for the environmental dataset, values of .707 and .000 were obtained, while for the combined socio-economic and environmental PCA values of .897 and .000 were obtained. Thus, all the data used were indeed suitable for PCA. For the socio-economic dataset, the PCA produced two components whose eigenvalues were greater than one, and together they explain 64% of the total variance (Table 2). The first component explains 52.48% of the variance and has very high loadings with most of its constituent variables including the percent of households with one room, percent of households without a phone, and percent of houses with dirt floors.

Table 2: Socio-economic factor loading matrix showing loadings for each variable, eigenvalues, and variance explained per component.

Socio-Economic Variables	Component 1	Component 2
Percent unemployed	.452	-.313
Percent no health insurance	.841	.022
Percent illiterate	.804	.075
Percent 12 to 15 no school	.647	.041
Percent 25 w/college education	-.787	.425
Percent child mortality	.688	-.189
Percent 12 older no school	.611	.084
Percent dirt floors	.620	.472
Percent no internet	.861	-.324
Percent no phone	.911	.035
Percent no car, washer, refrigerator	.855	.176
Percent one room	.832	.258
Population density	.027	-.848
Initial eigenvalue	6.82	1.5
% variance explained	52.48	11.55
Cumulative %	52.48	64.04

These variables are indicative of low socio-economic status, therefore highs scores on component one indicate adverse conditions. The second component explains 11.55% of the variance and clearly corresponds to population density since this variables has the highest loading with a value of -.848 followed by relatively weak loadings whose values were less than .472. Very high population densities in cities of the developing world are considered detrimental given that they decrease the environmental quality of a place by increasing the amount of impervious surfaces, increasing air and noise pollution and by decreasing the vegetated land cover, hence high scores on component two are also indicative of negative conditions. It is also important to mention that most socio-economic variables used here describe mainly negative socio-economic conditions, therefore high scores of this index are inversely related to high socio-economic status. Based on this results, the synthetic index of socio-economic conditions (SSI) was calculated for each AGEB unit following Equation 2:

$$SSI= (52.48 * \text{Factor } 1 + 11.55 * \text{Factor } 2)/100 \qquad (4)$$

The PCA run for the environmental dataset produced only one significant component with an eigenvalue of 2.47 that is able to explain over 82% of the variance. The component matrix revealed that the highest loading belongs to NDVI with a high negative value (-.942) followed by other very high positive loadings (.915 and .866) that indicate that all the variables are highly correlated (Table 3). For this particular case, since there was only one significant factor, there was no need to employ Equation 2, since PCA scores were mapped directly for each AGEB unit; higher values indicate better environmental conditions.

Table 3: Environmental factor loading matrix showing loadings for each variable, eigenvalues, and variance explained per component.

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Environmental variables	Component 1
Surface temperatures	.915
NDVI	-.942
Percent of impervious surfaces	.866
Initial eigenvalue	2.47
% variance explained	82.47
Cumulative %	82.47

The PCA of the combined socio-economic and environmental variables resulted in two significant components accounting for 62% of the overall variance. The first component explains 44.3% of the variance while the second explains only 18.4%. Component one is clearly related to the socio-economic variables only since all the environmental variables load poorly while the rest load highly, especially the percent of households without phone, percent of households without internet, percent of people without access to health care, percent of people who are illiterate, etc. These variables are all indicative of low socio-economic status. Therefore, high scores of this component are indicative of negative conditions.

Table 4: Socio-economic and environmental factor loading matrix showing loadings for each variable, eigenvalues, and variance explained per component.

