Spatiotemporal Patterns, Monitoring Network Design, and Environmental Justice of Air Pollution in the Phoenix Metropolitan Region: A Landscape Approach

by

Ronald L. Pope

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Graduate Supervisory Committee:

Jianguo Wu, Chair
Christopher Boone
Anthony Brazel
Erica Forzani
Matthew Fraser

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ABSTRACT

Air pollution is a serious problem in most urban areas around the world, which has a number of negative ecological and human health impacts. As a result, it's vitally important to detect and characterize air pollutants to protect the health of the urban environment and our citizens. An important early step in this process is ensuring that the air pollution monitoring network is properly designed to capture the patterns of pollution and that all social demographics in the urban population are represented. An important aspect in characterizing air pollution patterns is scale in space and time which, along with pattern and process relationships, is a key subject in the field of landscape ecology. Thus, using multiple landscape ecological methods, this dissertation research begins by characterizing and quantifying the multi-scalar patterns of ozone (O_3) and particulate matter (PM_{10}) in the Phoenix, Arizona, metropolitan region. Results showed that pollution patterns are scale-dependent, O_3 is a regionally-scaled pollutant at longer temporal scales, and PM_{10} is a locally-scaled pollutant with patterns sensitive to season. Next, this dissertation examines the monitoring network within Maricopa County. Using a novel multiscale indicator-based approach, the adequacy of the network was quantified by integrating inputs from various academic and government stakeholders. Furthermore, deficiencies were spatially defined and recommendations were made on how to strengthen the design of the network. A sustainability ranking system also provided new insight into the strengths and weaknesses of the network. Lastly, the study addresses the question of whether distinct social groups were experiencing inequitable exposure to pollutants – a key issue of distributive environmental injustice. A novel interdisciplinary method using multi-scalar ambient pollution data and hierarchical multiple regression models revealed environmental inequities between air pollutants and race, ethnicity, age, and socioeconomic classes. The results indicate that changing the scale of the analysis can change the equitable relationship between pollution and demographics. The scientific findings of the scale-dependent relationships among air pollution patterns, network design, and population demographics, brought to light through this study, can help policymakers make informed decisions for protecting the human health and the urban environment in the Phoenix metropolitan region and beyond.

DEDICATION

I have many people to thank for supporting me in my graduate education, starting of course with my parents. Though I did well in primary school, I was far from a studious student in high school and it took years of military service to give me the maturity (and the G.I. benefits!) to start post-secondary education. Yet Mom & Dad were always there for me, quietly supporting and encouraging me. I still remember the day, around thirty years ago, when I told Mom that someday I wanted to earn a Doctorate. At that time in my life, Mom had every right to disbelieve my commitment, but her words of encouragement have always stuck in my memory. And Dad has always been there with the support and wise advice. Thank you Mom and Dad!

Most of all, I thank my wife and three children; how much time together have we sacrificed over all these years of school? But my wife Lene deserves the most credit. I was just starting my undergraduate education when we married, and now almost twenty years of marriage have gone by of part-time school along with full-time work; and yet you've always been my beacon of positive energy to keep me on track. Thank you dear, I love you!

ACKNOWLEDGEMENTS

I would like to express my deep appreciation and gratitude to my advisor and long-time mentor, Dr. Jianguo Wu, for the patient guidance he has provided to me, all the way from when I was a new undergrad at ASU to the completion of my degree. I first met Dr. Wu as an undergrad student in 1996 when he invited me to work in his lab, and he has taught me much over the years. Jingle, it has truly been an honor to be your student.

I would also like to thank my committee members, Drs. Chris Boone, Tony Brazel, Erica Forzani, and Matt Fraser for the congeniality, guidance and support that each has offered me. I sought this committee out because I desired a team from many differing disciplines that could assist me with my desire to make my work truly interdisciplinary, and I have been most pleased with my decision to do so!

Lastly, I thank the friends and colleagues that I work with, both in the Landscape Ecology and Sustainability Lab, and with my employer, Maricopa County Air Quality Department. Studying as a graduate student while also working in a full-time career would have been even more difficult if it wasn't for the accommodation that I've received; thank you all for your assistance.

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CHAPTER 1: INTRODUCTION

Background

Air pollution is a problem that has been known in urban areas for millennia; however, historically it was not adequately understood, or in some cases was even taken to be a sign of modern progress (Fenger 2009) . As the industrial and transportation infrastructure of cities grew, the problem of air pollution emerged as one that could no longer be ignored if the health of our citizens was to be protected. With epidemiological and ecological studies showing negative links between air pollution, human health and the environment, it is now recognized that it is vitally important to detect and characterize air pollutants so that citizens can make informed choices as to their residence and lifestyle (Dockery et al. 1993, Suh et al. 2000, Grineski 2007b, Grimm et al. 2008, Fenger 2009, Fernando et al. 2009a).

With the advent of modern monitoring technology, the ability to detect and measure pollutants has greatly improved. However, ensuring that air monitoring networks are adequately designed and that all social demographics in the population are represented and protected is difficult (Langstaff et al. 1987, Mofarrah and Husain 2009). Thus, in this dissertation research I characterize the spatiotemporal patterns of criteria air pollution in the Phoenix metropolitan region, Arizona, based on which the local air monitoring network is evaluated for its adequacy and effectiveness. Furthermore, by coupling the spatiotemporal patterns of air pollution with social demographics, I assess if any social group is being disproportionately affected or under-represented.

The Phoenix metropolitan area, known locally as the 'Valley of the Sun' or just the 'Valley', is a thriving, rapidly growing urban center centrally located within the deserts of Maricopa County, Arizona, and is home to more than more than 4 million people. It is also home to the Central Arizona-Phoenix Long-Term Ecological Research project, making it a prime location for urban ecological studies (Grimm and Redman 2004, Brazel and Heisler 2009). The city is situated in the Salt River valley, with scattered low mountain ranges and hills surrounding it. This combination of terrain, dense population, frenzied growth, semi-arid climate, light wind and abundant sunshine creates an environment that is conducive to the formation of anthropogenic air pollutants such as ozone (O_3) or particulate matter <10 microns (PM_{10}) (Bolin et al. 2000). Maricopa County was listed by the United States Environmental Protection Agency (EPA) as being in non-attainment of the primary, i.e. protection of human health, standards for both O_3 and carbon monoxide (CO) in 1978, although CO was later delisted in 2004. PM_{10} was classified in non-attainment status in 1990 and primary standard violations of this pollutant are such that in 2006 the EPA threatened economic sanctions if an effective reduction strategy is not implemented (ADEQ 2009, EPA 2009a).

A critical early step in developing this reduction strategy is to spatially and temporally characterize these pollutants so as to gain a better understanding of their dynamics in relation to stationary sources, transportation corridors, population densities, meteorology, and landscape features. Local government agencies currently employ two main methods for determining pollution concentrations: ambient monitoring and emissions inventories (ADEQ 2009, MCAQD 2011). Between State, County, and Tribal agencies, there were 34 monitoring sites operating and reporting data in 2008 (EPA

2009b). For a metropolitan land area of 2,387 km^2 in area (Luck et al. 2001), this government-operated ambient monitoring network within Maricopa County is relatively sparse.

Although the network is sparse for an area this size, it still far exceeds the number of monitors required by the federal government for a metropolitan area of this population size (Code of Federal Regulations 2009b). An emissions inventory is a comprehensive listing of air pollutants emitted into the atmosphere and contains point, area, mobile, and biogenic sources (ADEQ 2009, MCAQD 2009). While characterizing air pollution patterns, it is worth considering merging both ambient monitoring data and emissions inventories, similar to the study performed by Diem & Comrie (2001) in Tucson, AZ. In this manner deficiencies and redundancies in the monitoring network, in regards to known source emissions listed in the inventory, can be located and evaluated. Likewise, unexplained anomalies in the monitoring data, e.g. 'hotspots', which do not conform to the inventory list of sources can be noted and the information passed on to pollution control agencies to search for possible unregulated emission sources.

Other important factors that should be considered when evaluating pollution patterns and the monitoring network include population demographics and the location of distinct social classes. This research can lend evidence to environmental justice issues. Although environmental injustice can have various meanings, it can be simply defined as distinct social groups carrying a disproportionate amount of burden from environmental hazard (Fisher et al. 2006, Bryant and Callewaert 2008). The Valley is a sprawling urban area with a population-dense core surrounded by less-dense suburban residential areas. Industry is decentralized within the Valley; primary industrial sources, including sand &

gravel mining, semi-conductor manufacturing, high technology industry, and aerospace manufacturing, are spread out across the Valley including in areas near residential suburbia (Bolin et al. 2000). The urban fringe is surrounded by agricultural areas that merge into the desert; however, new development within the Valley, which occurs mostly on the urban fringe, is growing at such a fast rate that it has frequently surpassed and enveloped these agricultural patches leaving isolated islands within the suburban areas (Wu et al. 2003, Berling-Wolff and Wu 2004, Keys et al. 2007). Within these heterogeneous patches of industry, agriculture, and residential areas, are many relatively segregated social groups of racial, ethnic, age, and socioeconomic classes (Bolin et al. 2000, Grineski et al. 2007).

With the decentralized nature of industry within the Valley, patches of agricultural land located within the urban fringe, and major transportation corridors linking all communities, there is ample opportunity for the various social groups to be exposed to air pollutants. Several prior environmental justice studies were performed in the Phoenix metropolitan area; these studies did find evidence of environmental inequity in racial minority and lower-income social groups (Bolin et al. 2000, Bolin et al. 2002, Grineski et al. 2007, Grineski 2007b). However, these studies either used toxic release inventories (TRI), or an ambient air model using limited temporal scale as the basis for their determination. While the toxicity of the emissions and periods of acute exposure are vitally important, it is also important to understand the extent of long-term chronic exposure to pollutants (Schwartz 1989, Dockery et al. 1993). Thus the need for additional research using a model of air pollutants generated from a combination of ambient monitoring and emissions inventories and representing several spatiotemporal scales.

Research Goals and Significance

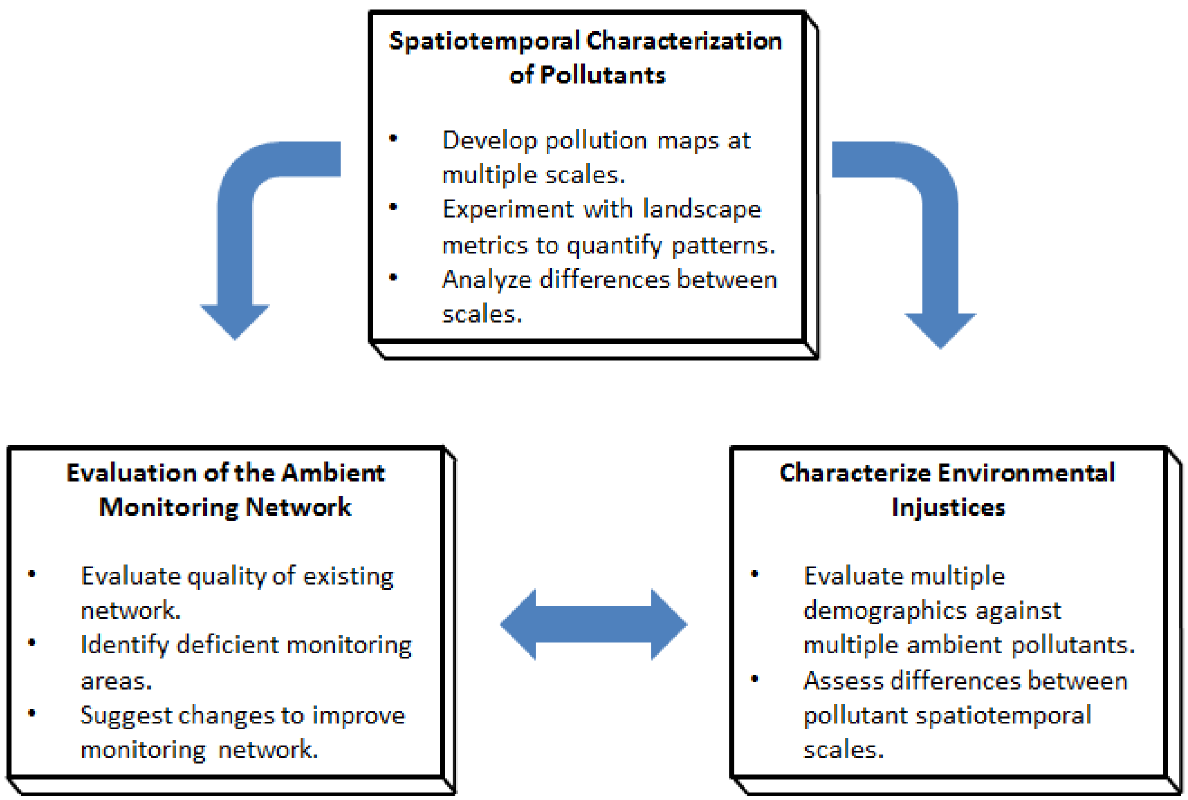

Figure 1 Conceptual Framework of the Three Phases of the Dissertation

In this dissertation, I investigate the relationship of the spatiotemporal patterns of air pollutants, the ambient monitoring network, and environmental justice issues in the Phoenix metropolitan area (Figure 1). My key research questions are:

1. What are the spatiotemporal patterns of air pollution and their key determinants in the Phoenix metropolitan region?
2. What implications do the spatiotemporal patterns of air pollution have for designing a monitoring network in the Phoenix metropolitan region, and is the current government ambient monitoring network adequate?
3. Using a comprehensive, multi-scale point of view, are there environmental justice problems in the Phoenix metropolitan region, and does the current ambient monitoring network adequately give representation to these vulnerable populations?

This dissertation develops a multi-scale approach to the study of air pollution in urban areas which integrates principles and methods used in landscape ecology, urban ecology, and the social sciences. It fills several gaps in air pollution research through case studies focusing on the Phoenix metropolitan region. This research is significant because:

1. While pollutants are frequently monitored and modeled within the region, there is a notable absence in the literature of investigating air pollution and its underlying factors at different spatiotemporal scales. To fill this gap, a landscape pattern analysis approach was appropriate and effective.
2. There is a lack of research in evaluating the adequacy of ambient air monitoring networks and their relations to the spatial characteristics of industrial and agricultural sources and social demographics in the Phoenix area. The Phoenix metropolitan region is an ideal place to address this

problem because of its rapid urbanization, diverse industries, and presence of minority ethnicities.

3. Although various environmental justice issues have attracted increasingly greater attention from researchers, many of these studies in the Phoenix area have focused only on a specific pollution category, a limited temporal scale, or limited social groups. A comprehensive approach using multiple pollutants, scales, and population demographics is needed. A hierarchical, spatially explicit, landscape ecological modeling approach provides an effective method of studying these issues (Luck and Wu 2002, Wu 2008). This research develops a more comprehensive approach that considers multiple pollutants, scales, and population demographics using the Phoenix metropolitan region as a test-bed.

Expected Results

My research (1) quantifies the spatiotemporal patterns of the criteria pollutants O_3 and PM_{10} within the Phoenix metropolitan area; (2) evaluates the existing ambient air monitoring network in the Phoenix metropolitan area for discrepancies or redundant sites, with a special emphasis on monitoring for pollution near possible environmental justice issues; and (3) completes a comprehensive environmental justice survey at various spatiotemporal scales to determine if unique social groups are under a disproportionate risk from air pollution.

The following deliverables were produced from this dissertation research:

(1) Production of distinct dissertation chapters and relevant articles written for publication in suitable scientific journals. At the time of this writing, two of these articles have been published in peer-review journals, and one is in draft.

(2) A comprehensive report regarding the status of the Maricopa County monitoring network was produced for government environmental agencies and policy makers, including the EPA, state and local agencies, and the regional planning agency; reports regarding the status of environmental justice issues are pending. The EPA requires all air pollution control districts to assess the adequacy of their monitoring networks every five years; this assessment must relate to “the ability of existing and proposed sites to support air quality characterization for areas with relatively high populations of susceptible individuals”, i.e. environmental justice issues (Code of Federal Regulations 2009c). Using methods developed in this research, a report was provided to the EPA which satisfied the requirements of the Code of Federal Regulations.

(3) This report was also made available to the citizens of the Phoenix metropolitan area, and press releases and public meetings were held to answer citizen’s questions. This report contained information on the spatial location and concentrations of air pollutants and the performance of the air pollution monitoring network. Citizens can access this report, which is posted on the websites of the local government environmental and planning agencies, so as to make informed decisions regarding their residence and lifestyle. In addition, recommendations from the report on how to improve the quality of the air pollution monitoring network have already begun to be implemented, and it is expected that the evaluation methods will become a model for other air quality agencies within the country.

Air quality issues are of vital concern for the health of our citizens, and research on these issues is in high demand, especially in areas that are in violation of the primary air pollution standards, such as in the Phoenix metropolitan area. This dissertation adds valuable research to advance the body of literature, provide immediate ongoing results for use by governmental policy-makers, and provide citizens with the information they need to better their lives. Lastly, these studies will provide a strong base for future research in deciding how to address and remediate air pollution problems within the Valley of the Sun.

CHAPTER 2: CHARACTERIZING AIR POLLUTION PATTERNS ON MULTIPLE TIME SCALES IN URBAN AREAS: A LANDSCAPE ECOLOGICAL APPROACH[1]

Abstract

Quantifying the spatiotemporal patterns of air pollution in urban areas is essential for studying ecological processes, environmental quality, and human health in cities. To adequately characterize or monitor air pollution patterns, one important issue is scale because the concentrations of air pollutants are temporally dynamic and spatially heterogeneous. My research addresses the scale issue in air quality monitoring and analysis by considering the following research questions: (1) How does the spatial pattern of O_3 change with the temporal scale of analysis? (2) How does the spatial pattern of PM_{10} change with the temporal scale of analysis? (3) What implications do these scale effects have for designing and evaluating air pollution monitoring networks? I systematically examined these questions based on data from official air pollution monitoring networks in the Phoenix metropolitan region, Arizona, USA. My results showed that spatial patterns of both O_3 and PM_{10} may change substantially with the temporal scale of analysis. O_3 patterns at broader (but not finer) temporal scales were more consistent across years, and exhibited a more uniform, regionalized pattern. PM_{10} patterns were less consistent across years than O_3, and exhibited a more localized effect. Spatial patterns of PM_{10} also varied seasonally. My study demonstrates that it is

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critically important to consider the temporal and spatial scales in designing or evaluating air monitoring networks in particular and in conducting air pollution research in general.

Introduction

Monitoring the spatial and temporal patterns of air pollutants in urban areas is necessary for protecting human health and ensuring environmental justice. To accurately assess air pollutants and identify populations at risk, a critically important first step is to determine how many air sampling stations are needed and where they should be placed. Although it would be desirable to have a dense network of air pollution monitors that covers the full spatial extent of an urban region, this is infeasible because of physical, fiscal, and technical constraints. Establishing an air monitoring site takes significant resources, and issues such as location, objective, power, and security all have to be considered (Arizona Department of Environmental Quality 2011b, MCAQD 2011). Thus, policy makers and resource managers need multiple sources of information in order to maximize their limited resources when designing or improving air monitoring networks. A fundamentally important but largely ignored issue in evaluating and designing air pollution monitoring networks is spatiotemporal scale. Scale is a central issue in ecological and geographic sciences and particularly in landscape ecology which studies the relationship between spatial pattern and ecological processes across a range of scales (Turner 1989, Pickett and Cadenasso 1995, Wu et al. 2000). Two key components of scale are grain size (corresponding to spatial or temporal resolutions) and extent (the spatial expanse or time duration of a study) (Wu et al. 2006). Spatial patterns, ecological processes, and their relationships are all scale-dependent, meaning that their characteristics and controls vary with the scale of observation or analysis (Levin 1992, Wu and Loucks 1995). Accurately assessing air pollution in an urban area requires the generation of time series of spatial patterns (maps) of air pollutants, and these patterns are most likely scale dependent as with ecological patterns. This scale dependence of air pollution patterns has important implications for the design of monitoring networks and the analysis of data obtained from them. Capturing spatial and temporally heterogeneous air pollution patterns can have important implications, including evaluating epidemiological effects or conducting social justice studies at different scales of exposure (Loo 2007, Digar et al. 2011). While the scale issues have been scrutinized extensively in ecology and geography, there is little landscape ecological work done on how scale matters in monitoring and analyzing the spatiotemporal patterns of air pollutants.

Thus, I attempted to address this research problem in the Phoenix metropolitan region, one of the fastest-growing urban areas in the United States and home to more than 4 million people (Luck and Wu 2002, Berling-Wolff and Wu 2004). With increasing anthropogenic activity, health standards for air pollution are frequently violated in this desert city (Bolin et al. 2000, Arizona Department of Environmental Quality 2011a). Ground-level O_3 and PM_{10} are the two pollutants currently of most local concern, as the region is classified as being in non-attainment of standards for these pollutants (Arizona Department of Environmental Quality 2009, U.S. EPA 2009a). Specifically, my study was designed to address the following research questions:

1. How does the spatial pattern of O_3 change with the temporal scale of analysis (i.e. temporal extent)?
2. How does the spatial pattern of PM_{10} change with the temporal scale of analysis?

3. What implications do these scale effects have for designing and evaluating air pollution monitoring networks?

I hypothesized that, due to its chemical characteristics, O_3 would be a regionally-scaled pollutant and its spatial pattern would be more uniform across space and more consistent between sampling years. I also hypothesized that O_3 would have a more apparent urban-to-rural gradient and be more stable outside of the urban area. By contrast, I hypothesized that the spatial pattern of PM_{10} would be more localized in relation to sources and less consistent across temporal scales.

Methods

Study Area

The study is in the Phoenix metropolitan statistical area (MSA) in South-Central Arizona (Figure 2). The MSA, within Maricopa and Pinal Counties, is a thriving area with more than 20 self-governing municipalities. The rural areas of Maricopa and Pinal counties contain significant agriculture, including livestock and irrigated cropland. The region has experienced dramatic growth since the end of World War II, with population in the MSA expanding from 331,000 in 1950 to almost 4.2 million in 2010 (Wu et al. 2011). This growth has been exponential ,with populations in Pinal and Maricopa Counties increasing by 99.9% and 24.2%, respectively, between the 2000 and 2010 census (U.S. Census Bureau 2011).

The Phoenix region is geographically situated in a river valley and is surrounded by mountainous topography. The region is located in arid, sub-tropical latitudes and has predominantly high atmospheric pressure, and thus light winds and weak atmospheric circulation. This prevailing lack of strong atmospheric circulation, in combination with the valley location, impedes the dispersion of pollutants out of the urban area (Ellis et al. 1999, Ellis et al. 2000).

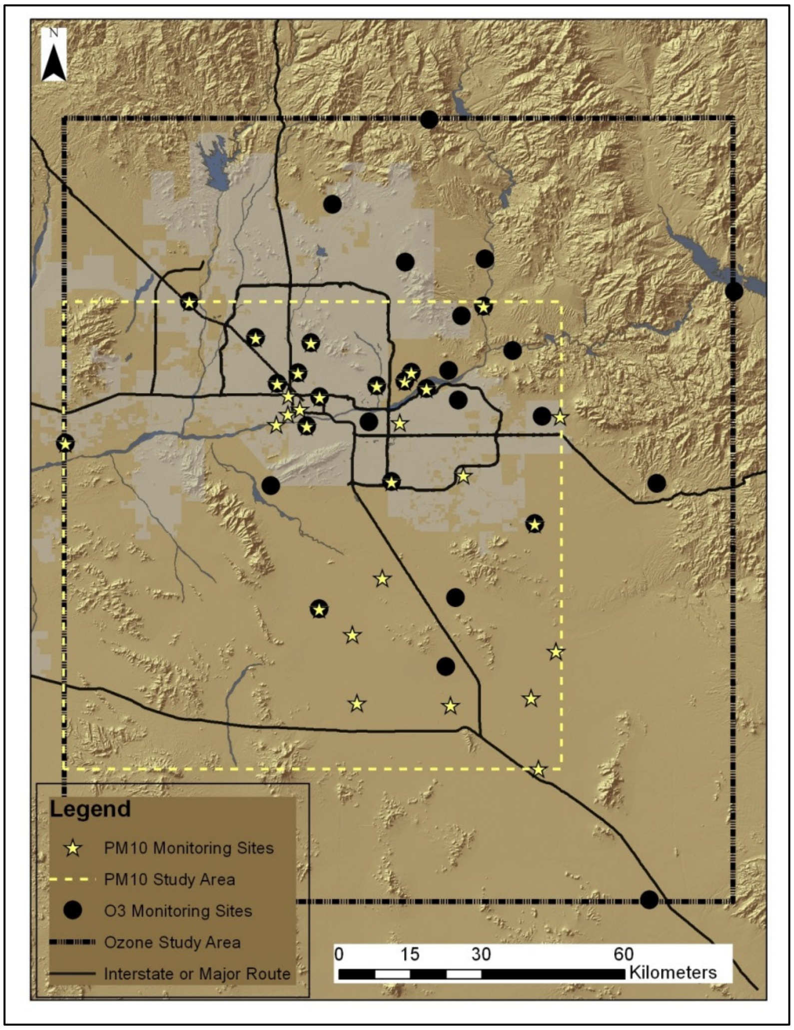

Figure 2 Topographical Map of the Phoenix Metropolitan Area (Shaded) and Surrounding Rural Areas, Depicting the O_3 and PM_{10} Study Areas and Monitoring Sites. Note that some Sites Combined both O_3 and PM_{10} Monitors

Industries and transportation in the Phoenix MSA region, such as agriculture, sand and gravel mining, construction, vehicle traffic, and unpaved roads in the urban periphery, in combination with the dry desert climate, create considerable sources for PM_{10} pollutants (Bolin et al. 2000, MCAQD 2009). O_3 is a secondary pollutant and is not directly emitted; however, the abundant sources of O_3 precursors, e.g. volatile organic compounds (VOCs), carbon monoxide (CO), and oxides of nitrogen (NO_x), mixed with the commonly warm, sunny days, create an environment where active photochemical reactions produce significant amounts of O_3 pollutants near the ground level (Ellis et al. 1999, MCAQD 2009).

For this study, the Phoenix MSA region was divided into O_3 and PM_{10} study areas (Figure 2). I designed these study areas based on their geographic features and the location of existing pollution monitoring sites. I also explicitly chose these areas, i.e. the homogenous metropolitan area with a shallow buffer of nearby rural sites, for their assumed stationarity of data. O_3 is hypothesized to be a more regionally-scaled pollutant that is easily transported because of its chemical lifecycle, and as a secondary pollutant it can occur in broader areas not necessarily near its precursor sources. On a diurnal basis, precursors, e.g. CO, VOC, and NO_x, react with sunlight to produce O_3 molecules. However, at night, O_3 in the nocturnal boundary layer will react with nitric oxide (NO) in a titration reaction that converts NO to NO_2 while 'scavenging', or destroying, O_3 molecules. O_3 pollution in the urban core, with ample NO sources, can often virtually disappear overnight, only to begin the cycle anew the next morning; while rural areas have more persistent O_3 concentrations which can travel through the atmosphere (National Research Council 1991, Gregg et al. 2003, Seinfeld and Pandis 2006).