SE & Environmental variables	Component 1	Component 2
Percent unemployed	.493	-.180
Percent no health insurance	.829	.134
Percent illiterate	.781	.199
Percent 12 to 15 no school	.643	.061
Percent 25 w/college education	-.833	.166
Percent child mortality	.709	.-053
Percent 12 older no school	.571	.265
Percent dirt floors	.538	.503
Percent no internet	.892	-.080
Percent no phone	.894	.163
Percent no car, washer, refrigerator	.821	.253
Percent one room	.785	.320
Population density	.155	-.689
Surface temperatures	-.141	-.851
NDVI	.121	.903
Percent of impervious surfaces	-.076	-.807
Initial eigenvalue	7.08	2.94
% variance explained	44.3	18.4
Cumulative %	44.3	62.71

The second component is clearly related to environmental conditions since NDVI, percent of impervious surfaces, and surface temperatures load very highly with each other, while the socio-economic variables have very low loadings (Table 4). The only exception is population density with a high loading of -.689. Higher scores of this component represent better environmental quality. In accordance to Li and Weng's (2007) method, the significant factors have different contributions to quality of life since factor one represents negative socio-economic conditions while factor two is indicative of positive conditions. Consequently they must be subtracted from each other.

$$QLI = (44.3 * \text{Factor } 1 - 18.4 * \text{Factor } 2)/100 \quad (5)$$

It is important to mention that the original index values were not mathematically comparable, thus they were reclassified from very high to very low conditions based on five classes using the natural breaks classification with the only intent of displaying visually the areas with the highest and lowest conditions. The socio-economic index map **(Figure 4)** suggests that the worst conditions are in the northernmost tip of the city and along the southern periphery. This latter area is mostly contained within four boroughs: La Magdelana Contreras, Tlalpan, Xochimilco and Milpa

Alta, which have been historically considered more rural localities when compared to the rest of the boroughs. Positive socio-economic conditions are found in the west, mostly within the Alvaro Obregon, Benito Juarez and Miguel Hidalgo boroughs. The environmental index map shows that best conditions are also found in the west part of the city in accordance with the positive socio-economic conditions (Figure 5). However, AGEB units in the southern periphery also display very high environmental conditions, even when displaying some of the lowest socio-economic conditions in the city. Low environmental conditions are prominent throughout the city, especially in the Cuauhtémoc, Gustavo A. Madero, Azcapotzalco, Venustiano Carranza, Iztacalco and Iztapalapa boroughs. The quality of life index (Figure 6) shows that best conditions are found in the west, where high socio-economic and favorable environmental conditions are present. The southern periphery does not show the lowest status mostly because of its favorable environmental conditions, which balance the quality of life in this area. Instead the lowest conditions are found in the east prominently in the Iztapalapa borough, which has mostly negative socio-economic conditions coupled with negative environmental conditions.

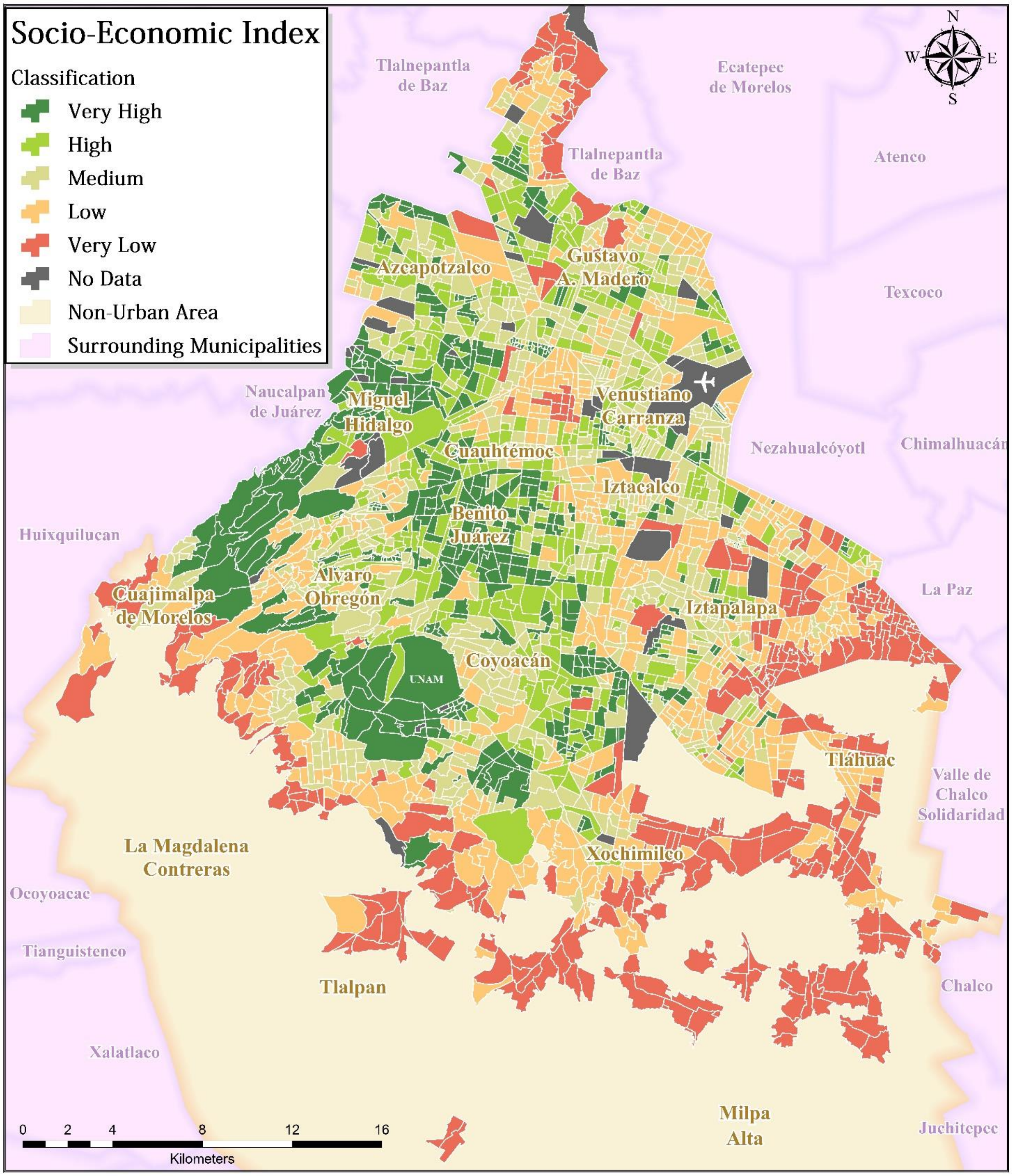

Figure 4: Socio-economic index map created from the socio-economic principal component analysis (PCA) and Equation 4.