Therefore, O_3 concentrations are also hypothesized to be much more temporally variable within urban areas while more stable in rural areas. Thus, I designed the O_3 study area to include rural areas further away from the urban center, increasing the number of sites for the statistical analyses, while still maintaining assumed stationarity. The O_3 study area is approximately 2.3 million hectares in size and contains 32 pollution monitoring sites, including several in downwind uninhabited wilderness areas (Figure 2).

PM_{10}, in contrast, is hypothesized to be a more localized pollutant. The PM_{10} study area is approximately one million hectares in size, and contains 30 pollution monitoring sites (Figure 2). Because of the limitations of this assumed stationarity and the location of existing monitoring sites, the PM_{10} study area is much smaller than the O_3 study area. PM_{10} is hypothesized to be a far more temporally variable and spatially localized pollutant than O_3, and the size of the study area was designed to be smaller to maintain a reasonable assumption of stationarity (Pohjola et al. 2002, Seinfeld and Pandis 2006).

<u>Data Acquisition and Processing</u>

I obtained air pollution data for the study from the United States Environmental Protection Agency's (EPA) Air Quality System (AQS) database. These data were generated and submitted to AQS by local government air pollution agencies at the state, county, and tribal levels. This study utilizes data from 32 O_3 and 30 PM_{10} monitoring stations operated by these local agencies within the Phoenix MSA (Table 1). These air pollution monitors all complied with the EPA's Federal Reference Method or Federal Equivalency Method; thus the sampling equipment was approved for taking official air pollution measurements and rigorous maintenance and quality assurance plans for the equipment and data were required and verified (Code of Federal Regulations 2009a, Arizona Department of Environmental Quality 2011a, MCAQD 2011).

Table 1 List of Agencies Operating Monitoring Stations within the Study Area. Agencies Submit Their Data to the EPA's AQS Database, Which Was the Source of Data for This Study

Agency	Type of Agency	# O_3 Stations	# PM_{10} Stations
Arizona Department of Environmental Quality	State	3	2
Fort McDowell Yavapai Nation	Tribal	1	1
Gila River Indian Community	Tribal	2	1
Maricopa County Air Quality Department	Local (County)	17	14
Pinal County Air Quality Control District	Local (County)	5	9
Salt River Pima-Maricopa Indian Community	Tribal	4	3

I collected O_3 data for the study in the time span of 2008 through 2010, with each of the three years being analyzed separately and compared with each other. The finest temporal resolution (or grain size) of these data is one hour (i.e., raw data were one-hour averages). To examine the effects of different temporal scales on the air pollution pattern analysis, I focused on four temporal extents (i.e., time durations over which average values of measurements were derived): one hour (at 15:00 on July 15), eight hours (15:00-22:00 on July 15), one month (July), and a season (April-October) (Table 2). The seasonal average was chosen instead of an annual average because many of the O_3 monitoring sites only operate during this time period.

I also analyzed PM_{10} data and compared them independently for the years 2008 through 2010. The temporal resolution for PM_{10} was a 24-hour average measured one day out of every six (1-in-6 day basis), as this is the operating schedule for some of the PM_{10} monitors. Most PM_{10} monitors operate on a finer time scale, collecting daily 24- or 1-hour averages; however, all finer averages were rolled into a 24-hour average and all data outside of the 1-in-6 day schedule were eliminated to create a consistent coarse resolution. These data were then analyzed at three different temporal extents: daily, monthly, and annual; daily and monthly extents included both winter and summer seasons (Table 2).

Table 2 Multiple Time Scales Used to Analyze the Spatiotemporal Patterns of O3 and PM10 in the Phoenix Metropolitan Region. Note That for PM10, the Daily Extent Is Applied to Different Days in the Different Sampling Years Based On the Running Time of the 1-in-6 Day Schedule

Pollutant	**Temporal Resolution**	**Study Years**	**Temporal Extents**				
O_3	1-hour Averages, continuous sample grain	2008-2010	Seasonal (Apr-Oct)	Monthly (July)	8-hour (July 15, 15:00-22:00)	1-hour (July 15, 15:00)	
PM_{10}	24-hour Averages, 1-in-6 day sample grain	2008-2010	Annual	Monthly (Jan)	Monthly (Aug)	Daily (Jan 7 [2008, 2009], Jan 8 [2010])	Daily (Aug 22 [2008], 23 [2009], 24 [2010])

<u>Data analysis</u>

It is desirable to use a number of methods when performing geostatistical or spatial analysis, such as variograms, covariances, or correlograms (Rossi et al. (1992). Comparing and contrasting the results from multiple methods and at multiple scales provide a more comprehensive understanding with more robust conclusions (Jelinski and Wu 1996, Wu 2004). In that spirit, this study uses several techniques to explore the data and address the research questions.

Trend Analysis

The first technique used was trend analysis, a useful method of exploring data when no a priori knowledge exists. For non-spatial data, a common procedure is to use regression to explore the relationship between independent and dependent variables. This procedure is also appropriate for spatial data, with the X-Y coordinates as the independent variable and the pollution concentrations, or Z-value, as the dependent variable (Fortin and Dale 2005).

The data exploration was accomplished with the Trend Analysis tool in the ArcMap Geostatistical Analysis Extension, a Geographical Information System (GIS) application (ESRI 2010) . Using the tool, the study area was overlaid with a grid within which monitoring sites were placed according to their X-Y coordinates. The measured pollution concentrations from each site were then displayed as vertical sticks in the Z axis (Figure 3). The pollution concentrations were projected on the X-Z and Y-Z plane to give a graphical depiction in a spatially-explicit manner, i.e. north to south and east to west. A second-order polynomial (quadratic) multiple regression trend line was fitted to the two Z planes to show the spatial trend of the data (Figure 3).

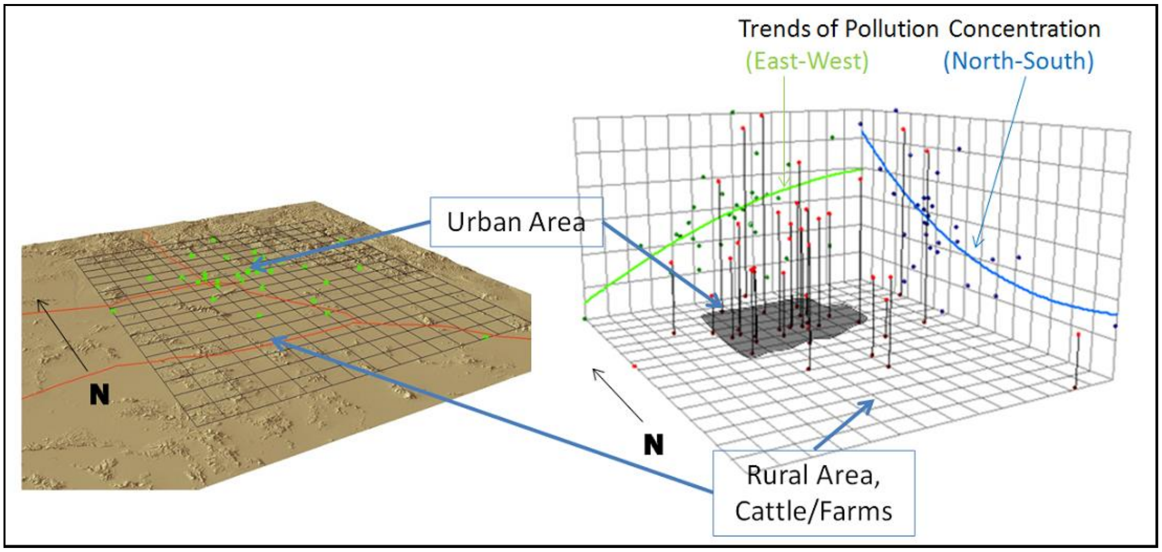

Figure 3 Illustration of the Use of the Trend Analysis Tool for Depicting the Spatial Pattern of Air Pollutants in the Phoenix Metropolitan Region. The Monitoring Sites for O_3 Are Marked in Green on the Gridded Map on the Left, and Their Concentrations Are Displayed in a 3-Dimensional Space on the Right. The Height of the Z-Axis 'Stick' Is Proportional to the Pollution Concentration Over a Given Temporal Extent. The Urban Areas of Phoenix Are Also Depicted As a Reference in Relation to the Surrounding Rural Areas

This analysis is a generalized ad hoc interpolation of the data with clear representation of the spatial trends. It is a global interpolation and not intended to model local spatial patterns of pollution. I compared multiple temporal extents and multiple years against each other to examine how those trends would change with scale.

Correlation Analysis

The second technique used was correlation analysis, similar to the method used by Ito et al (2001, 2005). I compared data from all 32 O_3 and 30 PM_{10} monitoring sites in a matrix format and calculated the coefficient of determination between each pair of sites. These correlations were cross-referenced with the distance between the sites and displayed in a correlogram. A trend line was also fitted to each correlogram.

Correlograms provide a useful method of visualizing the spatial dependence between data points in relation to distance, although it is a general method that makes no determination of exogenous or endogenous processes effecting the pattern (Fortin and Dale 2005). The primary reason for using correlation analysis in this study was to explore how the spatial dependence of air pollution patterns would change with scale.

Semivariance Analysis

The third technique used was semivariance analysis, which is useful for quantifying the structure of spatial autocorrelation, and necessary for determining the values of unmeasured locations using kriging (q.v. next section). Semivariance usually is plotted against the separation distances (or lag distance, h) between two points in space to create a semivariogram (Figure 4). The range in the semivariance plot indicates the distance within which spatial autocorrelation exists and beyond which statistical independence in the data begins (Griffith 1992, Rossi et al. 1992, Fortin and Dale 2005). Semivariance between each pair of samples is computed based on the following equation:

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n} \left[z_i - z_{i+h} \right]^2 \qquad (1)$$

where: $\hat{\gamma}(h)$ is the semivariance for interval distance class *h, n(h)* is the number of pairs of samples for the lag interval h, z_i is the is the measured sample value at point i, and z_{i+h} is the measured sample value at point $i+h$.

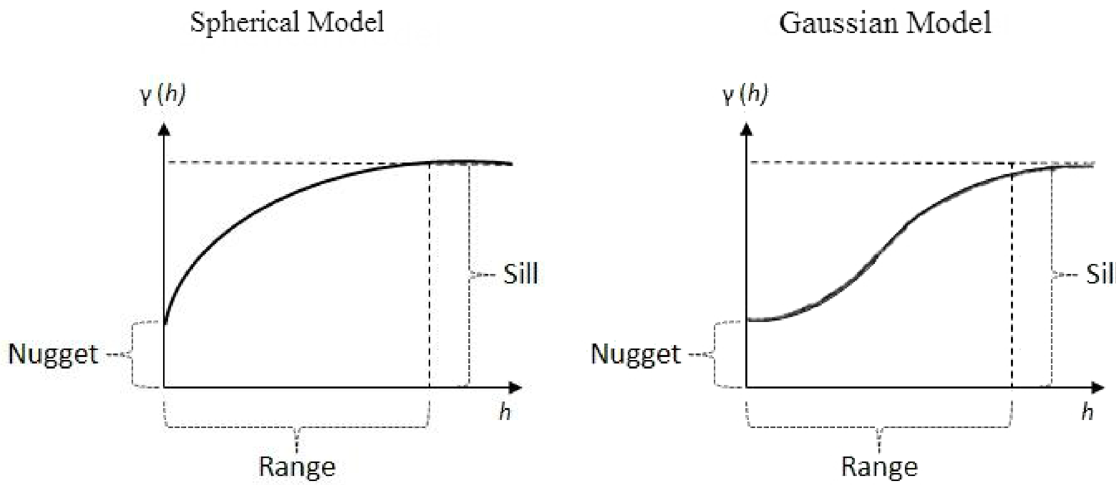

Figure 4 Examples of Semivariogram Models. The Solid Line Is the Theoretical Spherical or Gaussian Semivariogram Which Would Be Based upon Experimental Observations. Its Parameters Are: the Nugget (Variability Due to Local Random Effects or Measurement Error), Range (Distance up to which the Spatial Structure Varies) and Sill (Plateau of Semivariance Values, Or the End of Spatial Autocorrelation). The Spatial Lag, Or Distance between Points, Is *h*, and the Semivariance Value Is γ (*h*). This Study Found That O_3 Data Best Fit the Gaussian Model, While PM_{10} Data Best Fit the Spherical Model

The software, GS+: Geostatistics for the Environmental Sciences (Gamma Design Software 2006) was used for the semivariance analysis. Sample locations were formed into lag intervals with uniform distance. These lag intervals need to be small enough to capture the pattern, though if they are too small it will be unnecessarily patchy (Fortin and Dale 2005). Specifically, the maximum lag distance was set smaller than one half the spatial extent of the dataset (Meisel and Turner 1998). The shortest distance between sample points was used as the uniform distance with PM_{10} data, though a slightly longer distance was used for O_3 points to reduce excessive patchiness. Data were log or square-root transformed as appropriate to reduce skewness (Fortin and Dale 2005), and the *h*-lags were plotted in *h*-scattergrams to identify extreme outliers to be removed, as a necessary process described by Rossi, et al. (1992). The prepared data were modeled in isotropic semivariograms using the Gaussian model for O_3 and the spherical model for

PM_{10}, as these models consistently produced the least error when paired with the respective parameter (Figure 4). By definition of the GS+ software, the sill never meets the asymptote in the Gaussian model; therefore range is estimated as the distance at which the sill is within 5% of the asymptote (Gamma Design Software 2006). See Appendix A: Table 15 and Table 16, for further details on the parameters of the semivariance analysis.

Kriging Interpolation

Kriging is a geostatistical interpolation method to estimate values at unsampled locations based on the spatial autocorrelation structure quantified in the semivariance analysis (Cressie 1990, Fortin and Dale 2005). When additional sampling is too expensive or difficult to accomplish, as is often the case with air pollution monitoring, kriging provides an effective way of mapping out the spatial pattern of the pollutant over the large area. My kriging of the maps of O_3 and PM_{10} concentrations over the study area was conducted using the Geostatistical Analysis Extension within ArcMap (ESRI 2010). All input settings were matched with those of the GS+ software to maintain consistency with my semivariance analysis. Thematic maps were created at each temporal scale, for both O_3 and PM_{10}, so as to create a visual comparison of spatial patterns between scales.

Results

Spatiotemporal Patterns of O_3

Trend Analysis of O_3

My analysis of data from the 32 O_3 monitoring sites showed that the spatial trend of O_3 concentration varied with different temporal extents in each of the three study years

(2008-2010) (Figure 5). The O_3 pattern tended to be consistent across the three years on broader scales (i.e., the seasonal and monthly extents), but not on finer scales (i.e., the eight-hour and hourly extents). On the seasonal and monthly scales, the highest O_3 concentration consistently occurred in the northeastern section of the study area, but this was not the case on the finer scales (Figure 5) Because the urban core is located toward the top middle of the study area and because the dominant wind direction is to the northeast (Pardyjak et al. 2009), the highest O_3 concentration on the seasonal and monthly scales occurred in the rural mountainous areas downwind of the urban center. On shorter temporal scales (especially the hourly extent), the location of the highest concentration of O_3 was much closer to the urban core, with the urban areas generally having higher O_3 levels than the rural areas (Figure 5).

Correlation Analysis of O_3

The degree of correlation in O_3 concentration between monitoring sites generally decreased with increasing between-site distances, but the specific pattern differed between the long (seasonal and monthly) and short (8-hour) scales (Figure 6). The correlograms on the longer scales were also similar between years. However, the distance-based correlation pattern of O_3 at the 8-hour scale was different quantitatively

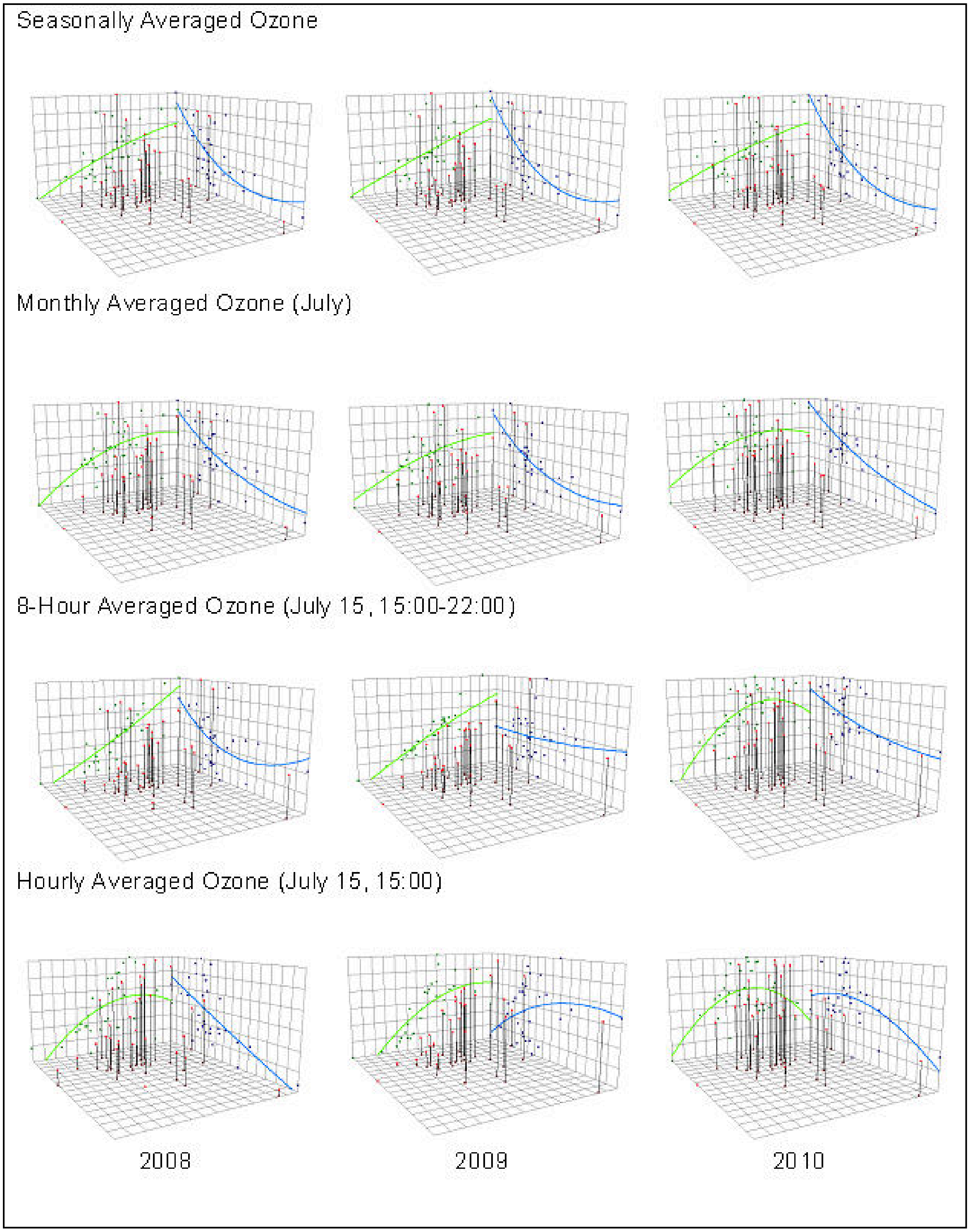

Figure 5 Trend Analysis Results Showing Spatial Patterns of O_3 Concentration at Different Temporal Extents and in Different Years in the Phoenix Metropolitan Region. The Trend Line on the 3D Graphs Depicts the Concentration Trend of Pollutants across the Study Area and Changes to the Trend Line between Scales Is the Focus of the Trend Analysis Method. Refer to Figure 3 for Details on the Elements within Each 3-D Graph

from that on the longer scales, and highly variable between the three study years (Figure 6). Except for the 8-hour scale in 2009, the results of correlation analysis showed that the majority of O_3 monitoring sites were highly correlated with each other (over 70%) within a distance of 30 km.

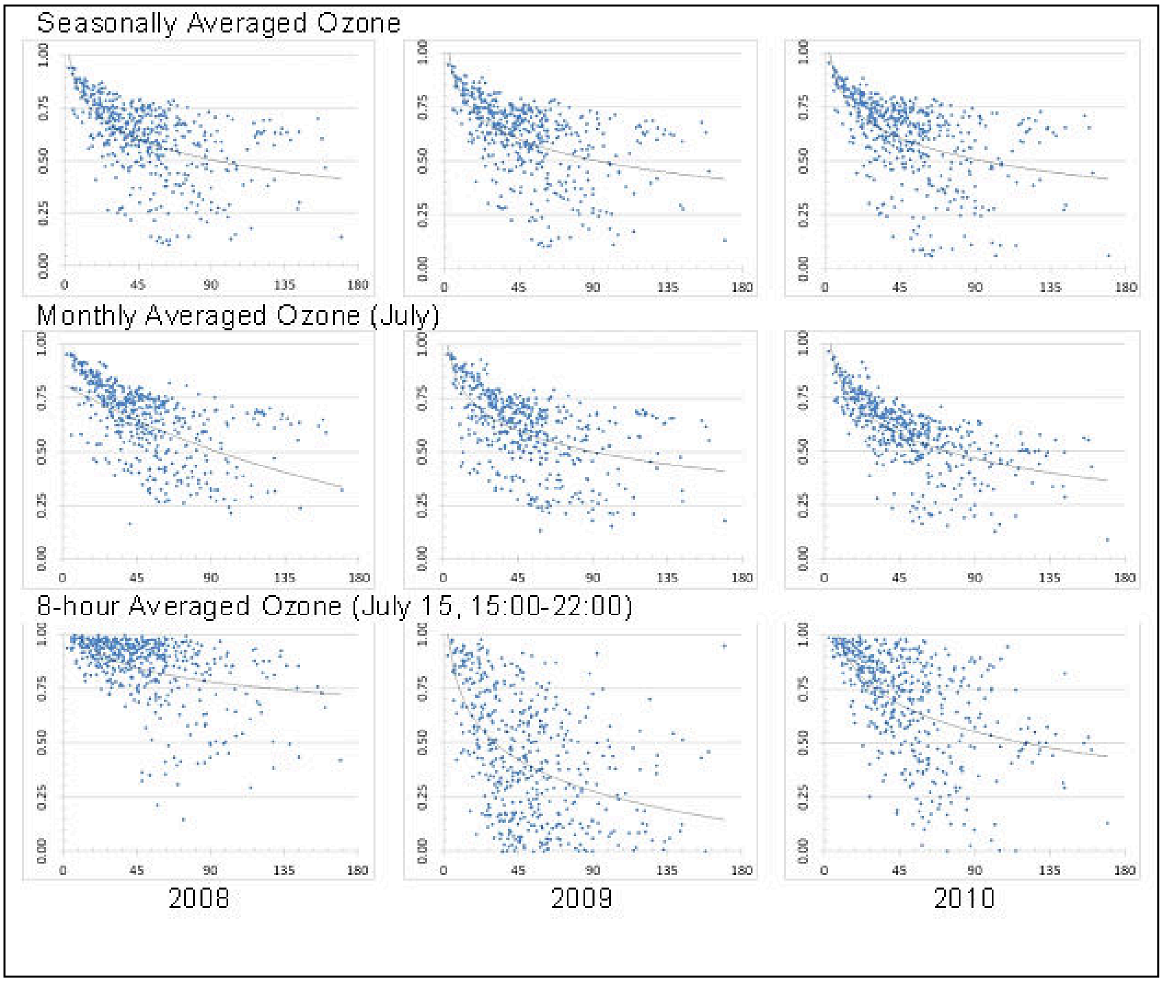

Figure 6 Correlograms of O_3 Concentration on Different Temporal Scales and in Different Years in the Phoenix Metropolitan Region. Each X Axis Represents Distance from 0-180 Km. Each Y Axis Represents the Coefficient of Determination (R^2) from 0.00-1.00

Semivariance Analysis of O_3

The range – the distance over which O_3 concentration was spatially autocorrelated – changed with temporal scales and between the three study years (Figure 7; Appendix A: Table 15). In certain cases, the range for O_3 was approaching 200 km, which is outside the spatial extent of the study area. The longest spatial autocorrelation range was found at the monthly scale, not at the longest temporal scale (seasonal). However, the range showed a consistent decreasing trend as the temporal scale became shorter than a month (Figure 7).

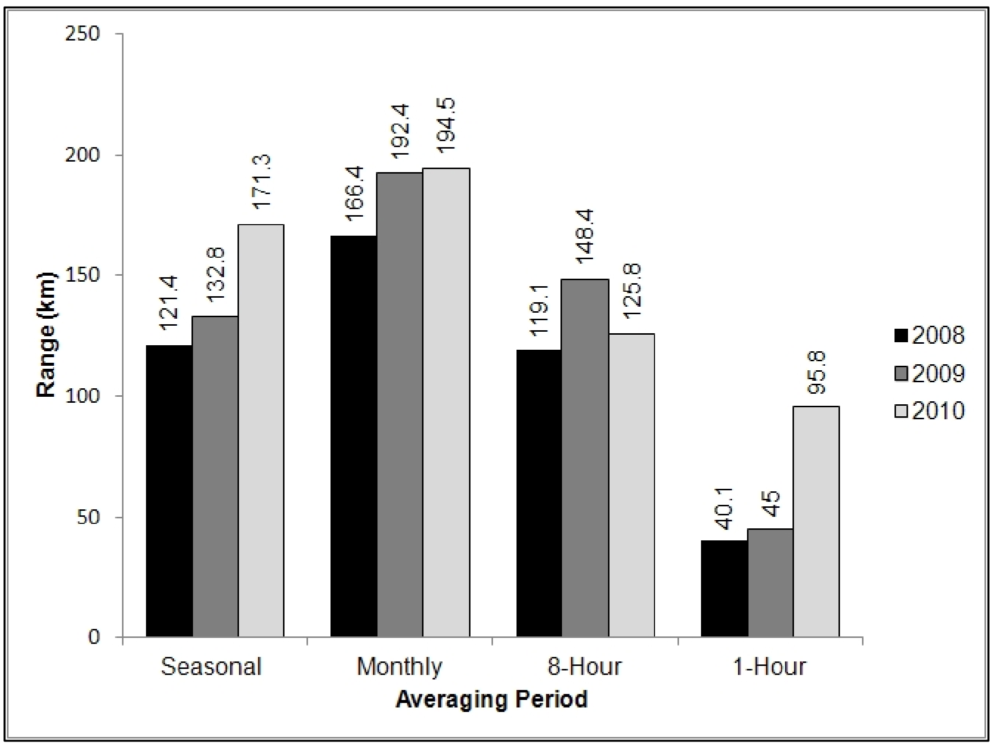

Figure 7 Effects of Temporal Scale (Extents) on Autocorrelation Ranges of O_3. Range Is the Distance (in km) Over Which Spatial Autocorrelation Exists among the O_3 Monitoring Sites, As Determined in the Semivariogram Analysis. Note That the 1-Hour Scale Has Much Shorter Ranges than the Other Scales, and More Variation between Years, Suggesting a Major Change in O_3 Patterns between the 1- and 8-Hour Scales

Kriging Interpolation of O_3

The kriged maps showed that O_3 concentrations across the study area were relatively low at the seasonal scale, but increased appreciably with decreasing temporal scales (Figure 8).

The northeast mountainous region of the study area had higher O_3 concentrations on the seasonal and monthly scales, with little variation in space and between years. This spatial pattern of O_3 began to change at the 8-hour scale as the areas of high O_3 concentrations intensified with appreciable differences between years. At the 1-hour scale, which is 3:00-4:00 P.M. in a summer afternoon, O_3 levels were almost at their highest for the entire region (Khoder 2009). At this fine scale, the spatial pattern of higher O_3 concentrations occurred in both the urban and rural areas, and also varied considerably between years (Figure 8).

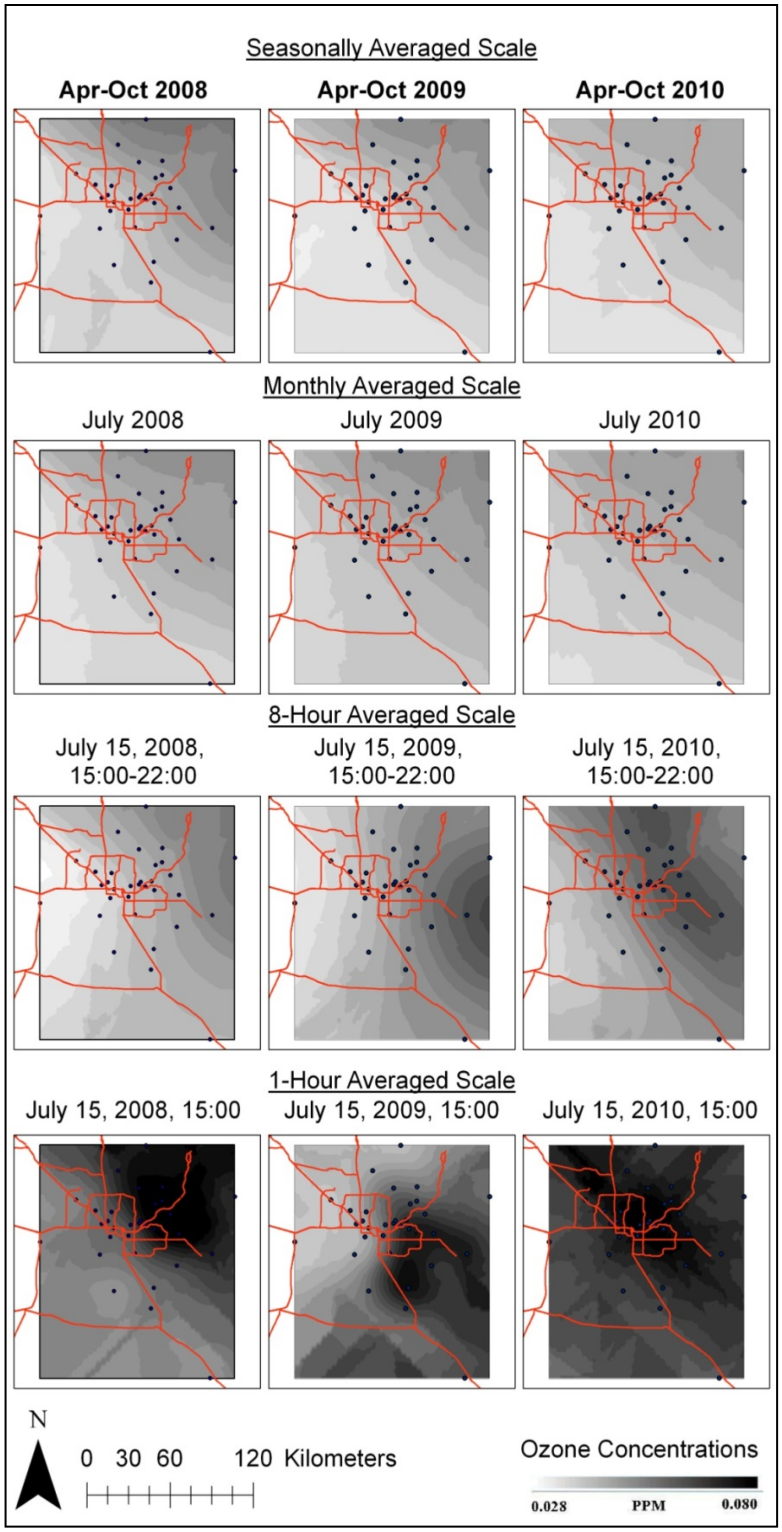

Figure 8 Kriged Maps of O_3 Concentrations, Each of Which Is Bordered by the O_3 Study Area Shown in Figure 2. Black Dots Represent the O_3 Monitoring Sites; Highways Are Represented As Lines. O_3 Concentrations Range from 0.028 to 0.080 PPM

Spatiotemporal Patterns of PM_{10}

Trend Analysis of PM_{10}

Data for PM_{10} were analyzed for summer and winter seasons on three different temporal scales: annual, monthly, and daily. The spatial pattern of PM_{10} was more variable between years than that of O_3, but the general trend shown in spatial pattern was similar (Figure 9). The spatial trend of PM_{10} did not change appreciably between the temporal scales, but differences were noticeable between summer and winter. In particular, PM_{10} levels tended to be higher in the urban areas in winter, but in the rural areas in summer (Figure 9). The spatial pattern at the annual scale closely resembled that of August, implying that the summer pattern was predominant most of the year.

One site, located in rural Pinal County south of the Phoenix metropolitan area, had higher PM_{10} concentrations than all other sites, regardless of scale or season. This site, known as the Cowtown monitor, was surrounded by agriculture operations (including cattle feedlots) and not far from housing developments (Arizona Department of Environmental Quality 2010). The Cowtown monitor was sited as a hotspot monitor of local agglomerated sources, and as such had particulate concentrations that were much higher than other monitors in the region (U.S. EPA 2009b, Arizona Department of Environmental Quality 2010). The Cowtown monitor was included in the trend analysis, but excluded as an outlier in the semivariogram analysis.

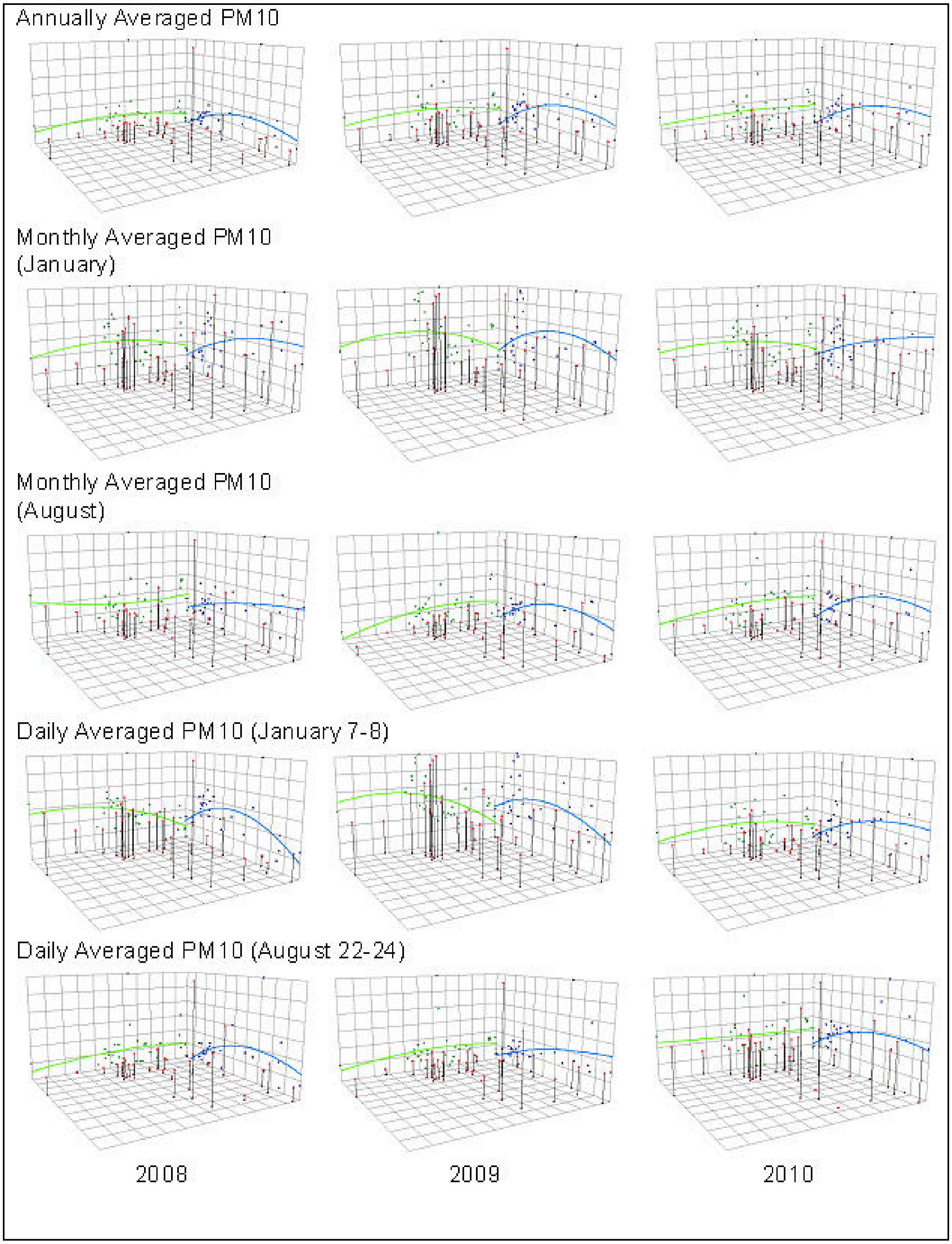

Figure 9 Spatial Patterns of PM_{10} Concentration at Different Temporal Extents and in Different Years. Refer to Figure 3 for Details on the Elements within Each 3-D Graph

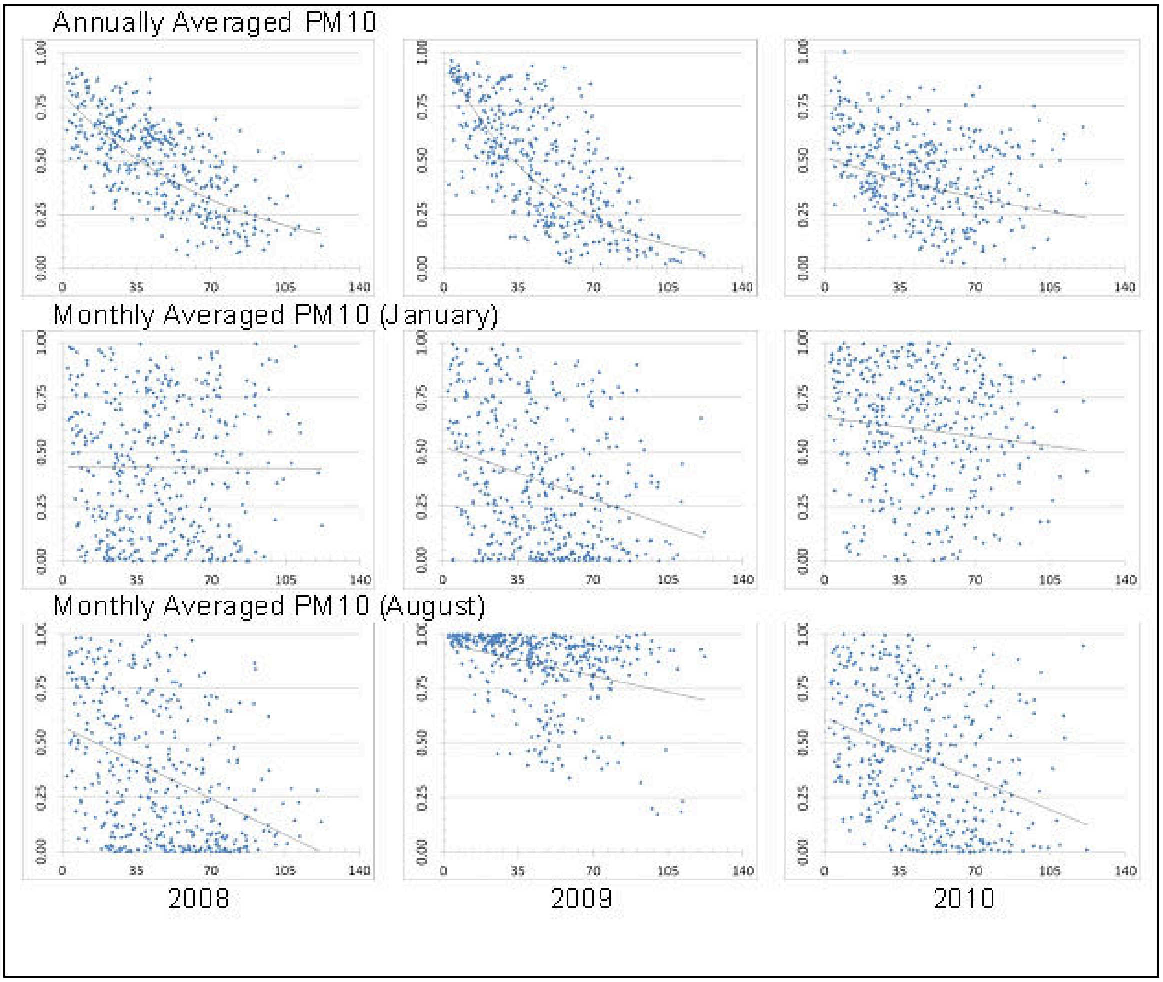

Figure 10 Correlograms of PM_{10} Concentration on Different Temporal Scales and in Different Years in the Phoenix Metropolitan Region. Each X Axis Represents Distance from 0-140 Km. Each Y Axis Represents the Coefficient of Determination (R^2) from 0.00-1.00

Correlation Analysis of PM_{10}

The PM_{10} correlation analysis was only conducted at the annual and monthly (winter and summer) scales because there was only a single value at the daily scale. The distance-based correlation patterns of PM_{10} were more variable between scales and between years than those of O_3 (Figure 10). For the annual-scale pattern, high-levels of correlation (>70%) appeared within 10 to 20 km. At the monthly scale, however, the correlation disappeared. August 2009 is an extreme exception, however, with most of the correlations being above the 80% level, even so far as 120 km. August 2009 had hotter and drier weather than August 2008 or 2010.

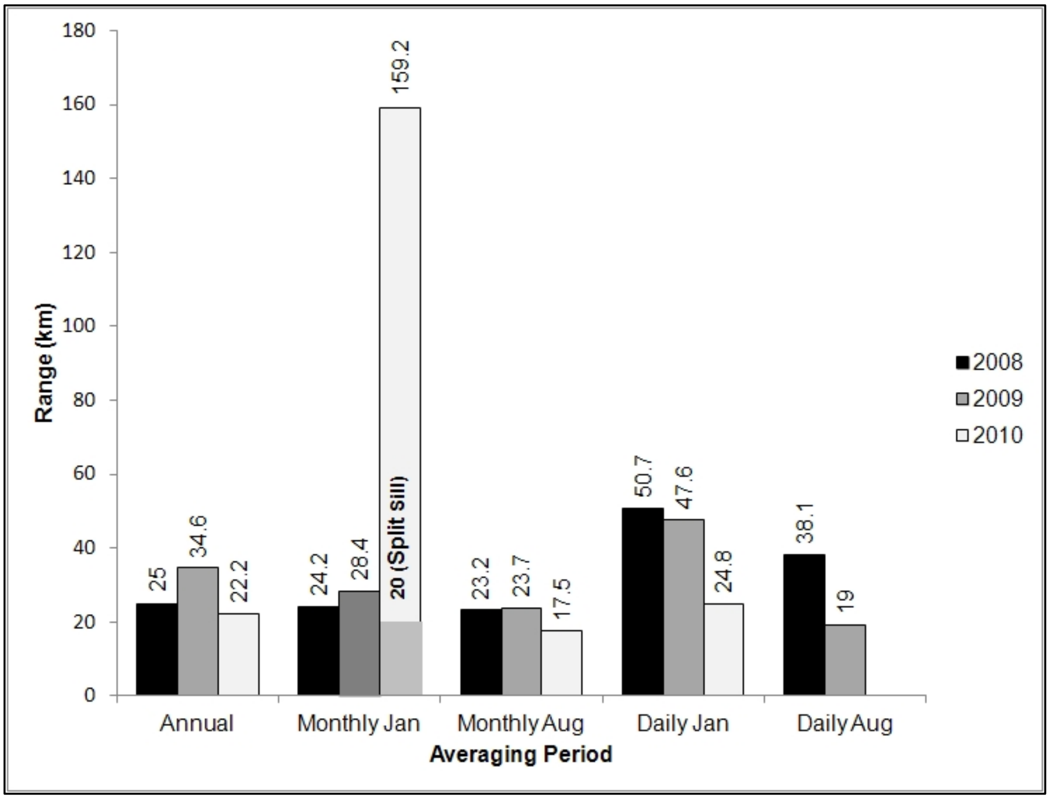

Figure 11 Effects of Temporal Scale (Extents) on Spatial Autocorrelation Ranges of PM_{10}, As Determined in the Semivariogram Analysis. The Semivariogram from Jan 2010 Exhibited Two Nested Sills Giving a Multi-Scalar Range. The Aug 2010 Daily Semivariogram Did Not Display a Sill, As the Data Appeared to Be Linear in Nature

Semivariance Analysis of PM_{10}

The ranges of PM_{10} were, in general, less than 50 km in distance for different temporal scales and study years (Figure 11) – much shorter than those of O_3. Unlike O_3, the ranges of PM_{10} tended to get longer with shorter temporal scales, with ranges longer in winter than summer. Major differences in the PM_{10} patterns occurred between the daily and monthly scales. January 2010, an exceptionally rainy month, exhibited a multi-scale nested semivariogram (Robertson and Gross 1994). The first sill evident in the semivariogram was reached at 20 km, similar to the other sample years. The second sill was estimated by the GS+ software to be reached at 159 km, which is outside of the study area. The semivariogram on August 24, 2010, was also different from the other sample years with an apparent linear pattern with no sill. The study area was experiencing a weather event on that day with windy conditions out of the north, which is unusual.

Kriging Interpolation of PM_{10}

The Kriged maps of PM_{10} showed that concentrations tended to be higher in the southern agricultural portion of the study area, while the urban areas in the northern portion had the lowest concentrations, especially at higher elevations (Figure 12). The overall spatial pattern at the annual scale was fairly consistent between the three study years, all showing a PM_{10} 'hotspot' in the south-central portion of the study area (the Cowtown monitor as mentioned previously).

At the monthly temporal scale, the PM_{10} pattern varied between winter and summer, with the summer pattern more closely resembling the annual pattern and having a distinct urban/rural gradient. PM_{10} winter concentrations in the southern agricultural areas were lower and more comparable with the northern urban areas. In January 2009, the urban area had the highest PM_{10} concentrations in the study area. The pattern between study years at the monthly scale was also similar to each other, although there appeared to be more variation between the summer months. At the daily scale, the spatial pattern of PM_{10} showed the greatest variability between scales and between years (Figure 12).

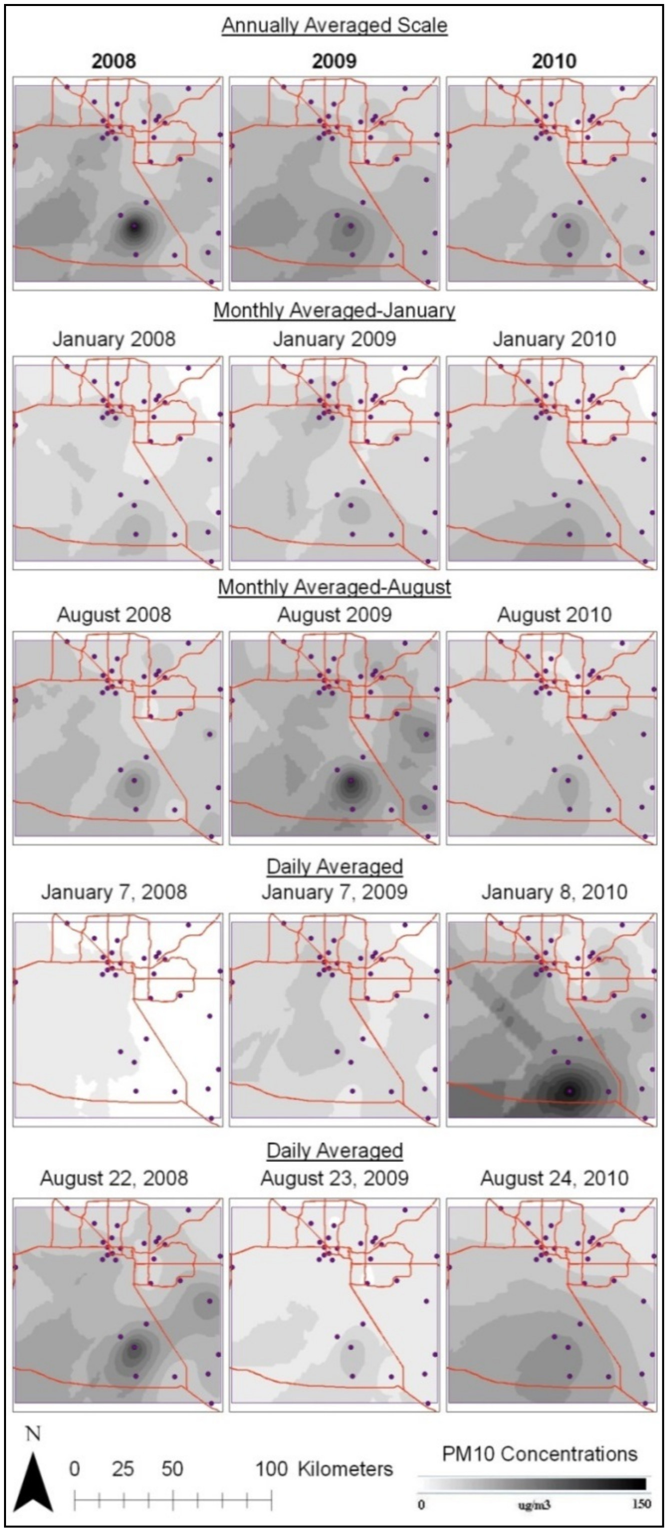

Figure 12 Kriged Maps of PM_{10} Concentrations, Each of Which Is Bordered by the PM_{10} Study Area Shown in Figure 2. Black Dots Represent the PM_{10} Monitoring Sites and Highways Are Represented As Lines. The PM_{10} Concentration Color Scale Ranges from 0 to 150 $\mu g/M^3$

Discussion

Changing O_3 Patterns on Different Temporal Scales

Our study has shown that spatial patterns of O_3 in the Phoenix metropolitan region may change substantially with the temporal scale of analysis. For example, the results of trend analysis and Kriging indicated consistently higher concentrations in the northeast portions of the study area on the longer time scales (i.e. seasonal and monthly), but this pattern dissipated on shorter time scales (i.e., the 8-hour and 1-hour scales). Likewise, the correlograms showed high degrees of correlation with strong trends at the seasonal and monthly scales, but not at the finer scales. My results from semivariance analysis further indicated that the spatial autocorrelation ranges for O_3 were quite sensitive to the temporal scale of analysis.

These patterns were not unexpected, given the meteorological conditions in this region of Arizona and the chemical lifecycle of O_3 and its relation to other urban pollutants, such as NO_x. O_3 requires the mix of VOCs, NO_x or CO, and sunshine to be created, but excessive NO_x also scavenges O_3 molecules at night when the O_3 reaction stops. Thus urban areas with high NO_x sources often have a reduction in O_3 concentrations overnight. In contrast, rural areas often maintain steady concentrations of O_3 after dark and over time, as there is not a sufficient amount of NO_x to scavenge it and the other sinks of O_3, such as dry deposition, occur much slower (Gregg et al. 2003). These dynamics likely account for the spatial patterns of higher O_3 concentrations in the downwind rural areas of the Phoenix metropolitan region. Also, the average wind direction in the region is from west to east, and there are also daytime anabatic winds which push O_3 out of the urban areas and up against the mountains east of the urban valley (Ellis et al. 1999). A nighttime katabatic wind will drain some of the pollution back into the urban area, but the long-term effect is to have higher O_3 concentrations in the eastern mountains.

These results confirm my hypothesis that O_3 is a regional-scaled pollutant with long-distance ranges for spatial autocorrelation (i.e. more uniform across space), at least over the longer seasonal and monthly temporal scales. At the shorter 8-hour and, especially, 1-hour scales, however, this hypothesis is no longer valid as O_3 exhibits short-ranged patterns more strongly influenced by local factors. A key message here is that the spatial patterns of O_3 do change with temporal scales.

Changing PM_{10} patterns on different temporal scales

The spatial patterns of PM_{10} also varied with temporal scales and between study years. In particular, major scale effects occurred between summer and winter months, with summer showing a much higher rural-to-urban pollution gradient than winter. The correlation analysis showed that PM_{10} concentrations had little correlation over long distances at the monthly scale, and this result was corroborated by the generally much shorter ranges from semivariance analysis. Once again, meteorological factors and source locations were likely the dominating determinants for the patterns of PM_{10}.

PM_{10} is not as easily transported as finer particles because it is heavier and tends to settle out of the atmosphere sooner (Chung et al. 2012). Nevertheless, some meteorological conditions such as wind speed and relative humidity have a strong effect on PM_{10} concentration levels, as well as the strong influence that nearby sources in the

Phoenix valley have on PM_{10} concentrations (Wise and Comrie 2005). However in the wintertime, the southwestern deserts are often subjected to atmospheric stagnation events. The atmosphere over this desert region is typically dry and cool during the winter, and as sunset approaches, the ground surface begins to cool faster than the atmosphere above it. The rapid cooling of the ground and boundary layer atmosphere, resulting in temperature inversion, can create stable atmospheric conditions at low altitudes (Pardyjak et al. 2009). This nighttime temperature inversion also creates stagnant atmospheric conditions that contribute to trapping particulate pollution close to its sources (Pardyjak et al. 2009). As the Phoenix metropolitan area is geographically located in a valley, this effect is compounded and likely accounts for the smaller urban-to-rural gradient observed in the winter. According to Wise and Comrie (2005), with the typically dry atmospheric conditions in the region (summer and else wise), the observed patterns at the annual scale are likely due to the effect of local sources of PM_{10}.