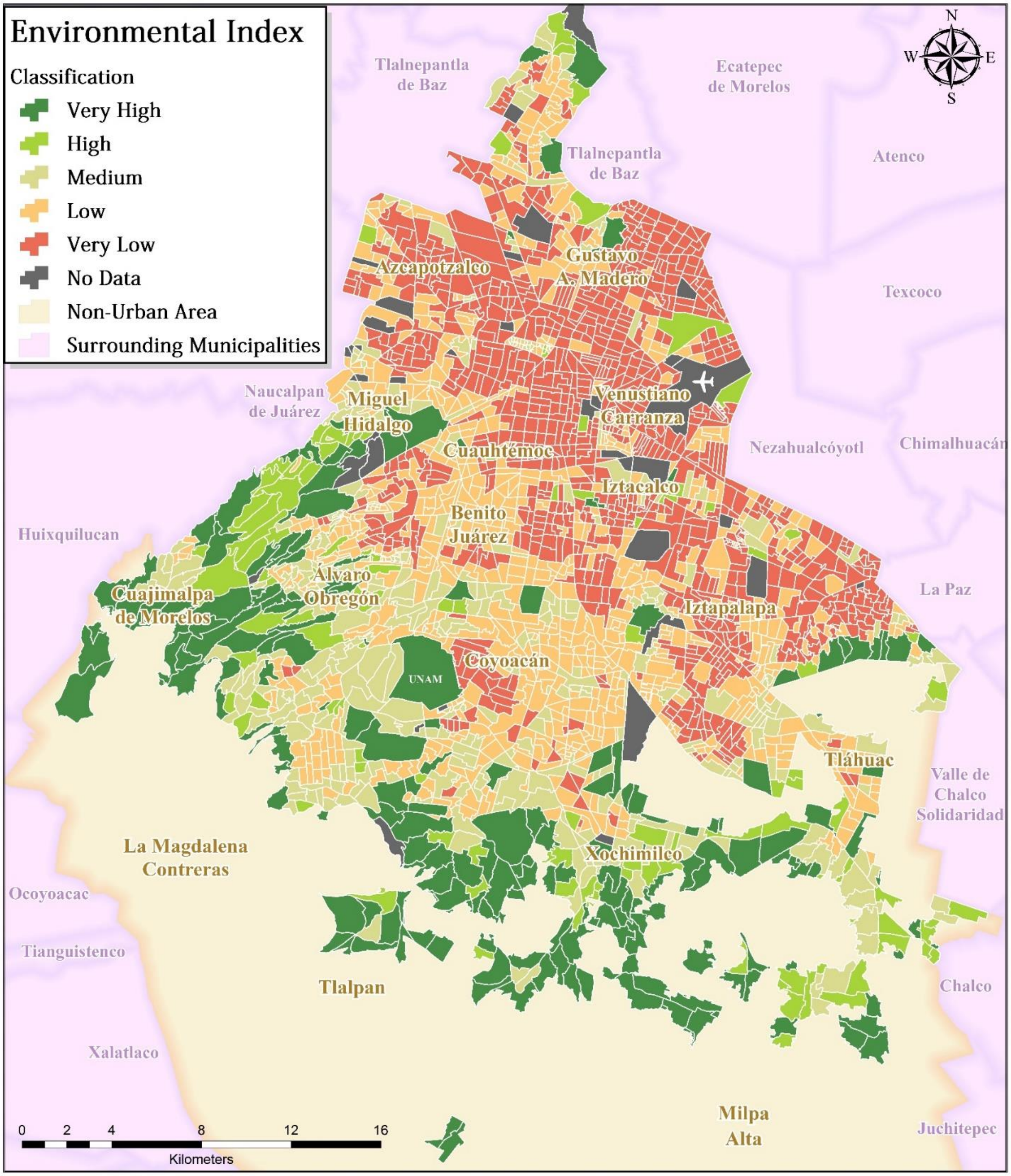

Figure 5: Environmental index map created directly from the environmental principal component analysis (PCA) without the need of employing the composite index formula from Equation 1.

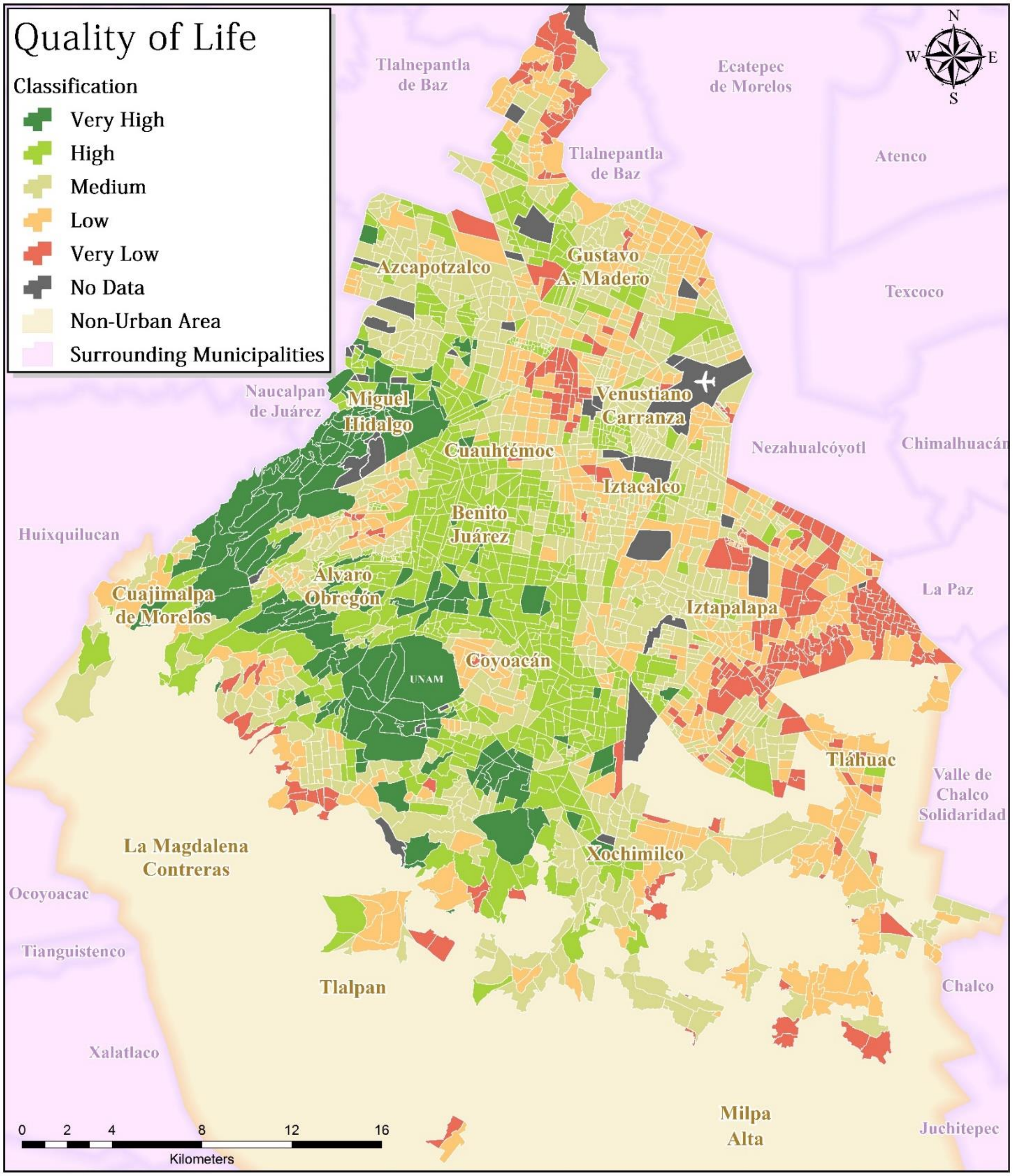

Figure 6: Quality of life map created from the socio-economic and environmental principal component analysis (PCA) and Equation 5.

4.2 Cluster analysis

The next aim of this research consisted of applying a local clustering technique to the three map indices in order to determine where high concentrations of low or high values exist (Figure 7). The G_i* analysis for the socio-economic index identified significant clusters of negative socio-economic conditions in the southeast and along the southernmost part of the city where the population is quasi rural, for the most part. Other clusters of low conditions were identified in the northernmost part of the city and in the downtown area. Clusters of positive socio-economic conditions were found in the west, mainly in the Miguel Hidalgo borough with smaller clusters scattered throughout the city mainly towards the south. The G_i* analysis for the environmental index identified clusters of positive environmental conditions in the west part of the city where clusters of positive socio-economic conditions were identified. However positive clusters were also identified along the periphery of the city where negative clusters of low socio-economic conditions were also evident.

The results for the overall quality of life index show major clusters of low conditions in the northernmost part of the city and specifically towards the south east in the Iztapalapa borough, creating a sharp contrast with the clusters of positive conditions on the opposite side of the city. Clusters of low quality of life values follow those represented in the index of quality of life where the low socio-economic characteristics overpower the positive environmental conditions as is the case in the northernmost and westernmost tips of the city. The southern periphery does not appear as one big cluster of neither positive nor negative conditions even when this area is a significant cluster in both the socio-economic and environmental cluster maps. Instead, a number of smaller negative clusters appear to spread throughout this area, also overpowering the positive environmental conditions shown in the other maps. One of the possible limitations of using hot spots in the ‘edge effect’ phenomena which is apparent in the east and the south-east parts of the city. Since other population settlements exist to the east beyond the borders of the Federal District, specifically for the municipalities of Netzahualcoyotl and La Paz, (see Figure 1) it is possible that the mean centers of low quality of life and socio-economic conditions might change, thus changing the location of the clusters as well. This study was intended to show results specifically for the Federal District, yet it is important to acknowledge the possibilities that clusters of low conditions might extend beyond the borders of the study area.