In general, the spatial patterns of PM_{10} showed more consistency between years than originally anticipated, but the considerable effects of temporal scale confirmed my hypothesis. Also, the results seem to support my hypothesis that PM_{10} is a local pollutant influenced mainly by nearby sources, though I found that seasonal meteorology is as important to PM_{10} patterns. In addition, the winter to summer pattern dynamics were as informative as the spatiotemporal dynamics between different temporal scales.

<u>Sample Size and Kriging</u>

The use of Kriging techniques when interpolating data from an air monitoring network with a small number of sampling sites has inherent risk involved. Kriging has reduced accuracy with small sample sizes and different alternatives to this method have been suggested (Diem 2003). For example, the study by Diem and Comrie (2002) specifically addressed the problem of a sparse sample size by using a linear regression model to improve the accuracy of the interpolation. However, linear regression models have their own disadvantages, such as the necessity of significant resources and high-quality data (Diem and Comrie 2002). Although I recognize the problems with Kriging to create accurate high-resolution pollution surfaces with a small sample size, this study has focus primarily on the landscape-level pattern and its changes between temporal scales. As such, I believe that my results are adequately robust for this purpose.

Implications of Scale in Air Pollution Analyses

The findings of this study have important implications for the design and evaluation of air pollution monitoring networks in large urban regions. In general, the temporal scale of observation and analysis may substantially affect what air pollution patterns will be revealed. These scale effects, if not adequately understood, may influence people's perception and misguide governmental policy decisions. To overcome this problem, researchers and decision makers need to better understand the multi-scale patterns of air pollution in time and space, and this scale multiplicity must be considered explicitly in designing or evaluating air monitoring networks.

More specifically, air pollution monitoring networks should be designed so that both grain size (the spatial and temporal resolutions of the monitoring network) and extent (the time duration and spatial expanse of the network) are appropriate. For example, in the US, much emphasis is often placed upon a community or region to comply with Federal air pollution health standards, with each standard having differing averaging intervals such as annual, 24 hours, or 8 hours. If the region's government focuses on only a few single sites or local areas that are exceeding specific standards, the density of monitors may be much higher than the rest of the region (Nejadkoorki et al. 2011). This may lead to a deficient monitoring network that is unable to capture the spatiotemporally heterogeneous patterns of air pollution over the entire region. With these implications in mind and building upon the results from this study, I have conducted a comprehensive evaluation of the air pollution monitoring network in the Phoenix metropolitan region, which will identify its deficiencies and redundancies based on integrated data on environmental settings, demographics, and air quality measurements (Chapter 3).

Scale multiplicity of air pollution patterns may also affect environmental justice research. The studies of environmental justice, or equity, seek to identify unique socioeconomic population groups exposed to disproportionate amounts of pollution risk. As shown in this study, pollution patterns may change when the temporal scale of analysis is changed. For example, if an environmental justice study only utilizes peak 1-hour values to find populations affected by acute pollution exposure, it risks missing those population groups affected by chronic exposure to monthly or annual pollution patterns. To cope with this problem, a multi-scale approach is needed (Wu 2004, 2007). Part of my ongoing research is to take such an approach, and as such, I am using the multi-temporal scale kriging results from this study to explore a number of environmental equity-related research questions in the Phoenix metropolitan region. For example, do certain population groups experience disproportionately higher pollution risks? How would the detection of such potential environmental injustices change with the scale of analysis?

Acknowledgements

I thank the members of the Landscape Ecology and Sustainability Laboratory (LESL) at Arizona State University for their suggestions on this study. I also thank Zhengjun Wang for his assistance with the GS+ software and two anonymous reviewers for valuable comments which helped improve the quality of the paper.

CHAPTER 3: A MULTI-OBJECTIVE ASSESSMENT OF AN AIR QUALITY MONITORING NETWORK USING ENVIRONMENTAL, ECONOMIC, AND SOCIAL INDICATORS AND GIS-BASED MODELS[2]

Abstract

In the United States, air pollution is primarily measured by Air Quality Monitoring Networks (AQMN). These AQMNs have multiple objectives, including characterizing pollution patterns, protecting the public health, and determining compliance with air quality standards. In 2006, the Environmental Protection Agency issued a directive that air pollution agencies assess the performance of their AQMNs. Although various methods to design and assess AQMNs exist, here I demonstrate a GIS-based approach that combines environmental, economic, and social indicators through the assessment of the O_3 and PM_{10} networks in Maricopa County, Arizona. The assessment was conducted in three phases: (1) to evaluate the performance of the existing networks, (2) to identify areas that would benefit from the addition of new monitoring stations, and (3) to recommend changes to the AQMN. A comprehensive set of indicators were created for evaluating differing aspects of the AQMN's objectives, and weights were applied to emphasize important indicators. Indicators were also classified according to their sustainable development goal. My results showed that O_3 was well represented in the county with some redundancy in terms of the urban monitors. The addition of weights to

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[2] This chapter has been published as: Pope, R. L., & Wu, J. (2014). A Multi-Objective Assessment of an Air Quality Monitoring Network Using Environmental, Economic, and Social Indicators and GIS-Based Models. *Journal of the Air & Waste Management Association*, doi:10.1080/10962247.2014.888378.

the indicators only had a minimal effect on the results. For O_3, urban monitors had greater social scores, while rural monitors had greater environmental scores. The results did not suggest a need for adding more O_3 monitoring sites. For PM_{10}, clustered urban monitors were redundant, and weights also had a minimal effect on the results. The clustered urban monitors had overall low scores; sites near point sources had high environmental scores. Several areas were identified as needing additional PM_{10} monitors. This study demonstrates the usefulness of a multi-indicator approach to assess AQMNs. Network managers and planners may use this method to assess the performance of air quality monitoring networks in urban regions.

Introduction

In the United States, the primary method of measuring ambient air is through a system of government-regulated air quality monitoring networks (AQMN), usually operated by state, tribal, or local agencies at regional or local scales (U.S. EPA 2011, 2012). These AQMNs have multiple design objectives, including characterizing population exposure to pollutants, monitoring source impacts, measuring maximum and background pollutant concentrations, providing data for modeling purposes, and documenting air quality trends over time. In addition, a primary mission of an AQMN is to determine compliance with U.S. National Ambient Air Quality Standards (NAAQS), which are defined levels of criteria pollutants considered potentially harmful to public health and the environment (U.S. EPA 2011). Thus, a properly designed AQMN is important for protecting the health and welfare of the public.

In 2006, the United States Environmental Protection Agency (EPA) introduced a requirement for air pollution control agencies to perform assessments of their monitoring networks once every five years (40 CFR pt 58.10 2007, Scheffe et al. 2009). These periodic assessments are intended to determine "…whether new sites are needed, whether existing sites are no longer needed and can be terminated, and whether new technologies are appropriate for incorporation in to the ambient air monitoring network." (40 CFR pt 58.10 2007). These periodic assessments are also expected to re-evaluate the objectives and budget for the network, and to determine its effectiveness and efficiency relative to its intended goals. Thus, recommendations to reconfigure and improve AQMNs are also expected in the assessments (Raffuse et al. 2007). To assist state and local entities in developing these assessments, the EPA supplied guidance documents detailing assessment projects performed at the regional level, including analytical techniques and indicators that state and local agencies could employ (U.S. EPA 2001, Raffuse et al. 2007, Scheffe et al. 2009).

A number of methods have been developed for designing and assessing AQMNs. Some early information theory-based approaches utilize Shannon's entropy as a measure of uncertainty to optimally locate monitoring stations (Lindley 1956, Husain and Khan 1983, Caselton and Zidek 1984). Other modeling approaches for AQMN design employ various techniques. For example, geostatistical modeling is used to locate monitors with the least amount of predictive error (Trujillo-Ventura and Ellis 1991, Haas 1992, Kanaroglou et al. 2005). The use of sampling campaigns to collect high-resolution data on the spatial pattern of pollutants is another method, which is often paired with geostatistical modeling when designing a network (Cocheo et al. 2008, Lozano et al.

2009, Ferradás et al. 2010). Simulation modeling (e.g., using atmospheric dispersion models such as Eulerian grid-based or Gaussian plume) also can be used to determine the spatial pattern of pollutants and thus help network design and assessment (McElroy et al. 1986, Bauldauf et al. 2002, Mazzeo and Venegas 2008, Mofarrah and Husain 2009, Zheng et al. 2011).

Because different air pollutants behave differently, multiple methods are necessary to optimally design an AQMN. For Example, Trujillo-Ventura and Ellis (1991) confront the problem of designing a suitable network for various air pollutants by applying multiple methods such as geostatistics, pollutant violation of standards, data validity, and network cost. Mofarrah and Husain (2009) integrated the multiple-criteria method with spatial correlation techniques, using data from a Gaussian plume model and applying environmental, social, and economic criteria via a weighting scheme to identify potential site locations. These locations were then evaluated with the sphere-of-influence spatial correlation technique suggested by Liu et al. (1986). Chen et al. (2006) proposed that sustainable development principles be considered when designing an AQMN. In their study, environmental objectives were related to the concentrations of air pollutants and the emission quantity of sources; social objectives were related to the location of monitoring stations with population, sensitive receptors (e.g., schools and hospitals), traffic areas, and air pollution complaints; and economic objectives focused on lowering the cost for the AQMN. Their sustainable development procedure combines system analysis and multi-objective planning to determine optimal locations for monitoring stations (Chen et al. 2006).

However, most of today's AQMNs did not begin operation as planned integrative wholes; instead they began as small number of stations which grew and evolved over time as circumstances dictated (Pope Demerjian 2000, Chen et al. 2006, 2011). The growth of these government AQMNs in the United States was often planned using the EPA's monitoring objectives mentioned previously, and these objectives have changed over time as air pollution regulations have matured (Demerjian 2000). Thus, while the previously mentioned design methods can be used to assess certain aspects of an existing network, it is necessary to employ multiple measures in order to adequately assess the multi-dimensional objectives of AQMNs; environmental indicators and indices are effective measures for communicating air quality information to network managers, and are especially relevant at the city scale (Engel-Cox et al. 2013, Hsu et al. 2013).

Some previous studies have considered multiple indicators or objectives for performing assessment. For example, Gramsch et al. (2006) assessed the AQMN of Santiago, Chile using a cluster analysis approach based on the Pearson's correlation between monitoring stations. The study followed earlier attempts to optimize the AQMN in Santiago using Shannon's information index which excluded the least informative stations (Silva and Quiroz 2003), and a simulation modeling study in the Santiago airshed (Schmitz 2005). Another cluster analysis assessment was performed by Ignaccolo et al. (2008) in Italy, which used a functional data analysis approach. Other types of assessment studies include correlation analysis (Morawska et al. 2002), principal component analysis (Pires et al. 2009), and geostatistical methods (Van Egmond and Onderdelinden 1981, Briggs et al. 1997).

In this study, I develop a GIS-based, multi-objective assessment approach that integrates environmental, economic, and social indicators, and demonstrate its use through assessing the O_3 and PM_{10} monitoring networks in the Phoenix metropolitan area. The assessment was conducted in three phases:

1. A site-to-site comparison of each monitoring station by a series of indicators, this section scores each station as compared to its assessed objective.
2. Geographic Information System (GIS)-based spatial models identify areas where the existing AQMN does not adequately represent potential air pollution problems to show where additional sites are needed.
3. Recommendations are developed on reconfigurations necessary to improve the AQMN.

The original periodic network assessment performed for the Maricopa County Air Quality Department (MCAQD) was conducted for the time period 2005-2009 and included the criteria pollutants carbon monoxide (CO), nitrogen dioxide (NO_2), ground-level O_3, particulate matter less than 10 and 2.5 microns (PM_{10} and $PM_{2.5,}$, respectively) and sulfur dioxide (SO_2) (Pope 2011). For brevity, this paper will only detail the results for O_3 and PM_{10}, as the Phoenix metropolitan area is in NAAQS non-attainment for these pollutants, and therefore has the largest network of stations (Pope and Wu 2014). This paper emphasizes the sustainable development approach as detailed by Chen et al. (2006) and Moldan et al. (2012), and indicators are classified as supporting environmental, social, or economic objectives, if applicable. This study also includes indicators to emphasize environmental justice issues, i.e., it includes analyses to determine if minority populations were experiencing a disproportionate amount of risk from air pollution. This study describes a multi-objective assessment technique to answer the following research question: Does the monitoring network of the Phoenix metropolitan area effectively and efficiently represent spatial pollution patterns and trends, and does it provide all population groups with adequate information on the quality of their air?

Methods

Study Area and Data Sources

The study addresses the Phoenix metropolitan area in South-Central Arizona (Figure 13), a thriving area comprised of more than 20 self-governing municipalities. The region, including the rural areas of Maricopa and adjacent Pinal counties, contains significant agriculture, including livestock and irrigated cropland. The region has experienced dramatic growth since the end of World War II, with population expanding from 331,000 in 1950 to almost 4.2 million in 2010 (Wu et al. 2011). This growth has been exponential, with populations in Pinal and Maricopa Counties increasing by 99.9% and 24.2%, respectively, between 2000 and 2010 (U.S. Census Bureau 2011).

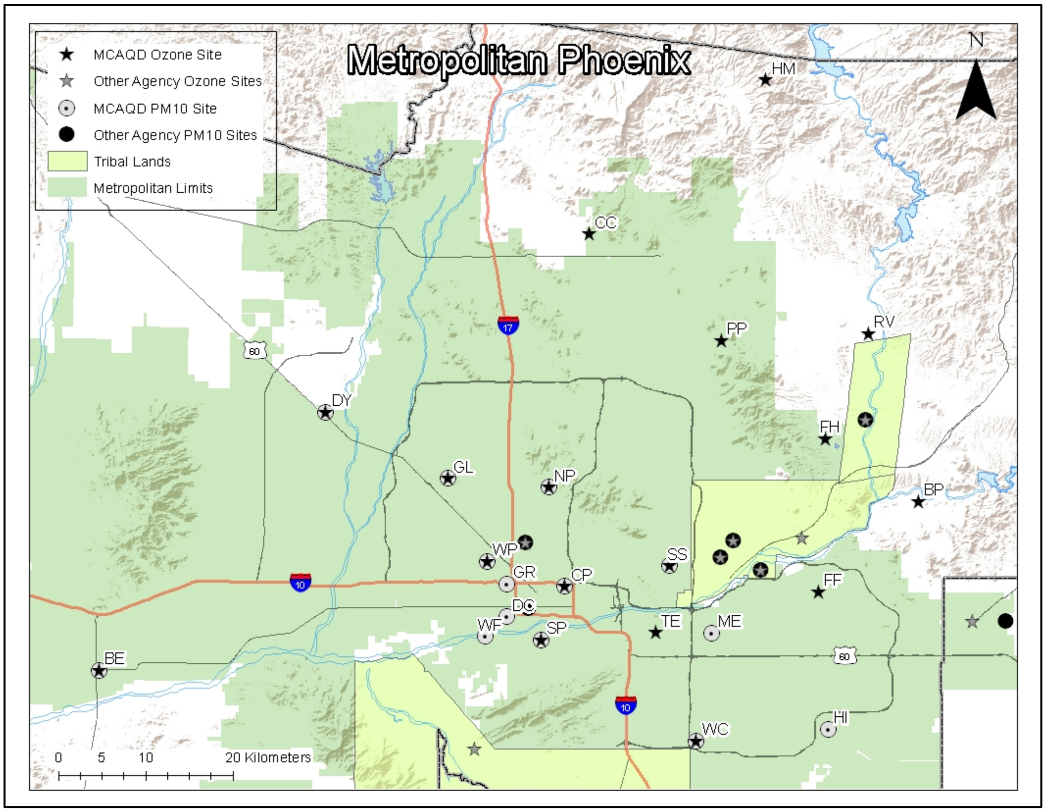
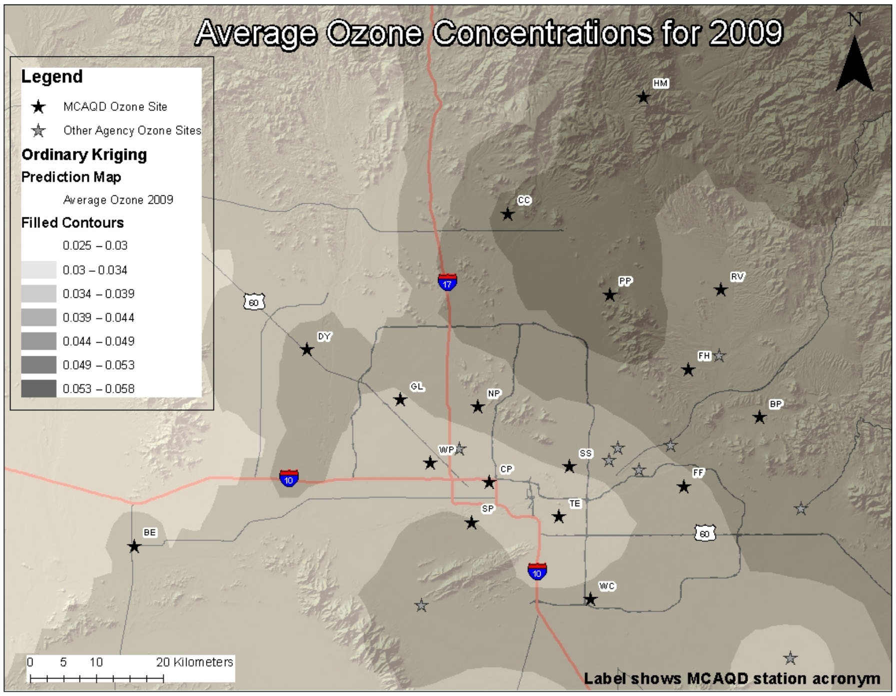


Figure 13 Map of the Metropolitan Phoenix Area Including O_3 and PM_{10} Monitoring Stations for MCAQD (Labeled) and Other Area Agencies. Note That Some Site Locations Contain Monitoring Stations for Both O_3 and PM_{10}

The Phoenix region is situated in a river valley surrounded by mountainous topography and desert vegetation. The region is located in arid, sub-tropical latitudes and has predominantly high atmospheric pressure, and thus light winds and weak atmospheric circulation. This prevailing lack of strong atmospheric circulation, in combination with the valley location, impedes the dispersion of pollutants out of the urban area (Ellis et al. 1999, Ellis et al. 2000). Industries (e.g., agriculture, mining, and construction) and transportation (e.g., vehicle traffic on unpaved roads or re-entrainment from paved roads) in the South-Central Arizona region, in combination with windblown dust, create considerable sources for PM_{10} pollutants (Bolin et al. 2000, MCAQD 2009). Abundant sources of O_3 precursors – i.e., volatile organic compounds (VOC), CO, and oxides of nitrogen (NO_x) – and the commonly warm, sunny days together create an environment where active photochemical reactions produce significant amounts of ground-level O_3 (Ellis et al. 1999, MCAQD 2009).

Though the original assessment performed for the MCAQD (Pope 2011) included all the criteria pollutants (note that air toxic species are not monitored by the MCAQD and were not included), for brevity, only O_3 and PM_{10} are highlighted in this paper as they are of most concern within Maricopa County (Figure 14). While concentrations of other criteria pollutants in the region are below the NAAQS, O_3 and PM_{10} have both been classified as being in non-attainment of the NAAQS. Thus these pollutants are given a high priority for air pollution monitoring and have the largest network of monitoring stations to use within a multi-objective assessment (MCAQD 2011). Although this study focuses primarily on the 17 O_3 and 14 PM_{10} monitoring stations operated by the MCAQD (Table 3), other federal, tribal, state, and local agencies in Arizona also operate O_3 and PM_{10} stations (Table 4). Where applicable, these stations were also included in the assessment to increase the robustness of the analyses, giving a total of 45 O_3 and 48 PM_{10} stations to draw data from (Figure 15).

(a)



(b)

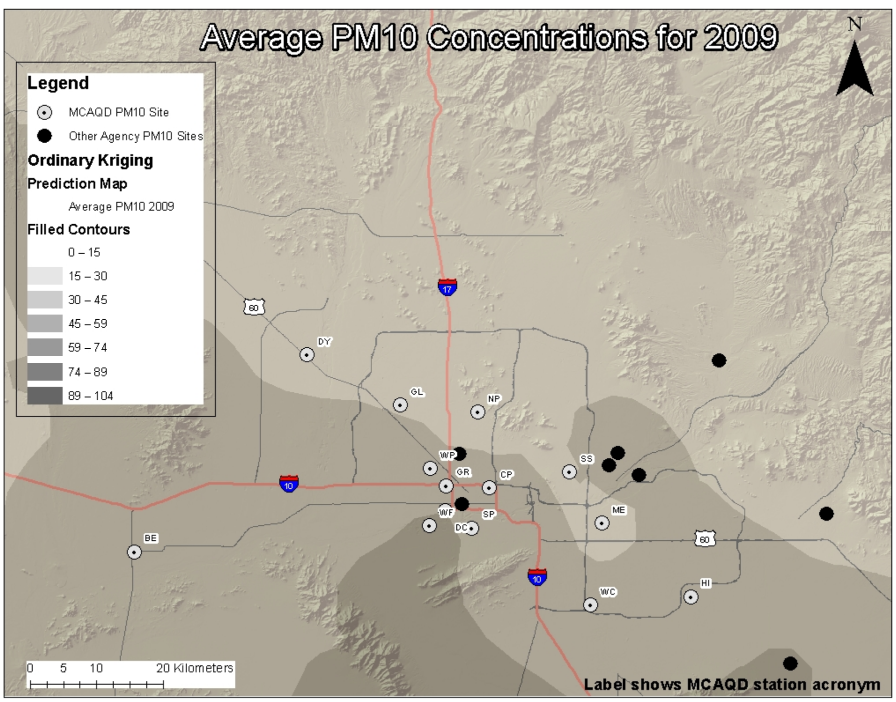


Figure 14 Map Depicting Pattern of Average 2009 Pollution Concentrations in Metropolitan Phoenix. (a) Depicts O_3 Concentrations and Monitoring Stations. (b) Depicts PM_{10} Concentrations and Monitoring Stations. Note That Though the Map Differentiates between MCAQD and Other Agency Monitoring Stations, This Ordinary Kriging Interpolation Was Created from All Stations

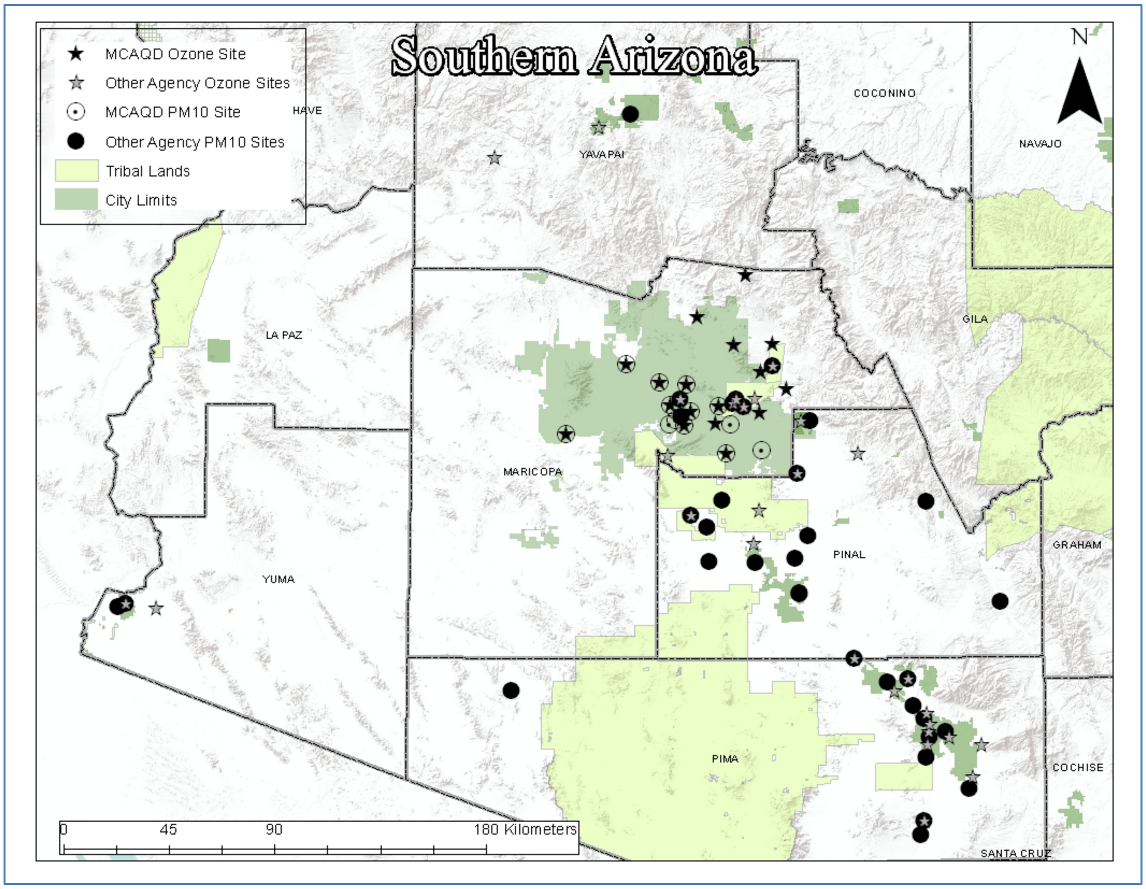


Figure 15 Map of Southern Arizona Including Location of All O_3 and PM_{10} Monitoring Stations Used for Data Purposes in the Study. The Two Largest Metropolitan Areas on This Map Are Phoenix, Located in Maricopa County, and Tucson, Located in Pima County to the South

Table 3 MCAQD Monitoring Stations Assessed within This Study

Station Name	Acronym	Pollutants Monitored	Station Name	Acronym	Pollutants Monitored
Buckeye	BE	O_3, PM_{10}	Mesa	ME	PM_{10}
Blue Point	BP	O_3	Humboldt Mountain	HM	O_3
Cave Creek	CC	O_3	North Phoenix	NP	O_3, PM_{10}
Central Phoenix	CP	O_3, PM_{10}	Pinnacle Peak	PP	O_3
Durango Complex	DC	PM_{10}	Rio Verde	RV	O_3
Dysart	DY	O_3, PM_{10}	South Phoenix	SP	O_3, PM_{10}
Falcon Field	FF	O_3	South Scottsdale	SS	O_3, PM_{10}
Fountain Hills	FH	O_3	Tempe	TE	O_3
Glendale	GL	O_3, PM_{10}	West Chandler	WC	O_3, PM_{10}
Greenwood	GR	PM_{10}	West 43rd Avenue	WF	PM_{10}
Higley	HI	PM_{10}	West Phoenix	WP	O_3, PM_{10}

Table 4 Agencies Providing Data and the Number of Monitoring Stations Used within This Study

Agency	Type of Agency	# O_3 Stations	# PM_{10} Stations
Maricopa County Air Quality Department	Local (County)	17	14
Arizona Department of Environmental Quality	State	6	8
Fort McDowell Yavapai Nation	Tribal	1	1
Gila River Indian Community	Tribal	2	1
National Park Service	Federal	1	0
Pima County Department of Environmental Quality	Local (County)	9	8
Pinal County Air Quality Control District	Local (County)	5	13
Salt River Pima-Maricopa Indian Community	Tribal	4	3

I obtained O_3 and PM_{10} data from the Air Quality System (AQS) database maintained by the U.S. EPA. Each of the previously mentioned agencies is responsible for entering data from their stations into AQS. These stations all complied with the U.S. EPA's Federal Reference Method or Federal Equivalency Method; thus the sampling equipment was approved for taking official air pollution measurements and quality assurance plans for the equipment and data were required and verified (40 CFR pt 58 appx A 2010, MCAQD 2011, ADEQ 2013). Raw pollution values were averaged into yearly and 5-year numbers for use in the assessment. Note that not all stations were fully operational during the 2005-2009 time period; stations that did not meet a 75% data completeness level, as required by the U.S. EPA (40 CFR pt 50 1971), were excluded where applicable.