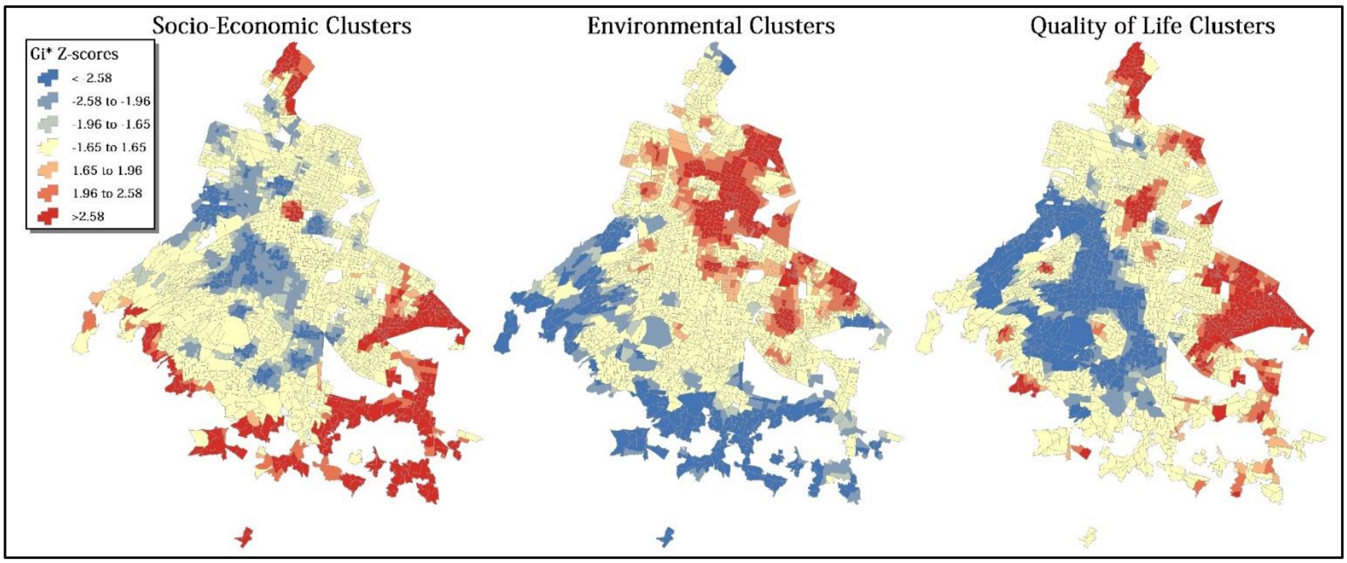

Figure 7: G_i* significance results from the three indices created from principal component analysis (PCA) and equation 1.

4.3 OLS regression

Pearson's correlation was computed for all variables as part of the regression analysis. As expected, the environmental variables had high negative correlations with NDVI which had r values of -.723 with percent of impervious surfaces and -.833. NDVI also had a significant negative correlation with population density (-.514) but a positive correlation with other socio-economic variables including percent of households with one room (.346), percent of households with dirt floors (.455) and percent of people without cars (.279). Surface temperatures had significant positive correlations with population density (.399), and negative correlations with percent of households with one room (-.340), percent of households with dirt floors (-.424) and percent of people 12 and older who work without school (-.274). Impervious surfaces had a positive correlation with population density (.382) and negative correlations particularly with percent of households with dirt floors (-.358) and percent of people 12 and older who work without school (-.285). The results of the linear regression between the environmental index and all socio-economic variables resulted in an adjusted R^2 of .393. Hence, the mostly negative socio-economic variables are able to explain over 39 percent of the variance of the environmental conditions in Mexico City.

CHAPTER V

DISCUSSION AND CONCLUSIONS

5.1 Discussion

The results of this research have demonstrated that areas of high socio-economic status can be identified and modeled for quality of life studies without the use of income-related variables. Urban studies for other Latin American cities that do not have access to income information, could benefit by using a similar methodology employing surrogate variables, as was done in this study. Furthermore, the use of environmental information such as NDVI to measure greenness vigor, can be regularly employed in the assessment of urban quality of life given the ease with which it can be calculated using freely available satellite images. Although sometimes the cost of imagery or GIS software can be restrictive for planning agencies and non-governmental organizations in developing countries, open-source alternatives exist that can perform the same calculations with the same relative ease, such as QGIS (previously known as Quantum GIS) and geographic resource analysis support system (GRASS GIS). The maps of quality of life and clusters of quality of life show evidence of socio-economic and environmental segregation as a clear divide between the west and the east/south-east can be appreciated. Furthermore, environmental injustice may also be present since the AGEB units in the western boroughs of Miguel Hidalgo, parts of Cuajimalpa, and Alvaro Obregon show the best environmental conditions, especially when compared to the negative environmental conditions in most of the city but particularly in the eastern boroughs. The existence of clusters of positive and negative socio-economic conditions distributed throughout the city confirm the claim that inequality and segregation are important traits of the socio-economic structure of Mexico City. Additionally, these traits extend to the environmental realm as the socio-economic clusters often overlap with clusters of positive and negative environmental conditions. Although the R^2 obtained from the regression analysis was relatively low, this can be in part explained by the fact that the southern periphery showed negative socio-economic conditions as well as very high environmental conditions. Nevertheless, this is one of the most important findings of this research, especially since this area consistently had significant clusters of adverse socio-economic conditions, and the biggest clusters of positive environmental quality. This fact seems to indicate that urban areas in peripheral locations, even when suffering from high levels of poverty, might be inadvertently taking advantage of environmental benefits such as lower surface temperatures and more green areas available mostly to people living in areas of high socio-economic status. Additional research is needed to determine if this is characteristic of other cities throughout the developing world, particularly in Latin America.

The fact that in Mexico City the southern periphery enjoys these environmental conditions is due to the rural-like conditions of this area, where AGEB units have low impervious surface cover, lower surface temperature, and high greenness values in the form of NDVI. This part of the city is included in the Preservation Zone (Suelo de Conservacion; SC). The SC is a special zonation category created by the urban development plan of the Federal District in 1980 in order to divide the urban area from the non-urban area, which has very high levels of biodiversity, recreational activities, and scenic value (Aguilar 2008). The SC has been continuously populated by illegal settlements of mostly squalid conditions. Some estimates indicate that in 2010 there were over 2000 illegal settlements spreading in multiple parts of the SC (Aguilar and Santos 2011). AGEB units in this area, as documented by the INEGI, do not cover all the smaller settlements that have been established throughout this area. In addition, the official boundaries do not always coincide with those of the settlements (Aguilar 2008; Aguilar and Santos 2011). Therefore, more detailed research is needed in order to quantify the real area that these settlements comprise and then to determine their socio-economic conditions in order to have a better model of quality of life conditions for the entire Federal District.

Some limitations of the AGEB units in general include the fact that information in some areas is inaccessible, or is restricted by law and cannot be made public (Aguilar 2008). This is visible in the indices maps where no values were present or were restricted and therefore classified as 'No data' (Figures 4, 5 and 6). Such AGEB units were excluded from the analysis. Another limitation is that AGEB units, even when they are disaggregated at very high levels, are not completely homogenous. Each unit often covers several thousands of people and can sometimes overlook important internal socio-economic variation, thus lowering the precision of the quality of life index (Ward 2009). It is also important to mention that the maps produced in this research are not panaceas that address every social and environmental issue in Mexico City. As mentioned before, more environmental variables could be integrated into the model, but at the moment, only these three variables have been determined as having acceptable results using Landsat data.