Phase I: Indicators for Evaluating the Existing Monitoring Network

The first phase of the study consists of a site-to-site comparative assessment of each monitoring station. The purpose of this assessment is to evaluate the performance of existing stations of the AQMN using multi-objective indicators (Table 5). The mix of indicators were chosen to reflect multiple aspect of the AQMN and they score for a comprehensive array of traits desired in monitoring stations, e.g., one indicator gives the highest scores for stations located in urban areas measuring the highest concentration of pollutants; whereas another indicator favors rural stations monitoring background concentrations of pollutants. Most of the indicators were based on existing guidance documents, e.g. Raffuse et al. (2007), though some were developed independently. These indicators are used to obtain information about the performance of each station, and, after aggregating and applying appropriate weights, the scores give an overall network performance for each station. The indicators also provide information on the three sustainability aspects of the station (environment, social, and economy).

Table 5 Indicators and Their Categories Used in Phase I and II of the Study

Phase I			Phase II		
#	**Indicator**	**Sustainability Group**	**#**	**Indicator**	**Category**
1	Measured Concentrations	Environmental	1	Emissions Inventory Point Sources	Source-Oriented
2	Deviation from the NAAQS	Environmental	2	Arterial Road Traffic Count	Source-Oriented
3	Area Served	Environmental/Social	3	Freeway Traffic Count	Source-Oriented
4a	Emissions Inventory	Environmental	4	Road Density	Source-Oriented
4b	Emissions Inventory - Predicted Ozone	Environmental	5	Population Density	Population-Oriented
5	Traffic Counts	Environmental	6	Minority Population Density	Population-Oriented
6	Monitor-to-Monitor Correlation	Environmental/Economic	7	Euclidean Distance between Sites	Spatially-Oriented
7	Removal Bias	Environmental/Economic	8	Standard Error from Predicted Pollution	Spatially-Oriented
8	Population Served	Social			
9	Environmental Justice-Minority Population served	Social			
10	Trends Impact	Social/Economic			
11	Number of other Parameters Monitored	Economic			

Sustainability descriptors of environmental, social, or economic were assigned to the 11 different indicators following the format described by Chen et al. (2006), i.e., environmental indicators are related to the emissions and concentrations of sources and air pollutants; social indicators are related to population and sensitive receptors; and economic indicators are related to the cost-effectiveness, efficiency, and leveraging capability of stations within the AQMN. The specific indicators are as follows:

1. Measured Concentrations (Environmental): This indicator scored stations on the concentration of measured pollutants using the design value of each station; the design value is generally the highest annual concentration measured in that averaging interval, which is based upon the NAAQS. Higher design values received higher scores. This indicator provides information that is important from a regulatory standpoint for determining NAAQS compliance and for performing model evaluations (Schmidt 2001, Raffuse et al. 2007).

2. Deviation from the NAAQS (Environmental): This indicator also uses the design values from each monitoring station; however, this technique uses the absolute value between the design value and the NAAQS exceedance threshold. Monitoring stations whose design values are closest to the exceedance threshold, either below or above, were given the highest score as they were considered to provide more information in terms of NAAQS compliance (Schmidt 2001, Raffuse et al. 2007).

3. Area Served (Environmental/Social): This indicator scored monitoring stations based upon their area of coverage. Using ArcView 10.0 GIS to create Thiessen polygons (a standard technique used in geography to assign a zone of influence around a

point), spatial areas that are closest to an existing station were collected into one proximity polygon (O'Sullivan and Unwin 2003, ESRI 2010). Stations having the largest proximity polygons were scored the highest, which tends to give those stations in suburban or rural areas a higher score. Though these stations often have low concentration scores, they have high value for determining background concentrations, conducting air quality modeling, adding spatial coverage and interpolation points to a large metropolitan area, and giving air quality information to people living in less densely populated areas (U.S. EPA 2001).

4a. Emissions Inventory (Environmental): This indicator scores stations based on their proximity to point sources of pollution and the density of emissions in the surrounding area. Using the 2008 Periodic Emissions Inventory reports from the MCAQD, which includes reported emissions from approximately 1000 permitted sources within Maricopa County (MCAQD 2011), point sources were geolocated using a GIS and emissions from these sources were spatially aggregated using the township, range, and section grid system, with each section being 1.6 km square in size . Though PM_{10} monitoring stations used reported emissions of corresponding PM_{10}, O_3 stations used reported emissions of VOCs instead, as O_3 formation in the Phoenix metropolitan area is VOC-limited (Kleinman et al. 2005). Emissions were summed within the area served by each station's Thiessen proximity polygon from the Area Served indicator. These results were normalized for emission density by dividing the emission sums by the Thiessen polygon area; this aids the technique by taking weight away from the rural and urban fringe stations that have large Thiessen proximity polygons, and thus emission sources that are farther away from the station. Since this analysis only included point sources within the limits of Maricopa County, the Thiessen polygons were trimmed to only include areas within the county. Stations with higher emission densities in their area served were scored higher.

4b. Emissions Inventory-Predicted Ozone (Environmental): This indicator, which was only used for the O_3 parameter, scores stations based upon their proximity to long-term O_3 concentrations. Since ground-level O_3 is a secondary pollutant, emissions inventory lists of primary sources are insufficient at longer temporal scales. Furthermore, although O_3 needs NO_x in its formation reaction, it is also scavenged by NO_x in the atmosphere (Seinfeld and Pandis 2006). Because of these chemical dynamics, O_3 concentrations follow different patterns than other primary pollutants. In the short-term (several hours or less), O_3 will form near its precursor sources and increase as the plume moves downwind and has more time to react with the sun. At night, with the photochemical reaction stopped, O_3 concentrations within the urban area will decrease as NO_x compounds in the area scavenge them. However, outside of the urban areas, where NO_x concentrations are low, O_3 will persist longer in the environment before deposition or decomposition. Thus O_3 concentrations tend to be much higher in the rural areas downwind of an urban area when averaged over long temporal periods (Gregg et al. 2003, Pope and Wu 2014). Therefore it is insufficient to only use emission densities of VOC point sources to score O_3 stations. To address this, I created an interpolated O_3 surface using the longer scaled 2008 annual average. The mean O_3 concentrations were calculated within each O_3 station's area served Thiessen polygon, and stations with higher mean concentrations were scored higher. Thus O_3 stations were scored for both proximity to VOC sources (for the short term) and proximity to annual O_3 concentrations (for the long term).

5. Traffic Counts (Environmental): Point sources only account for a portion of the pollution emission sources within an area, with other major sources including mobile sources and transported pollutants. Transports were not addressed in this study, but this indicator does consider mobile source emissions. Emissions from mobile sources can vary; factors which can affect the amount of pollution released include road type, as fast-moving vehicles on a freeway generally emit less pollution per mile than vehicles on arterial roads and collectors; vehicle type, e.g., diesel vs. gasoline powered vehicles; traffic congestion; and age and size of vehicles. Ideally, a method which attempts to account for traffic emissions would account for all of these variables in a model which would give high spatial detail to mobile sources of pollution. Such traffic modeling is outside the scope of this study; instead, traffic count and road density were used as a proxy to approximate the spatial variability of mobile source pollution.

The average weekday traffic (AWT) counts for Maricopa County in 2007 were obtained from the Maricopa Association of Governments, which in turn collected them from various state, county, and municipal agencies. The dataset includes counts for freeways and arterial roads with extensive sample location coverage; however, it is difficult to ascertain if AWT sample locations cover all arterial roads with the same density and it is likely that additional new roads were not sampled. To normalize these data for evaluation, both the AWT and the length of roads within each monitoring station's area served Thiessen proximity polygon were selected. These were divided by the area of the polygon to determine the traffic and road density. The densities were averaged together to obtain the score for each station.

6. Monitor-to-Monitor Correlation (Environmental/Economic): This indicator scored stations based upon their distinctiveness of pollution data. Using annual-average data from 2009, the concentration of each station was compared to every other station by evaluation within a matrix where the coefficient of determination (r^2) was generated for each pair of stations. Stations were scored based on their maximum correlation with higher values, showing more redundancy, receiving a lower score. This indicator was useful in identifying redundancy between stations and can be used as evidence in justifying the cost-effectiveness of shutting down a station (U.S. EPA 2003, Ito et al. 2005).

7. Removal Bias (Environmental/Economic): This indicator evaluates the long-term contribution of each station to the creation of an interpolation map. Using the five-year average from each monitoring station, a kriging interpolation map was created which incorporates all stations. Each station was then systematically removed from the dataset and the interpolation map was recreated. The difference, or removal bias, between the actual value from the station and the predicted value from the interpolation once the station was removed was recorded. Sites were then scored using the absolute value of the bias; a higher value equates a higher score.

Removal bias is a useful technique for noting redundancies in the monitoring network. Sites with high bias are important for creating the interpolation map, thus their values add a unique perspective to the overall modeled pollution surface. Sites with a low bias could possibly be redundant with other sites, at least in the long-term temporal scale of this analysis (Schmidt 2001, U.S. EPA 2002, Cimorelli et al. 2003).

8. Population Served (Social): This indicator used data from the 2000 U.S. Census to create a GIS polygon map of census block groups within Maricopa County, which was then converted to centroid points containing the population count information. Using Thiessen polygons, the total population within the area served by each monitoring station was counted and stations with the highest population counts were given the highest score. This technique provides more weight to stations that have a high surrounding population and a large area of representation. Note that in the case of large areas served, population far away from the monitoring site might not necessarily be adequately represented by that station. However, it is the closest perspective station, so this technique assumes that it is the most representative, even though this is purely spatial in construction and does not consider meteorology, topology, or location of sources. (U.S. EPA 2001, O'Sullivan and Unwin 2003).

9. Environmental Justice-Minority Population Served (Social): The U.S. EPA has the goal of providing an environment where all people enjoy the same degree of protection from environmental and health hazards and equal access to the decision-making process to maintain a healthy environment in which to live, learn, and work (U.S. EPA 2010). This environmental justice mandate extends to all areas the U.S. EPA works with, including AQMN assessments. As this study was based upon the U.S. EPA's periodic assessment requirement, it includes this social indicator as a basic test of how the AQMN relates to environmental equity issues, in this case minority populations within Maricopa County. This indicator follows a methodology identical to the

population served indicator described earlier, but used the total population minus the non-Hispanic white population listed in the 2000 U.S. Census to determine the total minority population in each census block group. The percentage of minority population was determined within each monitoring station's area served Thiessen proximity polygon, and stations were then scored with the highest percentages having the greatest score.

10. Trends Impact (Social/Economic): This indicator was based on the historical monitoring record of the station, i.e., the length of time the station has been in operation as of 2009. Stations that have a long historical record are valuable for tracking trends; continuation of a long unbroken monitoring record is desirable for providing modeling data or determining chronic population exposure to pollutants. Note that if stations had alternating periods of operation, not including seasonal schedules, only the most recent operating period was considered. Seasonal O_3 stations were counted as if they were in continual operation (Cimorelli et al. 2003, Raffuse et al. 2007).

11. Number of other Parameters Monitored (Economic): This indicator counted the number of different parameters monitored at each site. Parameters counted were those that are entered into the AQS database, including criteria pollutants and wind meteorological parameters; ancillary parameters were not included. Multiple monitored parameters make a site more valuable, as they have increased cost effectiveness and collocated pollutant measurements can be compared and modeled together (Cimorelli et al. 2003, Raffuse et al. 2007, Scheffe et al. 2009).

Phase II: Identifying Areas of Insufficient AQMN Representation

The second phase of the study utilizes spatial indicators in the framework of a GIS to quantify the representation of the existing AQMN and identify areas that are possibly deficient in coverage and could benefit from the addition of a monitoring station. This phase has eight different spatial indicators grouped into three different groups: source-oriented, population-oriented, and spatially-oriented (Figure 16, Table 5). These groups consider characteristics that are associated with monitoring station representation, e.g., the location of point and mobile sources, the density of population, or the straight-line distance to the next closest monitoring station.

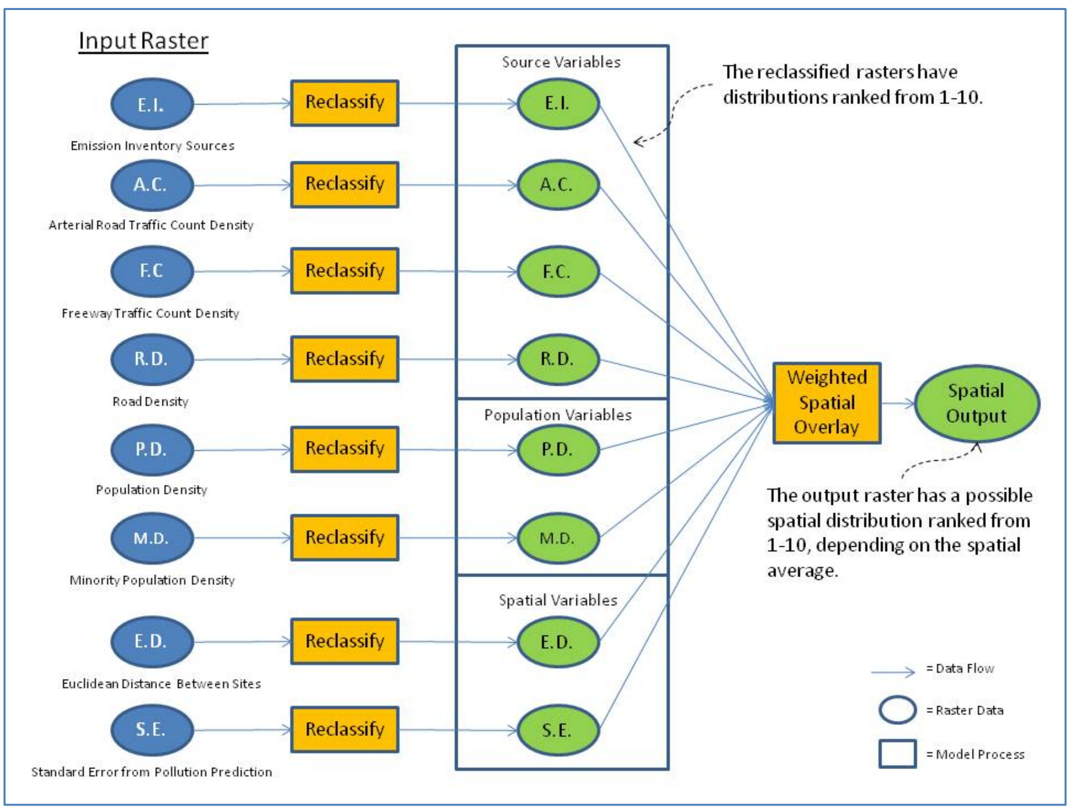


Figure 16 The Weighted Spatial Output Model. Spatial Indicators, i.e. Raster Maps, Are Inputted, Reclassified, and Spatially Averaged to Create the Final Spatial Output Map

Each spatial indicator consists of a GIS raster map with a 100m grid pattern. These rasters were reclassified in ArcView 10.0 so that the data distribution of each indicator was scored with values from one to ten. The reclassified rasters were then spatially averaged with calculated weights (q.v.) using the weighted spatial overlay tool of ArcView 10.0, giving each indicator a weighted-average score. A higher score signified a greater likelihood that a spatial location would benefit from additional monitoring representation. The specific indicators are as follows:

1. Emissions Inventory Point Sources (Source-Oriented): This indicator is a raster map of point emission sources taken from the MCAQD Periodic Emissions Inventory report (MCAQD 2009). The emission sources were aggregated into each township, range, and section; the sum of emissions in each sector was used as the raster value. When reclassifying the raster, the entire distribution of emissions was divided into 10 equal parts and assigned a score of 1-10 with 10 signifying the highest emission quantities.

2. Arterial Road Traffic Count (Source-Oriented): First of the mobile source indicators, this used the AWT count from arterial roads in Maricopa County. AWT counts were averaged in each township, range, and section, with the average result being used as the raster value. Higher AWT counts were assigned higher scores as they are representative of higher mobile-source emissions.

3. Freeway Traffic Count (Source-Oriented): Second of the mobile source indicators and similar to the Arterial Road Traffic Count, this indicator used the AWT from interstate and state highways in Maricopa County. AWT counts were also averaged

in each township, range, and section. As with arterial road traffic counts, higher freeway AWT counts were assigned higher scores.

4. Road Density (Source-Oriented): Third of the mobile source indicators, this assessed the density of roads, both arterial and freeways, in a given area and returned the result as the raster value. This indicator was designed to give support to the traffic counts indicator in determining emissions from mobile sources. Since traffic counts are based upon discrete sampling locations and it is difficult to ascertain if these locations are evenly sampled, the road density serves as another proxy in determining mobile source emissions. The densities of roads (lines) were calculated within 1 km cells; higher densities were assigned higher scores.

5. Population Density (Population-Oriented): This indicator used the 2000 U.S. Census block groups to account for total population. The population density of each block group was calculated and used for each raster cell. Higher population densities were assigned higher scores.

6. Minority Population Density (Population-Oriented): This indicator is identical in design to the Population Density indicator, except that instead of total population in each census block group, the total population minus the non-Hispanic white population was used. This indicator provides a method of accounting for environmental equity issues. Areas with higher minority population densities were assigned higher scores, as ensuring that these populations have adequate monitoring representation is necessary to identify equity issues.

7. Euclidean Distance between Sites (Spatially Oriented): This indicator is based on the straight-line distance away from an existing monitoring site. The implied assumption is that it is more desirable to have a new monitoring site farther away from an existing site. In practice this method created concentric rings of 3km for O_3 and 1.5km for PM_{10} around each monitoring site. This distance was an a priori decision based upon the spatial autocorrelation characteristics of each pollutant (Pope and Wu 2014). The score increases the farther away in space that the location is from existing monitoring sites.

8. Standard Error from Predicted Pollution (Spatially Oriented): This indicator accounts for the actual modeled pollution surface. This was accomplished by creating a kriging interpolation map for each pollution parameter using annual average data from each existing monitoring site. However, instead of a standard pollution surface output, a standard error map was generated. This map shows areas of highest uncertainty in the kriging model. After converting the map to a raster, the areas of highest uncertainty were reclassified with the highest score.

Weights

The methodology used in this study relies on different indicators to provide a comprehensive analysis of different factors. However, I did not assume that these factors were all equally important. Instead, weights were used to emphasize particularly important indicators. There are multiple weighting methods mentioned in the literature, including judgment-based expert opinion and data-dependent statistical methods (Garriga and Foguet 2010, Zheng et al. 2011). This study utilized the expert opinion method, as this is a common method of assigning weights, though it is likely biased toward the subjective perception of the expert or policymaker (Booysen 2002). Still, given the strong relationship of this study with air quality policymaking, I argue that this is an effective method for weighting these indicators. A panel of ten air quality experts, policymakers, and academics was invited to answer a survey with their opinions on the relative importance of Phase I and II indicators and how they should be weighted. Survey answers were averaged together and used for the weighting scheme (Table 6).

Table 6 (a) Weights for Phase I of the Study. (b) Weights for Phase II of the Study. Note That While Multiple Indicators Might Be Applicable to the Same Subject, e.g. the Traffic Indicators in Phase II, This Was Accounted for with the Weighting System

(a)

#	Phase I Indicator	Sustainability Descriptor	O_3 Weight	PM_{10} Weight
1	Measured Concentrations	Environmental	13.03%	13.81%
2	Deviation from the NAAQS	Environmental	9.32%	9.48%
3	Area Served	Environmental/Social	8.12%	8.48%
4	Emissions Inventory	Environmental	7.78%	11.59%
4b	Emissions Inventory-Predicted Ozone	Environmental	9.38%	N/A
5	Traffic Counts	Environmental	8.12%	8.49%
6	Monitor-to-Monitor Correlation	Environmental/Economic	7.12%	6.32%
7	Removal Bias	Environmental/Economic	8.27%	7.85%
8	Population Served	Social	8.32%	9.82%
9	Environmental Justice-Minority Population Served	Social	7.22%	9.22%
10	Trends Impact	Social /Economic	8.82%	10.08%
11	Number of Other Parameters Monitored	Economic	4.51%	4.89%
		Total	100.0%	100.0%

(b)

#	Phase II Indicator	Category	O_3 Weight	PM_{10} Weight
1	Emissions Inventory Point Sources	Source-Oriented	13.3%	20.0%
2	Arterial Road Traffic Count	Source-Oriented	8.9%	9.0%
3	Freeway Traffic Count	Source-Oriented	8.4%	8.4%
4	Road Density	Source-Oriented	9.9%	10.0%
5	Population Density	Population-Oriented	17.6%	16.3%
6	Minority Population Density	Population-Oriented	13.6%	12.9%
7	Euclidean Distance Between Sites	Spatially-Oriented	13.4%	11.1%
8	Standard Error from Predicted Pollution	Spatially-Oriented	15.0%	12.2%
		Total	100.0%	100.0%

To analyze the sensitivity of the chosen weights, results were also calculated from the unweighted indicators and compared to the weighted results. For the sustainability results, because there are an unequal number of indicators for each sustainability category, indicators from each category were averaged together and compared with the original results in the format demonstrated by Van de Kerk and Manuel (2008).

Results

Phase I: Indicators for Evaluating the Existing AQMN

Displaying Results

Each O_3 and PM_{10} monitoring station earned a score for the 11 individual indicators. The score was based upon that station's placing in each indicator's distribution, e.g., for the 17 assessed O_3 stations, there were 1-17 points possible depending on the station's placing. Tied results earned the stations an average score from the placing. For the original unweighted results, the 11 indicator scores were averaged together and a rank for the station was determined. Weights were then applied to each indicator score and the average and rank for each station was recalculated (Table 7a; see Table 17 and Table 18 in Appendix B for complete chart results).

Table 7 Raw and Weighted Average Scores and Ranks for the Phase I (a) O_3 and (b) PM_{10} Assessment

(a)

O_3 Site	Raw Indicator Scores Average	Raw Indicator Scores Rank	Weighted Indicator Scores Average	Weighted Indicator Scores Rank
BE	7.54	15	0.56	16
BP	6.08	17	0.50	17
CC	8.38	11	0.73	11
CP	9.46	8	0.75	10
DY	8.00	13	0.63	14
FF	9.83	6.5	0.83	6
FH	7.75	14	0.69	12
GL	11.00	2	0.92	2
HM	8.79	10	0.78	8
NP	11.04	1	0.94	1
PP	9.92	5	0.85	5
RV	6.42	16	0.60	15
SP	8.33	12	0.66	13
SS	9.29	9	0.77	9
TE	9.83	6.5	0.82	7
WC	10.58	4	0.88	3
WP	10.75	3	0.86	4

(b)

PM_{10} Site	Raw Indicator Scores Average	Raw Indicator Scores Rank	Weighted Indicator Scores Average	Weighted Indicator Scores Rank
BE	6.70	12	0.604	12
CP	8.86	1	0.811	1
DC	6.09	13	0.621	10
DY	5.86	14	0.522	14
GL	8.23	4	0.759	4
GR	7.45	7	0.720	6
HI	6.77	11	0.616	11
ME	8.77	2	0.772	2
NP	7.23	9	0.599	13
SP	7.95	5	0.742	5
SS	7.41	8	0.635	9
WC	7.77	6	0.682	7
WF	6.86	10	0.657	8
WP	8.36	3	0.761	3

Individual indicator results from each site were also displayed in a radar chart format with the indicators arranged by their sustainability descriptor, i.e., environmental, social, and economic. This provided a convenient visualization of individual sustainability aspects for the entire network (Figure 17a). The 11 individual indicator results were further aggregated into the three sustainability groups of environmental, social, and economic, and a score and rank for each group was generated for each monitoring station. These results were also displayed in radar charts which allow the viewer to quickly ascertain the network's sustainability strengths and weaknesses (Figure 17b; see Appendix B for complete chart results).

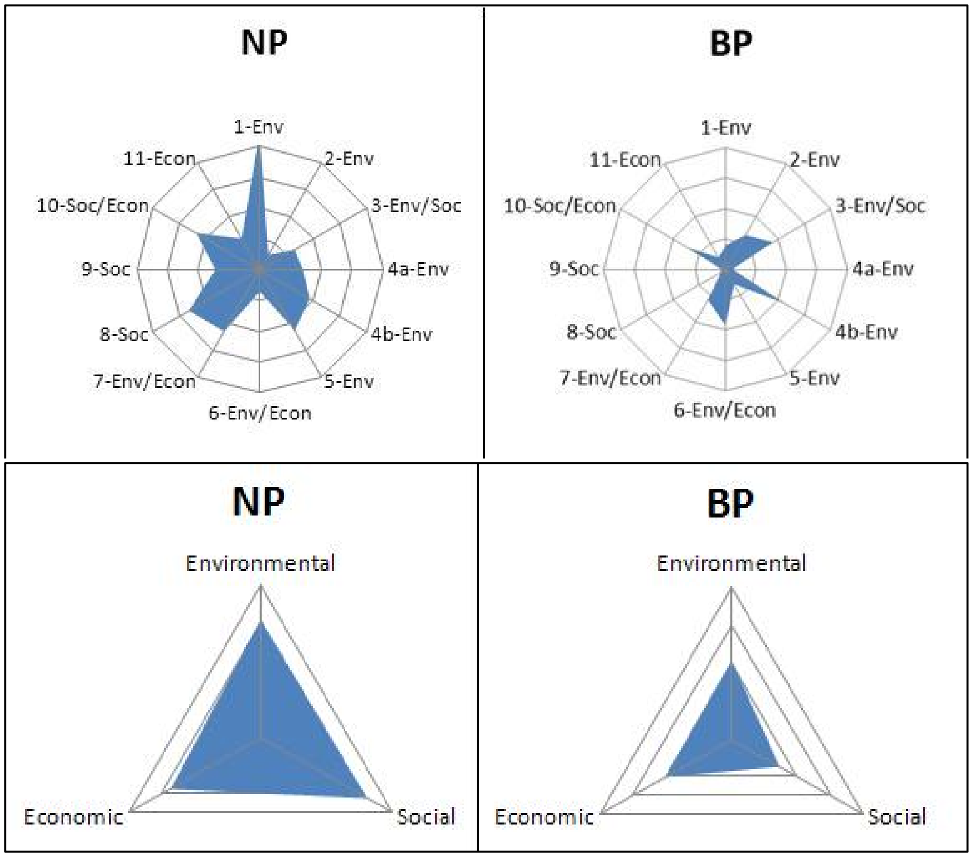


Figure 17 (a) Radar Charts of Phase I Indicator Results for the Highest and Lowest Ranked O_3 Monitoring Stations, North Phoenix and Blue Point, Respectively. Labeled Numbers Correspond to the 11 Phase I Indicators Listed on Table 5. Graph Gridlines Each Represent 0.5 Points of Score, from 0-2.0. (b) Radar Charts of Sustainability Results for the Same Stations. Each Sustainability Group Is An Aggregation of the Appropriate Phase I Indicators. Graph Gridlines Each Represent 0.3 Points of Score, from 0-1.2

Results for O_3 Monitoring Stations

The final weighted scores and rankings revealed that the three highest ranked stations, North Phoenix, Glendale, and West Chandler, are located within urban areas, while the bottom two ranked stations, Buckeye and Blue Point, are located in suburban or rural areas (Figure 18). Applying weight to the original scores did not affect the top or bottom ranked stations, but it did have effect on the stations in between (Table 8a). Individual indicator analyses, such as Monitor-to-Monitor Correlation and Removal Bias, revealed redundancy among the urban O_3 stations. On the other hand, the Population Served indicator demonstrated that the urban stations each represented a sizably higher number of people then the suburban and rural stations, even when considering the much greater area served of those stations.

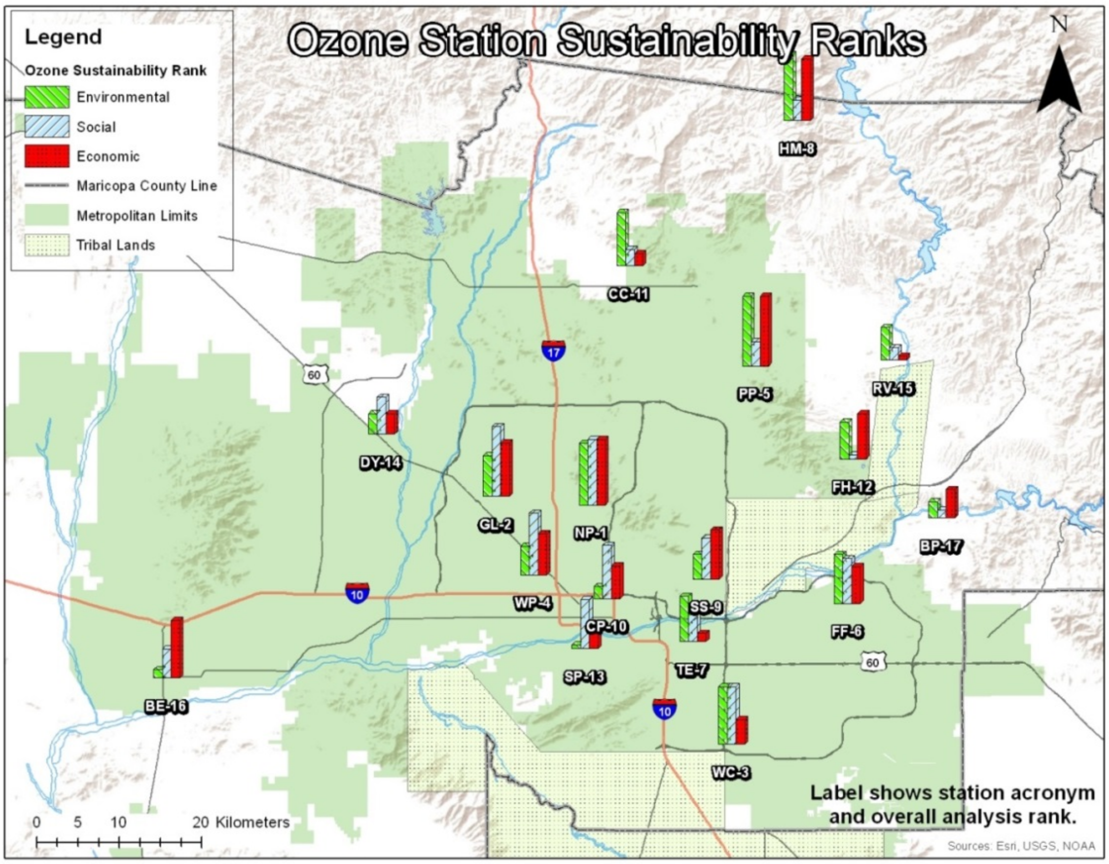


Figure 18 Map of Relative Sustainability Results for O_3 Monitoring Stations in MCAQD's Network. The Label for Each Monitoring Station Gives Its Overall Analysis Rank

Table 8 Comparison of Raw and Weighted Phase I Rankings for (a) O_3 and (b) PM_{10} Sites

(a)

Rank	Unweighted	Weighted
1	NP	NP
2	GL	GL
3	WP	WC
4	WC	WP
5	PP	PP
6	FF (Tie)	FF
7	TE (Tie)	TE
8	CP	HM
9	SS	SS
10	HM	CP
11	CC	CC
12	SP	FH
13	DY	SP
14	FH	DY
15	BE	RV
16	RV	BE
17	BP	BP

(b)

Rank	Unweighted	Weighted
1	CP	CP
2	ME	ME
3	WP	WP
4	GL	GL
5	SP	SP
6	WC	GR
7	GR	WC
8	SS	WF
9	NP	SS
10	WF	DC
11	HI	HI
12	BE	BE
13	DC	NP
14	DY	DY

The sustainability results for O_3 demonstrated that the monitoring stations located in urban settings tended to score higher on the social sustainability indicators. Rural monitoring stations to the northeast of the urban area tended to have higher environmental indicators, following the known patterns of O_3, which tends to accumulate in the mountainous downwind area northeast of the metropolitan area (Pope and Wu 2014) (Figure 14). However, this environmental pattern was nebulous, as several of the urban stations scored high and several of the rural stations scored low. Economic indicator scores were mixed between urban and rural stations; some of the large, long-term urban stations scored high, but several of the more remote rural stations also scored high as their unique data is useful for modeling purposes, thus bringing a high score on those indicators.

Results for PM_{10} Stations

The final weighted scores and results for the PM_{10} stations revealed that the highest ranking station, Central Phoenix, did not have any top scores in the heaviest weighted indicators and many of its scores were in the bottom half, but it did have the highest score in Traffic Count and high enough scores in other indicators to give it the top ranked average (Table 7b). The second overall ranked station was Mesa, even though it scored near the bottom in Measured Concentrations, which is the most heavily weighted indicator. The stations scoring highest in Measured Concentrations tended to rank poorly in the overall results. Applying weights to the raw scores did not change the rank of the five highest scoring stations, but it did have some effect on the ranks of the lower scoring stations (Table 8b). The Monitor-to-Monitor Correlation and Removal Bias indicators also displayed redundancy among the PM_{10} stations, especially among the clustered stations in southwest Phoenix. These same urban stations tended to score low in the social indicators, as their clustered positions caused them to serve smaller areas and populations.

Sustainability results for PM_{10} demonstrated a regional pattern with stations in the southern portion of the AQMN, which tend to be closer to agricultural, mining, and industrial sources, ranking higher in the environmental indicators (Figure 19). The clustered stations in southwest Phoenix tended to score the lowest in the social and economic indicators due to their redundancy and small service areas. Appendix B contains complete Phase I analysis results for each indicator for both O_3 and PM_{10} parameters.

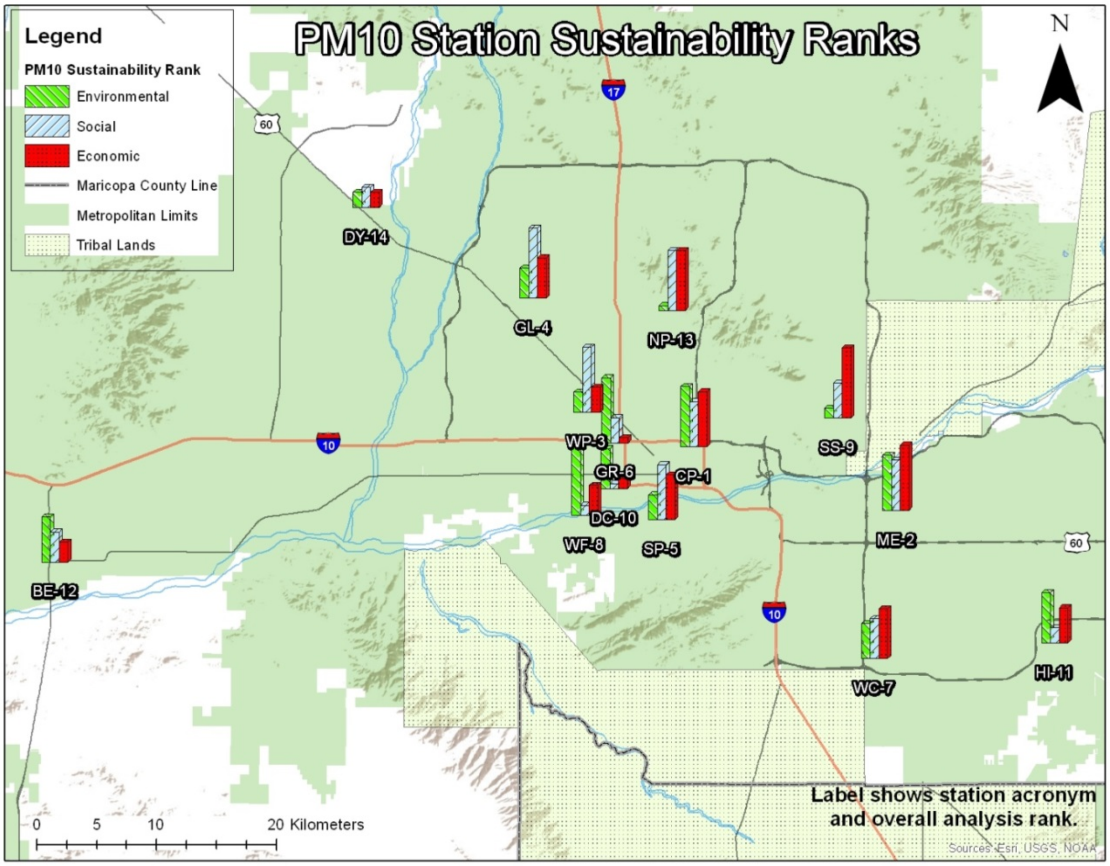


Figure 19 Map of Relative Sustainability Results for PM_{10} Monitoring Stations in MCAQD's Networks. The Label for Each Monitoring Station Gives Its Overall Analysis Rank

<u>Phase II: Identifying Areas of Insufficient AQMN Representation</u>

Displaying Results

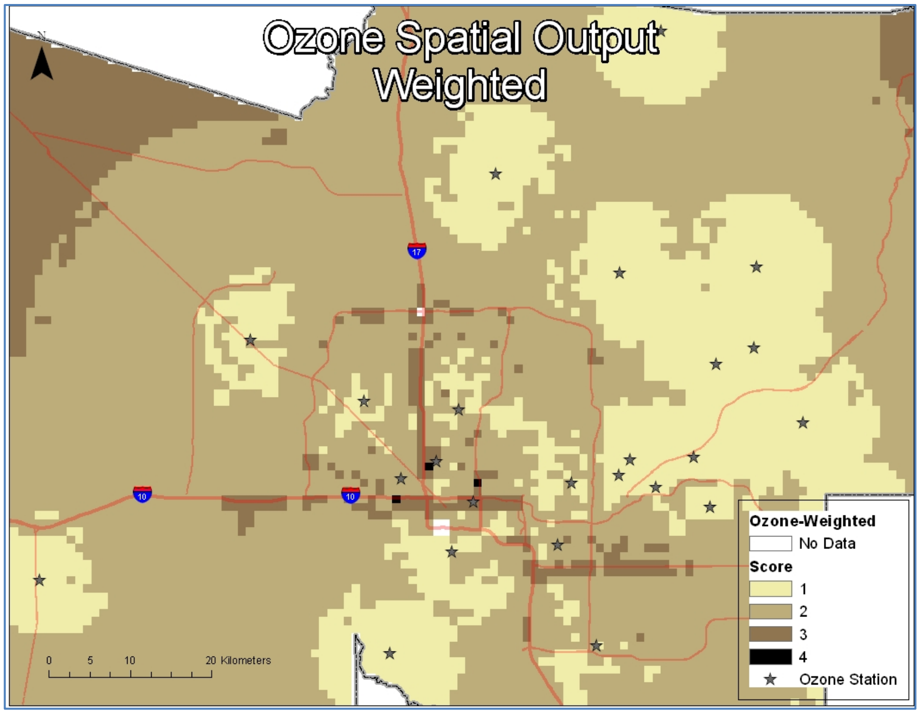
Each phase II spatial indicator was entered into the spatial output model (Figure 16) and two separate spatial outputs, i.e., raster maps, were created. The first output did not use any weights and equal emphasis was placed on each indicator in the spatial averaging; the second used the weights from the expert opinion survey as listed in Table 6b. Each spatial output raster consists of a scored map of the Phoenix metropolitan region with higher scores giving a relative representation of locations that could possibly benefit from the addition of a monitoring station. One to ten points were possible for each grid of the spatial output; however, for these results the spatially averaged scores did not exceed four or five points for O_3 and PM_{10}, respectively.

Results for O_3 Monitoring Stations

The spatial output for O_3 displayed relatively low scores for most of the metropolitan area, demonstrating that it is well-represented by existing monitoring stations (Figure 20a). Much of the region outside of the metropolitan area received higher scores, though this is because the low density of existing stations in those areas gave them maximum individual scores in the Euclidean distance and spatial error indicators. Inside of the metropolitan boundaries, areas nearby major transportation corridors mainly received the highest scores.

When the weights were removed from the input indicators, a similar pattern emerged, though scores were emphasized more along the transportation corridors (Figure 20b).

(a)



(b)

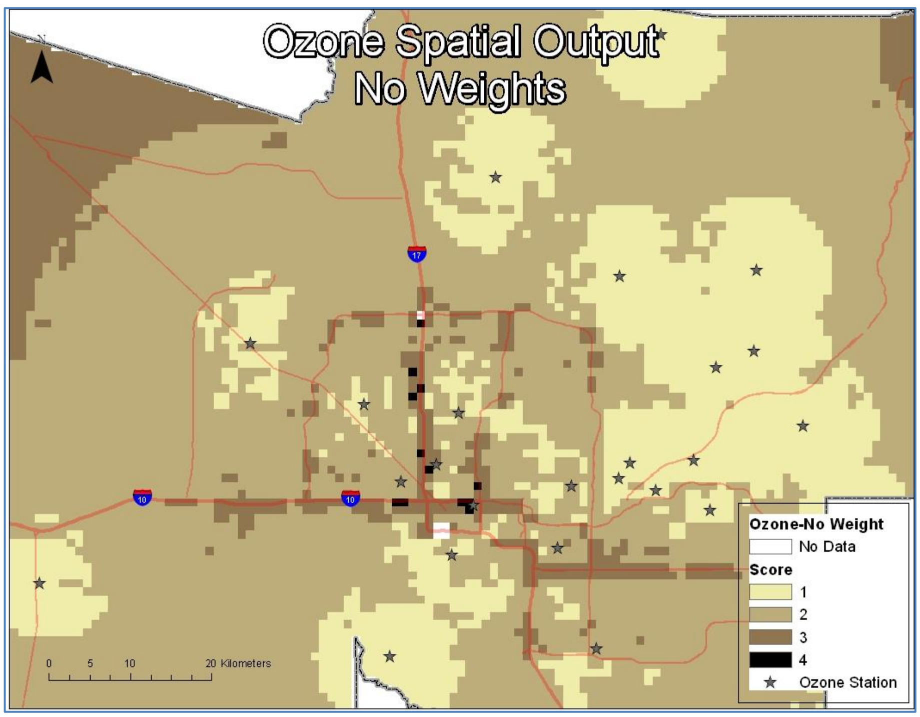


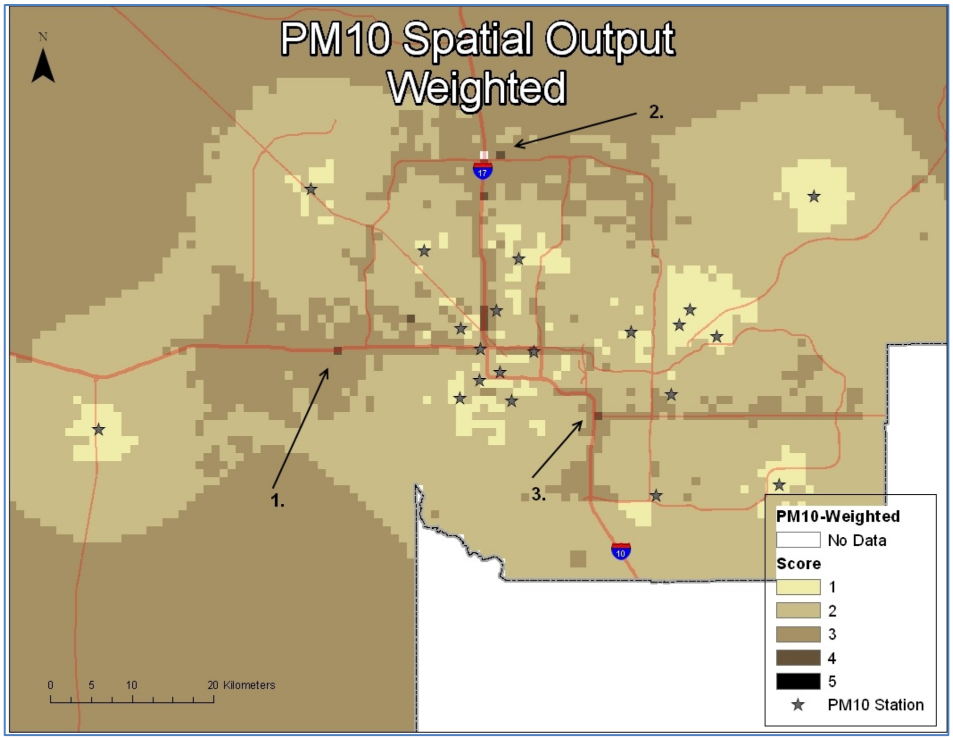
Figure 20 Scored Spatial Output Map for the O_3 Phase II Analysis Showing the Suitability for Adding Additional O_3 Monitoring Stations. Grid Scores Represent Relative Suitability for Adding a New O_3 Monitoring Station (Higher Score Equals Greater Suitability). (a) Weights Were Added to Spatial Indicators before Averaging the Output. (b) Shows the Results from Using Unweighted Indicators

Results for PM_{10} Monitoring Stations

The spatial output for PM_{10} displayed higher average scores then the O_3 output, even in areas close to existing monitoring stations (Figure 21a). Scores for the PM_{10} output ranged from one to five points out of the ten possible points; though only two grid cells, which are the location of power generating plants approximately 35 km west of the metropolitan area, scored five points. As with the O_3 stations, major transportation corridors within the metropolitan area tended to have the highest scores. However, there were also many locations within the metropolitan area which scored high because they have high population counts or large PM_{10} emission sources. Three locations in the spatial output map were particularly evident as being likely candidates for new monitoring stations: the town of Avondale in the western metropolitan area, Deer Valley and northern Scottsdale in the northern area, and Tempe and Mesa in the eastern area (Figure 21a).

Adding weights to the spatial indicators did not greatly change the pattern of the PM_{10} scores. The spatial output using unweighted indicators appears to emphasize the same portions of the metropolitan area, though, on average, scores in each location are higher (Figure 21b).

(a)



(b)

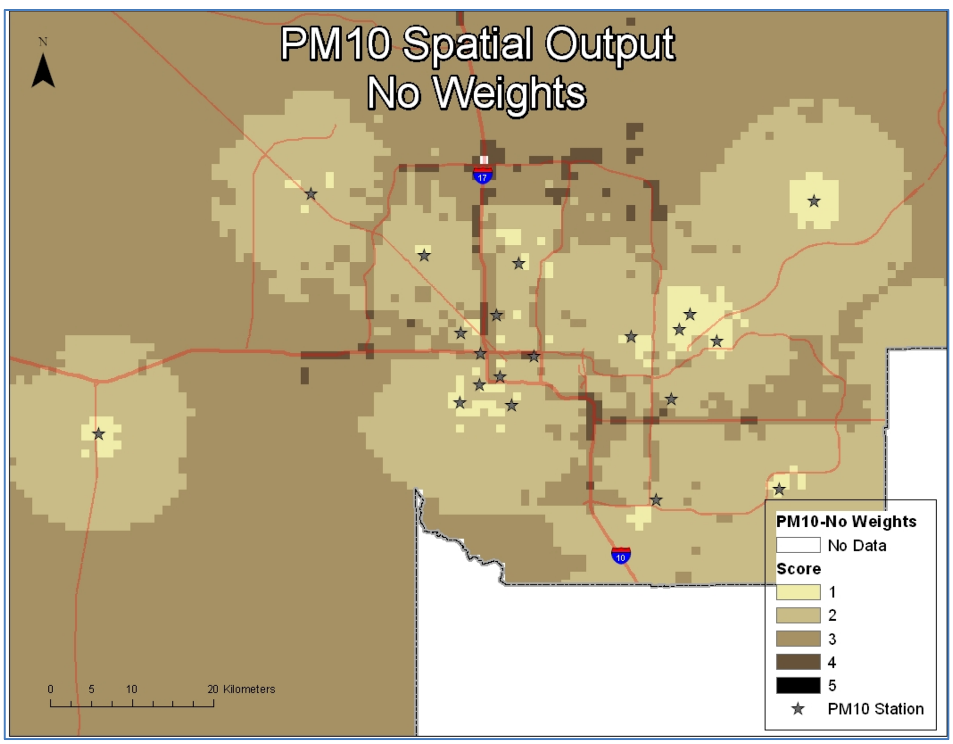


Figure 21 (a) Scored Spatial Output Map for the PM_{10} Analysis Using Weighted Indicator Inputs. Numbered Callouts Represent Areas Indicated for New PM_{10} Stations, 1=Avondale, 2=Deer Valley, 3=Tempe. Only Two Grid Cells, Not Pictured in This Map, Earned A Score of 5. These Cells Are Located in Western Maricopa County Approximately 35 Km from the Western Edge of This Map. (b) The Same Analysis Using Unweighted Indicators

Discussion

Station Design Objectives

The techniques and indicators used in this study are not meant to be used and applied in a rote manner; rather the intention is to use the indicator results and spatial outputs to gather greater knowledge about the existing monitoring stations and suitable locations for new stations. Indicators might be co-dependent on one another and this should be taken into account, e.g. the monitor-to-monitor correlation and the removal bias indicators. For example, even though they would likely score low in the monitor-to-monitor correlation and removal bias indicators, monitoring stations with high correlation but more distant apart are more valuable than those that correlate well in close proximity. Logic and reason must be applied to properly interpret the results and evaluate the AQMN. An important consideration that must be taken into account when applying this logic is the design objectives that are required for every monitoring station and network.

Design objectives can take several forms, such as the need to characterize population exposure to pollutants, monitoring the impact of certain sources, or measuring the maximum expected or background pollutant concentrations. These objectives were considered when creating the multiple indicators used in this study; nevertheless, when analyzing results individual station objectives should be reviewed. For instance, a station might rank poorly in the Phase I assessment because it scored poorly in all but one or two indicators, but those high-scoring indicators are that site's objective, e.g., it is a maximum concentration station or it's located near a specific industry to monitor its emissions. If this objective is uniquely fulfilled by that station, then it has worth outside of what the general assessment results might suggest and that should be taken into consideration when making decisions regarding the network.

O_3 Monitoring Stations

The assessment of O_3 stations revealed that the region is well represented by the AQMN, though there is likely redundancy in urban areas. The monitor-to-monitor correlation indicator found an average of 81% correlation among the O_3 stations, though when selecting only urban area stations the average changes to 88% as compared to rural/suburban stations with an average of 74%. From a sustainability standpoint, all of the urban stations do have strong social scores, though low performance in the correlation and removal bias indicators affects many of the urban stations in their environmental and economic scores. Spatial patterns for economic indicators were mixed; many of the urban stations scored well with the Trends Impact and Number of Parameters indicators, but their low scores in the correlation indicators hurt their overall economic average, thus giving an economic advantage to some of the rural stations.

Based on an evaluation of the Phase I assessment, the AQMN would likely benefit from closing or moving certain O_3 stations, such as some of the eastern downwind rural stations or the highly redundant urban stations, though at the current time this was not recommended. The reason for this decision was due to the objectives of these stations and the policy issues that could arise from closing them in a non-attainment area (see Scheffe et al. (2009) for greater detail on policy issues in these cases); the downwind sites were designed to measure maximum concentrations in areas that frequently violate health standards, and the urban sites provide neighborhood representation and are relied upon by many people for local air quality information (thus the high social scores).

However, the results do suggest that the objectives for some of the downwind stations should be reevaluated.

Especially when considering the Phase I results, the Phase II assessment did not find areas that were seriously under-represented by O_3 stations. However, there are several areas of the city, especially along freeway transportation corridors with adjacent high population densities, which would benefit from new stations. The recommendation is not to open a new site just for O_3 monitoring, but if another station is to be opened for other parameters or if an existing station needed to be moved, then adding or moving an O_3 monitor into those deficient areas should be considered.

PM_{10} Monitoring Stations

The assessment of PM_{10} stations shows areas that are over-represented, as well as areas that lack adequate representation. The PM_{10} stations in Maricopa County's AQMN are located in both urban and sub-urban areas and most show a great deal of redundancy. On average, stations throughout the metropolitan region exhibit 86% correlation; though the clustered stations in the south-central region exhibit 90% correlation. However, many of these clustered stations are positioned so as to monitor ambient pollution in areas near specific point sources and/or have an objective to measure maximum concentrations and thus receive much attention from managers and policy makers.

The Phase I assessment shows that these clustered stations score high in the Measured Concentrations and Emissions Inventory indicators, but their low Area and Population Served scores hurt them in the overall rankings. From a sustainability viewpoint, the most important stations were those that represent larger areas and populations, while also having significant environmental impact from surrounding sources. While this would suggest that the AQMN would benefit if some of these clustered stations were closed or moved, this is difficult to accomplish when considering their aforementioned objectives; also, these stations frequently violate health standards and have considerable political import. Therefore it was not recommended to close any PM_{10} stations, but evidence from these indicators should be closely considered while modifying the AQMN in the future.