Lastly, quality of life studies in areas in U.S locations have determined that the best environmental and socio-economic conditions are in suburbs and peripheral locations, while the central city is generally characterized by having low socio-economic conditions and negative environmental quality (Ogneva-Himmelberger et al. 2009; Li and Weng 2007). In Mexico City, peripheral locations are characterized as having both low and high socio-economic conditions separated on opposite sides of the city. This can be, in part, explained by the conceptual model of the socio-economic Latin American cities established by Griffin and Ford (1980) and then updated by Ford (1996). This model proposed that the elites and classes of higher socio-economic status tend to develop elite residential sectors emanating from the CDB towards the periphery following a spine or corridor of development. The model also suggest that the majority of the periphery would be reserved for people of low socio-economic status who are mostly immigrants seeking jobs.

The maps produced in this research are in accordance with the original model since it can be observed that the east and southernmost periphery of Mexico City has the lowest socio-economic status while the western periphery has the highest status. The maps also provide evidence of a clear divide between the west and the east and south-east, not only in terms of socio-economic conditions but also in terms and environmental and quality of life overall. Such a finding suggests that there are specific directions to the spread and separation in the periphery by high and low socio-economic status groups. Additionally, Biggs et al. (2014) proposed a revision to the Griffin and Ford model, which includes elite suburbs not only along corridors but also scattered away from central corridors. The maps presented in this research also show evidence of scattered clusters of high socio-economic status dispersed throughout the city, especially in the south, supporting the claim that further revisions to the original models are necessary.

5.2 Conclusions

This project has documented and explored the relationship between socio-economic and environmental variables in Mexico City by creating maps of quality of life, socio-economic, and environmental conditions in the city. The topic of quality of life has gained rapid popularity within the last decade especially since the fusion of remote sensing and GIS technologies which has enabled the integration of variables in a spatial manner that greatly enhances the effectiveness and ease of deriving satisfactory measures of quality of life. Cities in the developing world can take advantage of the use of these technologies to produce detailed estimates of socio-economic and environmental conditions in order develop plans and policies aiming at reducing negative conditions. Furthermore, these methodologies can also enhance the understanding of the socio-economic and environmental structure of the cities. This paper has demonstrated that in Mexico

City, segregation of people with high and low socio-economic status is evident throughout the city. Additionally, this segregation entails that environmental quality will often correspond to socio-economic status. An important finding of this work is that the southern peripheral area of Mexico City violates this apparent norm, since it has very low socio-economic status but also very high environmental quality. The same processes that produced this phenomenon can also be experienced in other cities around the world, however numerous questions arise. For example, what is the role of the climatic conditions in favoring natural environmental amenities in the periphery? In Mexico City the climate facilitates the development of vigorous vegetation without the need of irrigation, but could this process be similar in other cities where the lack of rainfall is more restrictive to growth of vegetation? Also, what is the role of high quality of life and good environmental conditions in relation to natural hazards such as flooding and earthquakes, which are common occurrences in Mexico City and in other global cities in the developing world? More particularly for Mexico City, more research is needed to quantify the area occupied by illegal settlements in the southern periphery in order estimate quality of life conditions and potential ecological damage to the preservation zone. Finally, measurements of socio-economic, environmental conditions and quality of life can be studied over time in order to determine trends in the changing structure of the city, which might allow researchers to spatially predict where issues of quality of life might be created in the future. Historical Landsat images for Mexico City are available back to the 1980s, likewise AGEB units have been available since the 1990 census, and therefore the possibility to create a longitudinal study is realistic.

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VITA

Gustavo Alberto Ovando Montejo

Candidate for the Degree of Geography

Master of Science

Thesis: GEOGRAPHIC ASSESSMENT OF URBAN QUALITY OF LIFE USING SOCIO-ECONOMIC AND ENVIRONMENTAL FACTORS ACROSS MEXICO CITY.

Major Field: Geography

Biographical:

Education:

Completed the requirements for the Master of Science in Geography at Oklahoma State University, Stillwater, Oklahoma in May, 2015.

Completed the requirements for the Bachelor of Science in Geography at Brigham Young University, Provo, Utah in April, 2013.

Experience:

Physical Geography Lab Assistant, 2014

Professional Memberships:

Asociación Mexicana de Geografía y Estadística, 2015
Association of American Geographers, 2014
Gama Theta Upsilon International Geographic Honor Society, 2012