The Phase II assessment does show areas that are deficient in monitoring representation. Rural areas were uniformly indicated as in need of representation, mainly because of the lack of rural stations, but monitoring objective considerations, such as population coverage in rural towns or monitoring major point sources, needs to be considered before adding stations to these areas. It was recommended to add PM_{10} stations to two small rural towns, Gila Bend and Wickenburg, located in Maricopa County to the southeast and northeast of the metropolitan area, respectively. Urban areas within the metropolitan region were also indicated as needing PM_{10} stations. After evaluating the spatial output maps, the location of existing monitors, and possible monitoring objectives, recommendations were made to add stations to the metropolitan neighborhoods of Avondale, Deer Valley, and Tempe (Figure 21a). MCAQD has added, or has preliminary plans to add, PM_{10} stations to all of these localities (Pope 2011).

Multiple Indicators for Multiple Objectives

This study has demonstrated the usefulness of using multiple indicators to assess the various objectives of an AQMN. This multi-objective technique has the advantage of providing a broad view of the various aspects of each monitoring station, though at the cost of greater detailed knowledge on each aspect. Nevertheless, when evaluating the performance of existing monitoring stations, or attempting to locate areas where new stations are needed, these various objectives all have worth and should be evaluated with differing indicators. The use of weights to provide emphasis to more critical aspects can be important, and this study has demonstrated, through the comparison of weighted and unweighted indicators, how much effect those weights can have. It should be noted that future assessments could be improved with the inclusion of additional indicators to evaluate further sources and objectives, e.g. including agricultural source indicators or evaluating the effects of transported sources, or more detailed indicators, such as including socio-economic status with race/ethnicity environmental justice indicators.

Adding the sustainability component to the assessment provides an effective method of aggregating the many indicators into a straightforward display of the results. The spatial patterns that result from this sustainability aggregation were also useful for evaluating network performance and finding areas of deficiency. Because of the usefulness of data that was produced with this technique, it is recommended that MCAQD utilize sustainability indicators in all future assessments of their AQMN.

Managers and planners should take note of the effect of multiple objectives on the AQMN and utilize their available resources appropriately. This has not always been done in the past, and resources were not always used to best effect. For example, there is often great concern among government planners regarding monitoring stations with the objective of measuring maximum concentrations. This concern is warranted, as pollution exceedances at maximum concentrations sites may cause the AQMN to be in violation of clean air regulations. However, while placing a large amount of resources, such as compliance inspectors or remediation efforts, around maximum concentration sites might be effective in controlling pollution in the area local to these sites, this could come at a cost of resources around monitors that represent greater numbers of population or more sensitive receptors, thus ignoring or exacerbating environmental justice issues. With more knowledge on environmental, social, and economic conditions, managers can make better decisions on how to deploy new monitoring resources to create a more comprehensive AQMN that best serves government regulations and the general public; thus giving information resources about air quality so that health risks can be recognized and citizens can make proper choices to benefit their lifestyles.

Acknowledgements:

The authors wish to thank the panel of experts from MCAQD, Arizona Department of Environmental Quality, Pinal County Air Quality Department, and the Landscape Ecology and Sustainability Laboratory at Arizona State University for their assistance in the creation of indicator weights. I would also like to thank Robert Downing of the MCAQD for his assistance in editing the draft manuscript. Finally, I thank the anonymous reviewers for their very constructive comments on the manuscript.

CHAPTER 4: A DISTRIBUTIVE ENVIRONMENTAL JUSTICE STUDY IN THE PHOENIX METROPOLITAN REGION USING A MULTI-SCALE LANDSCAPE APPROACH*

Chapter 4 Abstract

This study investigated the distributive environmental justice issue between distinct demographic groups and ambient air quality in the Phoenix metropolitan region of the United States. I used landscape ecological methods to create multiscale spatiotemporal pollution surfaces (maps) for O_3 and PM_{10}, and explicitly considered possible scale effects on statistical analysis as well as legacy effects of discriminatory policies of the past on minority groups. Specifically, I analyzed the patterns of O_3 and PM_{10} at three spatial scales and several temporal scales. The pollution surfaces were evaluated against the Census block group-scaled demographics of class (median household income), age (17 and under, 65 and older), race (African American, Native American), and ethnicity (Hispanic). The results of hierarchical multiple regressions, a total of 48 O_3 and 60 PM_{10} regression models, showed that significant relationships existed between the dependent and independent variables, signifying possible environmental inequity situations. These relationships seem robust as only in a few instances changing the spatiotemporal scales had significant effects on the results. Several consistent patterns emerged from these results. For example, people at the age of 17 and under were significant predictors for O_3

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and PM_{10}, but age 65 and older were only predictors for PM_{10}. African Americans were strong predictors for PM_{10}, while Native Americans were strong predictors for O_3. Hispanics had a strong negative correlation with O_3, but a less consistent positive relationship with PM_{10}. Interestingly, the PM_{10}–related patterns changed between seasons of analysis. Given the legacy conditions suffered by the racial and ethnic groups, and the relative lack of mobility of these groups, the distribution of these criteria pollutants suggests the existence of environmental inequity in the Phoenix metropolitan region.

Introduction

Environmental justice can be a field of study for researchers, a public policy goal for government regulators, or a social movement by stakeholders who are concerned about the environment in which they live (Brulle and Pellow 2006). The concept of environmental justice can have many facets, e.g., procedural justice is often defined as equal access to the environmental policy making process across all social demographics and distributive justice, often geographic in nature, is a fair and equitable distribution of environmental risk or burden (Rechtschaffen 2003). Studies in environmental justice examine relationships between social demographics, such as race and class, and patterns of environmental conditions, such as proximity to sources of pollution, the quality of ambient air or water resources available, or even blighted and polluted neighborhoods. When these inequitable conditions are brought to light, policy-makers can be notified that they must rectify the situation and citizens are given the knowledge and opportunity to pursue this improvement of their living environment.

This study focuses on ambient air quality and how distinct socioeconomic groups in the neighborhoods of Phoenix, Arizona, are exposed to ground-level O_3 and PM_{10}, the two criteria pollutants of most concern in this area. Acknowledging that environmental justice can be more complicated than just the distribution of pollutants, I discuss some of the legacy conditions experienced by minority populations in the Phoenix area; but I mainly focus on the utilization of landscape ecological methods to create multi-scale pollution models, based upon actual monitored pollution concentrations, to test for possible distributive justice issues within the modern population. Landscape ecology, a discipline devoted to understanding the spatial relationships between scales, patterns, and processes, offers useful methods and insight into the creation of these pollution models.

Legacy Conditions for Racial and Ethnic Minorities in Phoenix

The Phoenix metropolitan area today, a modern, thriving southwestern city with more than 20 self-governing municipalities, is one of the largest in the United States, with over 4.2 million residents in 2010 (Wu et al. 2011). However, the city of Phoenix, which was incorporated in 1870, began as a small agricultural community in the Salt River valley in the Arizona Territory. Unlike many other major southwestern cities, this area did not have pre-existing Mexican settlements and in the beginning Phoenix was a self-identified Anglo community (Bolin et al. 2005, Meeks 2007). Minority groups, such as Hispanics and African Americans, began to immigrate into the region in greater numbers in the late nineteenth-century, providing valuable labor services in agricultural and industrial development; however, they were greeted with racial segregation and political disenfranchisement as a policy (Bolin et al. 2013). As the city grew, transportation corridors further divided the segregated population with the affluent Anglo populations to the north of the main east-west railroad branch and the minority populations to the flood plains south of the tracks. Segregationist city zoning and planning services in the first half of the twentieth-century placed much of the industrial and waste-handling facilities in minority-dominated South Phoenix, and the neighborhoods that grew in that area were blighted with poverty and lacked many basic municipal services and resources (Grineski et al. 2007, Bolin et al. 2013). The civil rights reforms of the 1960's and 1970's brought some relief to the situation that Phoenix's minority populations endured, but the land use pattern had already been set. Post World War II Phoenix saw massive growth in high-technology manufacturing and this industry, seeking educated employees and in the beginning having a whites-only hiring policy, moved into more affluent areas; but many industrial and waste-handling facilities were still located in the southern and western portions of the city where most minority populations lived (Bolin et al. 2000, McCoy 2000). Even the last two decades of the twentieth-century, and into the twenty-first, has seen minority populations in south Phoenix fighting to protect their communities from encroachment from transportation corridors and industrial and hazardous-waste facilities, often unsuccessfully (Dimas 1999, Sicotte 2008, Bolin et al. 2013).

Native American Tribes in the Central Arizona Deserts

Native American Indians also faced patterns of subordination in Arizona history. There were several tribes of Native Americans living in and around the Salt and Gila rivers when the area was ceded to the United States from Mexico in 1848, including the Akimel O'odham (or Pima), Tohano O'odham, Maricopa, and Yavapai. The Pima and Maricopa people in particular were farmers who practiced irrigation agriculture along the ephemeral streams and seasonal rivers of this desert region. Early Anglo settlers described these people as industrious and hospitable, as they provided material and military aide, and they were praised as allies who should be defended by the government (Meeks 2007). However, in 1859 these two tribes were confined to the newly formed Gila River reservation which was much smaller than their original homeland range, though additional reservations, Ft. McDowell and Salt River, were also eventually opened for the Pima, Maricopa, and Yavapai people in the late 19th century.

Furthermore, the tribes were not granted any water rights, and Anglo settlers began upriver diversions for their own irrigated crops, depriving the reservation of the greater portion of its water supply. Unable to sustain their agriculture at their former level, the tribes became increasingly less self-sufficient and impoverished, and the Anglo depiction of them changed from industrious to ‘uncooperative’ and ‘degenerate’ (Meeks 2007), thus beginning the period of discrimination and forced assimilation into Anglo culture which followed. The other tribes of the area faced similar situations with the reservation system, water rights, and subordination, and were often forced to abandon their culture to become laborers in off-reservation industries, or to lease out their lands for various agricultural or industrial purposes. Reforms came slowly and sometime were veiled with exploitation attempts, such as land for water deals (Meeks 2007). Even though they were granted U.S. citizenship in 1924, Native Americans in Arizona were not granted suffrage until 1948, and water-right issues were still being addressed in the legal system in the 1970’s and 80’s (Meeks 2007). These aforementioned situations with the indigenous population, such as segregation within a reservation and exploitation by outside industries, have created many potential and realized environmental injustices which exist to this day, thus ethically requiring the inclusion of Native Americans in any justice research done within Arizona.

<u>Spatiotemporal Scale in the Environmental Justice Literature</u>

There have been a number of previously conducted environmental justice studies in the Phoenix metropolitan area using different techniques and scales. These techniques usually did find justice issues, depending on the observed scale, the method used, and the medium investigated. For instance, the Bolin et al. (2000) study investigated point-sources of toxic emissions to determine environmental equity problems with the location, volume, and toxicity of emissions. Their study found that minority populations in South Phoenix faced injustices when compared with the location of industries or volume of emissions, but not toxicity of emissions (as previously mentioned, most of the high-tech industries, implicated with emissions of greater toxicity, are located in more affluent areas of Phoenix).

A similar spatial analysis by Bolin et al. (2002) found equity issues between race and class and point sources of hazardous waste industries and large quantity generators. Grineski et al. (2007) quantified air pollution by laying a grid over an ambient pollution surface of carbon monoxide (CO), nitrous oxides (NO_x), and ground-level O_3, modeled in a 1-hour time resolution, and using it to compare to race and class. They found equity issues for Latinos and Native Americans, but not African Americans. Grineski (2007a) used the same pollution model, along with the Toxic Release Inventory (TRI) and a proxy for indoor pollution hazards, to look for equity issues with asthma cases. They found that African Americans experienced injustices, but Latinos were not significant predictors for rates of asthma hospitalization. Native Americans were not included in that study.

These Phoenix-based studies employed a number of different methods to find justice issues over different spatial scales, with some differing results, showing that the scale of observation is important. Other studies, outside of the Phoenix area, consider or address scale (i.e. the areal unit of analysis) or scope (i.e. the geographic bounds of the study) issues using various methods. For example, Cutter et al (1996) conducted a justice study in South Carolina to see how TRI and hazardous waste facilities affect low-income minority groups at three different spatial scales: counties, census tracks, and census block groups. Scale was important, as they found issues at the county level, but not the finer scales. On the other hand, though Huby et al.'s (2009) justice study in England stresses the need for multi-scale analysis, they note that the coarser scales can mask inequalities due to aggregation. Baden et al (2007) performed a review of the existing empirical justice literature and noted studies spanning the range of scale and scope method possibilities, and though some studies use multi-scale methods, they rarely use multiple units of analysis. Variation was observed across the methods, but the authors did note that studies typically found evidence of injustice, though smaller scales tended to exhibit more statistically insignificant findings, and they note that scale and scope may be influential factors that contribute to the results (Baden et al. 2007).

Choosing the scale of analysis is important, and different scales can produce different results-a phenomenon known as the modifiable areal unit problem (MAUP), a subject often addressed in landscape ecology. The MAUP presents two interrelated problems with spatial data analysis: the scaling problem and the zoning problem

(Openshaw 1984, Jelinski and Wu 1996). The scaling problem is due to the aggregation of smaller units into fewer and larger geographical units increasing correlation, but reducing variation; while the zoning problem results from the drawing of spatial boundaries and is related to gerrymandering. Researchers have tried different methods of analysis to avoid the issues of the MAUP, such as using the hedonic price method (Noonan et al. 2009) or dasymetric mapping (Giordano and Cheever 2010), with varying results; though presenting results from multiple scales can also be effective against the MAUP, as an inequity observed at any scale can arguably be considered evidence of an injustice (Baden et al. 2007).

The temporal scale of analysis is equally important in finding environmental inequity, especially when using ambient air pollution as the environmental medium. Although temporal scale of the analysis or data is frequently mentioned, e.g. the study by Jerrett et al (2001), there is a deficit of environmental justice literature addressing multiple-scale temporal analysis methods (Noonan 2008). This study does address both the spatial and temporal dimensions of environmental justice by using a novel approach of comparing race, ethnicity, class, and age at the Census block group level to multiple spatiotemporal scales of monitored O_3 and PM_{10} pollution, so as to determine the multi-scalar extent of environmental justice issues in the Phoenix area. Results with positive correlation between demographics and pollution, taken in the context of the historical patterns of inequitable planning or the location of vulnerable populations with low mobility, within the Phoenix metropolitan area, were used as evidence of possible injustices; though the primary aim of the study is to highlight the differences in results between multiple spatiotemporal scales in the analysis.

Methods

The study covers the Phoenix metropolitan statistical area (MSA) in South-Central Arizona (Figure 22). There are two distinct study areas in this project, one representing the O_3 monitoring network and the other representing the PM_{10} network; O_3 and PM_{10} are the two criteria pollutants of most concern in the Phoenix MSA, as they are listed as non-attainment for national ambient air quality standards (U.S. EPA 2009a). The O_3 area is approximately 2.3 million hectares in size, and the PM_{10} area is approximately 1 million hectares in size. Both of these areas are based upon Pope and Wu's (2014) study which characterized spatiotemporal patterns of O_3 and PM_{10} in the Phoenix MSA. The Pope and Wu study delineated the study areas based upon the spatial location of official pollution monitoring stations and the assumed stationarity of data within the metropolitan area, with a shallow buffer of nearby rural monitoring stations (Pope and Wu 2014).

There were 32 O_3 and 30 PM_{10} pollution monitoring stations within each respective study area; the stations were operated by various state, tribal, and local agencies (Table 9), and pollution monitoring complied with all federal regulations (Pope and Wu 2014). Air pollution data for the study were obtained from the United States Environmental Protection Agency's Air Quality System (AQS) database.

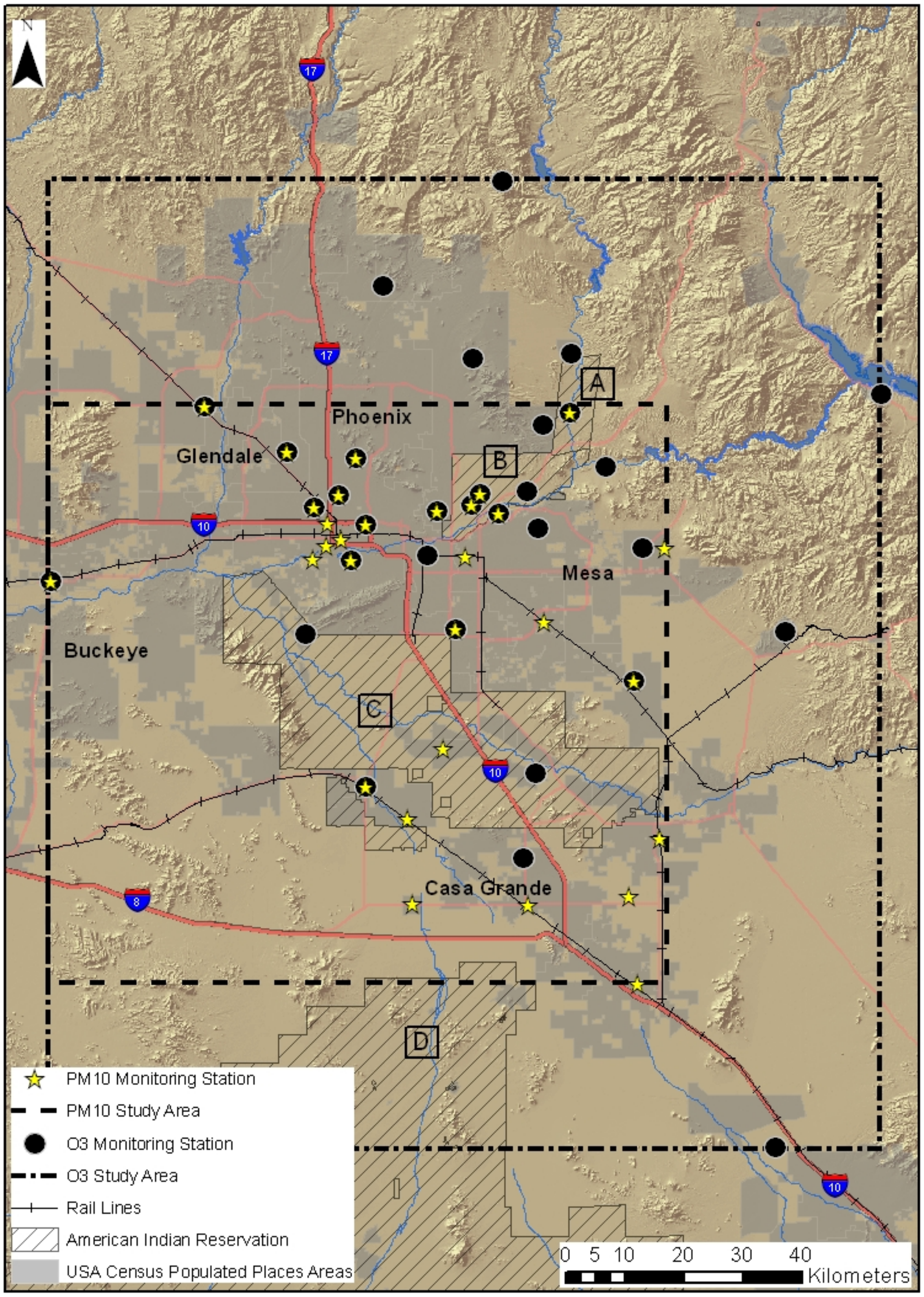

Figure 22 Map of Central Arizona Including the Phoenix Metropolitan Area. The Map Includes the Location of O_3 and PM_{10} Monitoring Stations, Note That Some Stations Contain Both Monitor Types. American Indian Reservations Are Labeled on the Map: A. Ft. McDowell Yavapai Nation, B. Salt River Pima-Maricopa Indian Community, C. Gila River Indian Community, and D. Tohono O'odham Nation

Table 9 List of Agencies Operating Monitoring Stations within the Study Area. Agencies Submit Their Data to the EPA's AQS Database Which Was the Source of Data for This Study

Agency	Type of Agency	# O_3 Stations	# PM_{10} Stations
Arizona Department of Environmental Quality	State	3	2
Fort McDowell Yavapai Nation	Tribal	1	1
Gila River Indian Community	Tribal	2	1
Maricopa County Air Quality Department	Local (County)	17	14
Pinal County Air Quality Control District	Local (County)	5	9
Salt River Pima-Maricopa Indian Community	Tribal	4	3

O_3 Data were collected for the time period of 2008-2010; the finest temporal resolution (or grain size) was one hour (i.e. raw data were one-hour averages). Four temporal extents (i.e. time durations over which average values of measurements were derived) were utilized: one hour (at 15:00 on July 15), eight hours (15:00-22:00 on July 15), one month (July), and seasonal (April-October) (Table 10). The seasonal average was chosen instead of an annual average because many of the O_3 monitoring sites only operate during this time period.

PM_{10} data were also collected from 2008-2010, though the temporal resolution for PM_{10} was a 24-hour average measured one day out of every six (1-in-6 day basis), as this is the operating schedule for some of the PM_{10} monitors. Most PM_{10} monitors operated on a finer time scale, collecting daily 24- or 1-hour averages; however, all finer averages were rolled into a 24-hour average and all data outside of the 1-in-6 day schedule were eliminated to create a consistent coarse resolution. These data were then utilized at three different temporal extents: annually, monthly, and daily; monthly and daily extents included both winter and summer seasons (Table 10).

Table 10 Details on the Temporal Scales Used within This Study. Note That the PM_{10} Daily Temporal Extent Occurs on Different Days in Each of the Study Years Because of the 1-in-6 Day Sample Resolution

Pollutant	Temporal Resolution	Study Years	Temporal Extents				
O_3	1-hour Averages, continuous sample grain	2008-2010	Seasonal (Apr-Oct)	Monthly (July)	8-hour (July 15, 15:00-22:00)	1-hour (July 15, 15:00)	
PM_{10}	24-hour Averages, 1-in-6 day sample grain	2008-2010	Annual	Monthly (Jan)	Monthly (Aug)	Daily (Jan) [Jan 7, 2008, Jan 7, 2009, Jan 8, 2010]	Daily (Aug) [Aug 22, 2008, Aug 23, 2009, Aug 24, 2010]

<u>Pollution Surface</u>

The pollution surface was modeled using the landscape ecological methods in Pope and Wu (2014), i.e. first a semivariance analysis was performed on the pollution data, and then a kriging interpolation model was created. The semivariance analysis was performed using the software GS+: Geostatistics for the Environmental Sciences (Gamma Design Software 2006). After the data were properly prepared, they were modeled in isotropic semivariograms using the Gaussian model for O_3 and the spherical model for PM_{10}, quantifying the structure of spatial autocorrelation (see Pope and Wu (2014) for further details).

Following the semivariance analysis, a kriging interpolation map of the pollution surface was created. Kriging is a geostatistical interpolation method to estimate values at unsampled locations based on the spatial autocorrelation structure quantified in the semivariance analysis (Cressie 1990, Fortin and Dale 2005). My kriging maps of O_3 and PM_{10} concentrations over the study area were created using the Geostatistical Analysis

Extension within ArcMap (ESRI 2010). All input settings were matched with those of the GS+ software to maintain consistency with my semivariance analysis. Thematic maps were created at each temporal scale, for both O_3 and PM_{10} (Figure 23; also see Appendix C: Figures 31-39).

<u>Census Data</u>

Census data were selected at the block group level, as this was the finest resolution available for all variables (Table 11 and Figure 24; also see Appendix C: Figures 40-51 for demographic summaries). There were six variables in four groups: socioeconomic status, age, race, and ethnicity (Table 12). My inclusion of status, race, and ethnicity was based upon previous environmental justice research in the Phoenix area. Although not typically used as a variable in environmental justice studies, age was chosen here because the Phoenix area is a popular retirement location with many elder-only communities in locations that could possibly be at risk of inequitable pollution levels. In addition, children and elders are more vulnerable to higher pollution values, so information regarding their unique risk is important (Andersen et al. 2007, Tecer et al. 2008).

Table 11 Spatial and Population Statistics for the Census Block Groups Located within the O_3 and PM_{10} Study Areas. Note That Only Block Groups That Were Completely inside the Respective Study Areas Were Included

	Census Block Groups Spatial Statistics					Census Block Groups Population Statistics				
Study Area	***N***	**Min. Size (km^2)**	**Max. Size (km^2)**	**Mean Size (km^2)**	**Std. Dev. (km^2)**	**Population *N***	**Min. Pop.**	**Max. Pop.**	**Mean Pop.**	**Std. Dev.**
O_3	2646	0.085	904.9	4.23	27.36	4,108,844	0	7293	1552.9	698.4
PM_{10}	2172	0.085	603.0	2.91	17.30	3,380,319	0	7293	1556.3	680.9

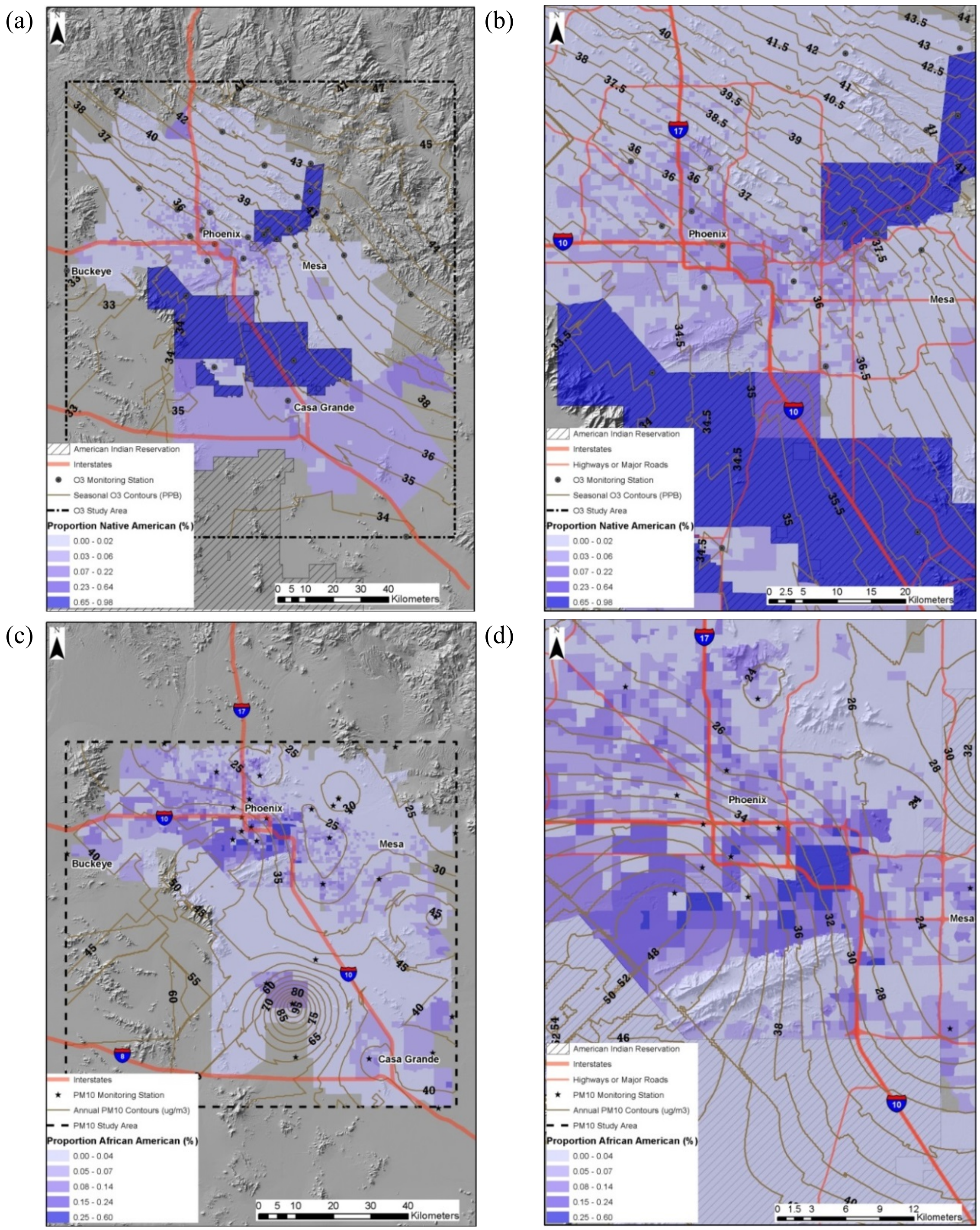

Figure 23 An Example of Pollution Contours Overlaying Population Proportion Maps. (a) Displays O_3 Pollution Contours (with Units of PPB) Taken at the Seasonal Temporal Extent and Averaged from 2008-2010, Overlaying the Population Proportion of Native Americans at the Census Block Group Level, (b) Is the Same Map at A Finer Resolution and Focused upon the Metropolitan Phoenix Urban Area to Display Details. (c) Repeats This for PM_{10} Contours (with Units of $\mu g/M^3$) Overlaying the Population Proportion of African Americans and (d) is A Finer Resolution in the Urban Metropolitan Area. See Appendix C: Figures 31-39, for Complete Maps from All Temporal Extents

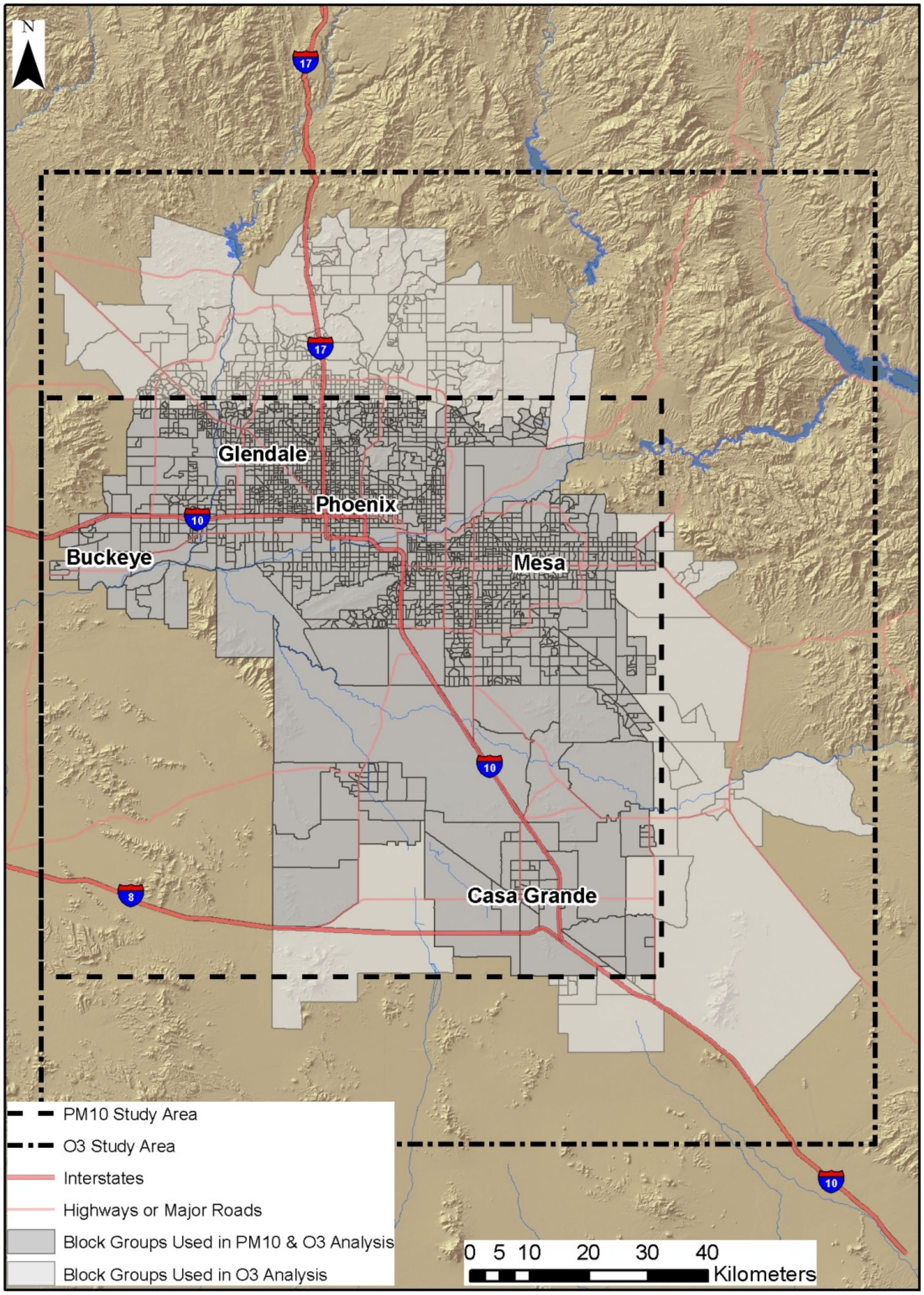

Figure 24 Map of the Census Block Groups That Were Used within the PM_{10} and O_3 Portions of the Study. Note That Only Those Block Groups That Were Fully Contained within the Respective Study Areas Were Included. The Very Large, Sparsely Populated Block Groups in Rural Areas That Crossed the Studies' Boundaries Were Excluded. Block Groups That Are Colored Light Grey Were Used in the O_3 Study, Those That Are Colored Dark Grey Were Used for Both the O_3 and PM_{10} Studies

Table 12 Descriptive Statistics for Study Variables, Based upon Census Block Groups

O_3 Study Area	***N***	**Range**	**Min.**	**Max.**	**Mean**	***SD***	**Vari.**
Socioeconomic Status							
Median Household Income (thousands)	2646	200.0	0.0	200.0	56.9	28.9	834.1
Age Proportion							
≤Age 17 (%)	2646	59	0	59	25	10	1
≥Age 65 (%)	2646	90	0	90	14	17	3
Race Proportion							
African American (%)	2646	60	0	60	5	5	0
Native American (%)	2646	98	0	98	2	7	1
Ethnicity Proportion							
Hispanic (%)	2646	94	0	94	28	24	6
O_3 Pollution							
Seasonal O_3 (PPB)	2646	11.6	33.0	44.5	36.9	2.0	4.1
Monthly(July) O_3 (PPB)	2646	8.4	35.0	43.4	39.3	1.5	2.3
8-hour O_3 (PPB)	2646	19.6	33.2	52.8	41.8	4.0	16.3
1-hour O_3 (PPB)	2646	20.3	46.3	66.6	55.6	5.2	27.4

PM_{10} Study Area	***N***	**Range**	**Min.**	**Max.**	**Mean**	***SD***	**Vari.**
Socioeconomic Status							
Median Household Income (thousands)	2172	200.0	0.0	200.0	54.4	28.0	782.8
Age Proportion							
≤Age 17 (%)	2172	59	0	59	26	10	1
≥Age 65 (%)	2172	86	0	86	13	15	2
Race Proportion							
African American (%)	2172	60	0	60	5	5	0
Native American (%)	2172	98	0	98	3	7	1
Ethnicity Proportion							
Hispanic (%)	2172	94	0	94	32	24	6
PM_{10} Pollution							
Annual PM_{10} ($\mu g/m^3$)	2172	74.0	20.7	94.6	30.4	6.9	47.5
Monthly (Jan) PM_{10} ($\mu g/m^3$)	2172	34.3	8.2	42.5	20.2	6.4	40.8
Monthly (Aug) PM_{10} ($\mu g/m^3$)	2172	57.0	24.0	81.0	31.3	5.3	28.4
Daily (Jan) PM_{10} ($\mu g/m^3$)	2172	35.8	10.0	45.8	21.3	6.0	36.1
Daily (Aug) PM_{10} ($\mu g/m^3$)	2172	50.3	17.9	68.2	24.7	4.8	23.4

GIS Model

Rasters for each 2008-2010 kriged pollution surface maps for each temporal extent were averaged together using the Raster Calculator tool in ArcMap, thus creating an average pollution surface for each extent with a 250m resolution. These average surfaces were categorized into three spatial scales: the initial pollution surface or raw data, pollution deciles, and pollution quartiles (the decile and quartile surfaces were created with the Reclassify tool in ArcMap). After converting to polygons, these pollution surfaces were spatially joined with the census data using the pollution score at the centroid of each block group; the spatially-explicit tables were then exported for statistical analysis (Figure 25).

Statistical Model

I used hierarchical multiple regression models to examine the independent effects of the four census groups (socioeconomic status, age, race, and ethnicity) with each pollution surface at each temporal extent and spatial aggregation. This resulted in a total of 48 and 60 regression equations for O_3 and PM_{10}, respectively. Models 1-4 were ordered in the hierarchical multiple regression using an *a priori* decision of socioeconomic status (median household income), age (proportion age≤17 and proportion age≥65), race (proportion African American and proportion Native American), and ethnicity (proportion Hispanic) (Table 13; also see Tables 42-43 in Appendix C).

The models were created in SPSS Version 22.0 (IBM Corp 2013). Input data were transformed as necessary, and homoskedasticity was tested for with the Breusch-Pagan and the Koenker tests. These tests revealed that data were significantly heteroskedastic, so the heteroskedasticity-consistent standard error estimator model HC3, run using a script developed for SPSS by Hayes and Cai (2007), was used to reduce bias.

Table 13 Dependent Variables Used in Each of the Hierarchical Multiple Regression Models.

Model #	Dependent Variables
1	Median Household Income
2	Median Household Income, Age 17 and under, Age 65and over
3	Median Household Income, Age 17 and under, Age 65and over, Proportion African American, Proportion Native American
4	Median Household Income, Age 17 and under, Age 65and over, Proportion African American, Proportion Native American, Proportion Hispanic

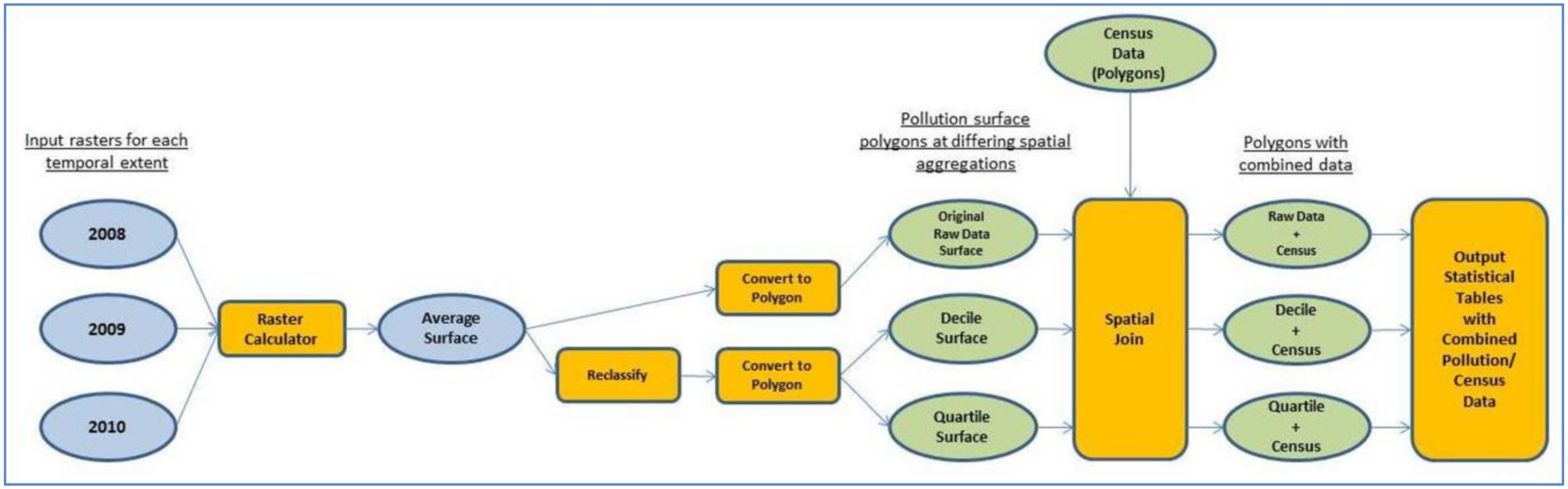

Figure 25 The Model Used to Generate Spatial Files which Combine Pollution Surface Data and Census Data. Ovals Represent Map Data Files, either Rasters or Polygons. Rectangles Represent Tools Or Processes within the GIS. The Spatial Join Added the Pollution Value at the Centroid of Each Block Group to the Census Files. The Spatially-Explicit Table Was Then Exported for Statistical Analysis

Results

The hierarchical multiple regression models did find significant relationships between the dependent pollution and independent demographic variables (see Appendix C: Tables 42-43 for complete statistical results). These relationships are summarized in Table 14, which is based upon model 4 of the regressions, and identifies those that could possibly be a justice issue, i.e. the independent variable is a significant predictor for the dependent variable. These positive relationships were noted as possible justice issues based upon the slope of the beta score in the regression, e.g. a negative beta would demonstrate a trend of the concentration of pollution increasing while the median household income of the Census block group decreases and a positive beta reveals a trend where the pollution concentration and the proportion of a demographic group increase together.

There were only a few instances where changing the temporal scale or spatial aggregation changed the relationship between the dependent and independent variables (Table 14). The only examples of this were O_3 with the variables median household income and proportion aged$\leq$17, and PM_{10} with income and proportion Hispanic; in all other cases the significant relationships between the variables were the same between all temporal extents or spatial aggregations.

There were many examples of where changing scale resulted in the model 4 relationship becoming non-significant (Table 14). This was especially prevalent in the median household income variable for both O_3 and PM_{10}. In many of these cases, income did act as a significant predictor for pollution levels in models 1 through 3; however, the addition of the proportion Hispanic independent variable in model 4 explained away the relationship between pollution and income causing the significant relationship to be lost (Appendix C: Table 42).

Table 14 Summary of Hierarchical Regression Results for Model 4 of the O_3 and PM_{10} Parameters and Demographic Variables at Each Spatial and Temporal Scale

		Median Household Income			Proportion Age ≤17			Proportion Age ≥65		
		Raw Data	Deciles	Quartiles	Raw Data	Deciles	Quartiles	Raw Data	Deciles	Quartiles
O_3	Seasonal	+	+	NS	+	+	NS	-	-	-
	Monthly	NS	NS	-	NS	-	-	-	-	-
	8-hour	NS	NS	NS	+	+	+	NS	NS	NS
	1-hour	NS	NS	NS	+	+	NS	-	-	-
PM_{10}	Annual	-	-	NS	+	+	+	+	+	+
	Jan Monthly	-	-	-	NS	NS	NS	NS	NS	+
	Jan Daily	NS	-	-	+	+	+	+	+	+
	Aug Monthly	NS	NS	+	+	+	+	+	+	+
	Aug Daily	-	NS	NS	+	+	+	+	+	+
		Proportion African American			**Proportion Native American**			**Proportion Hispanic**		
		Raw Data	Deciles	Quartiles	Raw Data	Deciles	Quartiles	Raw Data	Deciles	Quartiles
O_3	Seasonal	-	-	-	+	+	+	-	-	-
	Monthly	-	-	-	+	NS	+	-	-	-
	8-hour	-	-	-	+	+	+	-	-	-
	1-hour	-	-	-	+	+	+	-	-	-
PM_{10}	Annual	+	+	+	-	-	-	+	+	+
	Jan Monthly	+	+	+	-	-	-	+	+	+
	Jan Daily	+	+	+	-	-	-	+	+	+
	Aug Monthly	+	+	+	-	-	-	NS	NS	-
	Aug Daily	+	+	+	-	-	NS	+	NS	-

Key

NS	No Significant Relationship
-	No Justice Relationships Found
+	Possible Justice Relationship

There were several distinct, consistent patterns that emerged in the data. At most scales, the proportion of people age 17 and under was a significant predictor for both O_3 and PM_{10}; however, the proportion of people age 65 and over was only a significant predictor for PM_{10} and was negatively correlated with O_3. The proportion of African Americans was a strong predictor for PM_{10}, but had an equally strong negative relationship with O_3. In contrast, the proportion of Native Americans was a predictor for O_3, but had a negative relationship with PM_{10}. The proportion of Hispanics had a strong negative correlation with O_3, but a less consistent relationship with PM_{10}, with the August monthly and daily temporal scales varying between positive, negative, and non-significant beta scores (Table 14).

Discussion

Multi-Scalar Results

Though changing the temporal scale changed the slope of the model results, i.e. from negative to positive or vice versa, in a few instances, the effect was far less than anticipated (Table 14). A more common occurrence was to change the relationship from significant to non-significant, or vice versa, between the independent and dependent variables when the temporal scale was changed. This proves that, in most cases, even though the spatial pattern of the pollutant is visibly changed between time periods, the representative relationship between pollution sources/dynamics and demographics did not change. A more interesting result noted were the changes between the PM_{10} winter and summer scales, especially in relation to the Hispanic demographics. These changes in the spatial pattern of PM_{10} are likely the result of changes in meteorology between the seasons, as source apportionment likely remains the same (Pope and Wu 2014).

Changes in spatial aggregation of pollutant also resulted in less effect than expected. It was expected that aggregating into deciles, and especially into quartiles, would bring many changes from the MAUP scaling problem. In actuality, of the 54 regression models, aggregating to deciles only changed the results (including changing to non-significance) five times, or 9% of the time. Aggregating to quartiles changed the results a total of 13 times, or 24% of the time (Table 14).

Environmental Inequity with O_3 Pollution

Our analysis shows that significant relationships of possible environmental inequity exists between O_3 pollution and Native Americans, youth under 17 years of age (at most scales), and to a limited extent, with lower median household incomes (Table 14). This relationship, at least in regards to Native Americans, was not unexpected as the spatial patterns of O_3 show concentrations tending to increase toward the northeast portion of the study area, away from the urban area and close to the Ft. McDowell Yavapai Nation and Salt River Pima-Maricopa Indian Communities (Pope and Wu 2014, also see figures 31-34 in Appendix C). O_3, being a secondary pollutant, forms in sunlight from photoreactive precursor chemicals mainly emitted by industrial and transportation sources in the urban area. Prevailing easterly and/or anabatic winds push the precursors and O_3 plume up against the northeastern mountains in the daytime where it continues to react in sunlight, and the usually slower nighttime katabatic winds drain it back into the lower elevations, giving O_3 a tendency to pool at the edge of the urban areas and near the reservations (Ellis et al. 1999, Pope and Wu 2014). Furthermore, O_3 within the urban area is destroyed, or scavenged, during the night by nitrous oxide (NOx) emissions; but O_3 in rural areas, lacking scavenging NOx, persists longer in the environment before decay or deposition (Gregg et al. 2003).

Given that, in general, O_3 concentrations increase with an increasing population proportion of Native Americans; and more specifically, the increase in concentrations over the reservations, I contend that an inequitable situation in O_3 distribution exists for Native Americans. Although the O_3 patterns are more a function of geography and meteorology than a deliberate attempt to place polluting sources near minority populations, given the legacy conditions, such as forced segregation and economic hardship on the reservations, that Native Americans have endured, the pattern of environmental injustice is clear.

It should also be noted that my findings differ from earlier environmental justice studies using $O_{3.}$ The Grineski et al (2007) study found that Latino immigrants were significant predictors for O_3, while Native Americans had a significant negative relationship. However, their study differed in time and scale, as it was based upon modeled data from a single one-hour temporal scale, August 27, 1999 at 16:00.

The relational patterns between O_3 and people aged 17 and under are less clear than those with Native Americans. The density of young people is highest in the urban areas of west Phoenix and Mesa, but the block groups with a higher proportion of young people is scattered into rural areas and American Indian reservations (see Figure 45 and 48 in Appendix C). Furthermore, the relationships were less consistent, with the regression models always showing negative correlations, until the Hispanic demographics were added in model 4 (Appendix C: Table 42). In addition, this demographic was one of the few to show differing results with a change of temporal scales, and O_3 at a monthly scale was either non-significant or negatively correlated (Table 14). Thus while it is difficult to point directly to an overall pattern of inequity, there are certainly, on average, locales and temporal scales where youth are exposed to an excessive distribution of O_3 pollution.

Environmental Inequity with PM_{10} Pollution

Our analysis of the relationship between PM_{10} concentrations and independent demographics shows patterns that are often directly opposite those of O_3. At most scales, African Americans, Hispanics, and people aged 65 and older, while having negative relationships with O_3, became significant predictors for PM_{10}. People aged 17 and under were usually predictors for PM_{10}, except at the January monthly scale when the addition of the Hispanic population to the regression model explained away the relationship with youth. As in the O_3 analysis, income was an inconsistent predictor for PM_{10}, especially at the summer temporal scales. Lower incomes were usually predictors for PM_{10} in models 1-3 of the regression, but this relationship often changed after adding the Hispanic demographic in model 4 (Appendix C: Table 43).

As with O_3, the known characteristics and patterns of PM_{10} pollution in Phoenix supports these results. Unlike O_3, PM_{10} is a primary pollutant that tends to aggregate around its sources, in addition to windblown transport from the surrounding desert areas. Many of the PM_{10} 'hotspots' in the study area were created from localized sources including agriculture in rural Pinal county and extractive and material handling industries in South Phoenix (Fernando et al. 2009b, Dimitrova et al. 2012, Clements et al. 2013). In addition, South Phoenix is in the Salt River flood plain, and has the lowest average elevations in the metropolitan area; the river channel acts as a natural transport corridor and downwind sink for early morning particles emitted from other portions of the metropolitan area (Dimitrova et al. 2012). The South Phoenix area has high proportions of African American and Hispanic populations, though Hispanic populations are far more spatially distributed throughout the study area, and this likely accounts for much of the correlation in the results.

The spatial correlation between the youth and elder age groups and PM_{10} is more difficult to note with visual inspection of the maps. Youth proportions appear to be higher through the rural areas and urban fringe, which are areas tending to have higher PM_{10} concentrations (Appendix C: Figure 50). Elder proportions are highest in the retirement communities in the northwest portion of the study area (Sun City), east Mesa, and the center of the study area (Sun Lakes) (Appendix C: Figure 51). PM_{10} concentrations were relatively low at all scales in the Sun City area, therefore the correlation with PM_{10} is likely due to the elder populations living in Mesa and Sun Lakes.

The spatial pattern, quantified by the statistical results, confirms an inequitable situation between PM_{10} distribution and African American and Hispanic populations. Legacy conditions with these populations, e.g. historical segregation into South and West Phoenix along with most industrial sources, clarifies the origin of these long-term inequities with minority population in these areas.

Limitations

Environmental justice studies, including this study, often use classic regression models to test the relationship between independent and dependent variables

(Chakraborty et al. 2011). The classic global regression model makes two key assumptions, that observations and residuals are independent and the process under study is stationary. Assumptions regarding stationarity can be made if the region under study and the data set is small enough and the spatial units are as small as possible; as in the case of census block groups for this study (Páez 2004, Grineski and Collins 2008, Gilbert and Chakraborty 2011). However, the demographic data used in this study did show clustering, as Moran's I tests returned significant results for all groups ($P<0.01$).

Based on the results shown by changing the spatial aggregation of pollutant data, it is quite possible that bias in my regression model is low. However, future studies could be improved by using regression techniques that control for spatial dependence, such as geographically weighted regression (GWR) or simultaneous autoregressive models (SAR) (Brunsdon et al. 1999, Kissling and Carl 2008, Chakraborty 2009).

Conclusion

This study has shown that distributive inequities exist, across scales and spatial aggregation, in the two ambient pollutants of most concern in the Phoenix area, O_3 and PM_{10}. These inequities affect different social groups to varying degrees, based upon their location and population clustering in the metropolitan area. These populations have various legacy stories behind them: Native Americans were forcibly confined to reservations in the 19th century where the greater part of their freedom and livelihood was denied them. African Americans and Hispanic people, arriving after the 19th century Anglo settlers, were excluded from living in the prime areas of White privilege, and instead were segregated into South and West Phoenix, where city planners placed heavy industries and waste handling facilities. Youth and elder populations, being more vulnerable to pollution effects, have different situations. The elder population, while certainly not a unique group suffering oppression like minority populations in the past, has nevertheless often purchased their retirement homes with the expectation of a clean and healthy environment; and the youth are obviously under the authority of their guardians and have little say in the environment in which they live. All of these groups have distinct reasons for being protected from environmental inequities, which begins with identifying the relationships.

The occurrence of adverse health effects to these populations because of excessive exposure to O_3 or PM_{10} has not been confirmed with this study, though serious health complications can be implied from frequent acute or long-term chronic exposure to these pollutants (Lippmann 1989, Pope and Dockery 2006). The case to be made here is that conditions, either historical or current, are such that these populations of limited mobility are located in areas where they bear a larger burden of criteria pollutant exposure. With the inequitable relationships identified, policy makers and regulating agencies in the Phoenix area have the knowledge necessary for making the right decisions in regards to protecting the health of its citizens.

CHAPTER 5: SYNTHESIS: AIR POLLUTION, MONITORING NETWORK DESIGN, AND ENVIRONMENTAL JUSTICE

Overall Research Design Revisited

The design of air pollution monitoring networks is guided by regulations issued by the EPA. These regulations require monitoring sites to fill a series of objectives and monitoring scales, e.g. "Sites located to determine the highest concentrations expected to occur in the area covered by the network" or "Sites located to measure typical concentrations in areas of high population density" (Code of Federal Regulations 2009b). The government environmental agencies design their networks to meet these regulations, which in theory would give comprehensive representation to the metropolitan area, but is the network properly situated such that the distribution of known pollution is being adequately monitored? Is our knowledge of the pollution distribution limited by the design of the network? How does spatiotemporal scale affect this pollution distribution and network design features? These were the questions that led to this dissertation research.

The most important reason for monitoring air pollution is to protect the health of our citizens. While every citizen's health is important, a main priority is to identify those social groups that are experiencing an inequitable proportion of health risk. This is a priority of the EPA based on a 1994 presidential directive (U.S. EPA 2010). It is difficult to properly determine environmental inequity from air pollution unless that pollution is adequately characterized, and it is formidable to adequately characterize air pollution if the monitoring network is not properly designed. Thus, my dissertation research was designed to simultaneously tackle the interactive issues of pollution characterization, network evaluation, and environmental justice (Figure 1 and Figure 26).

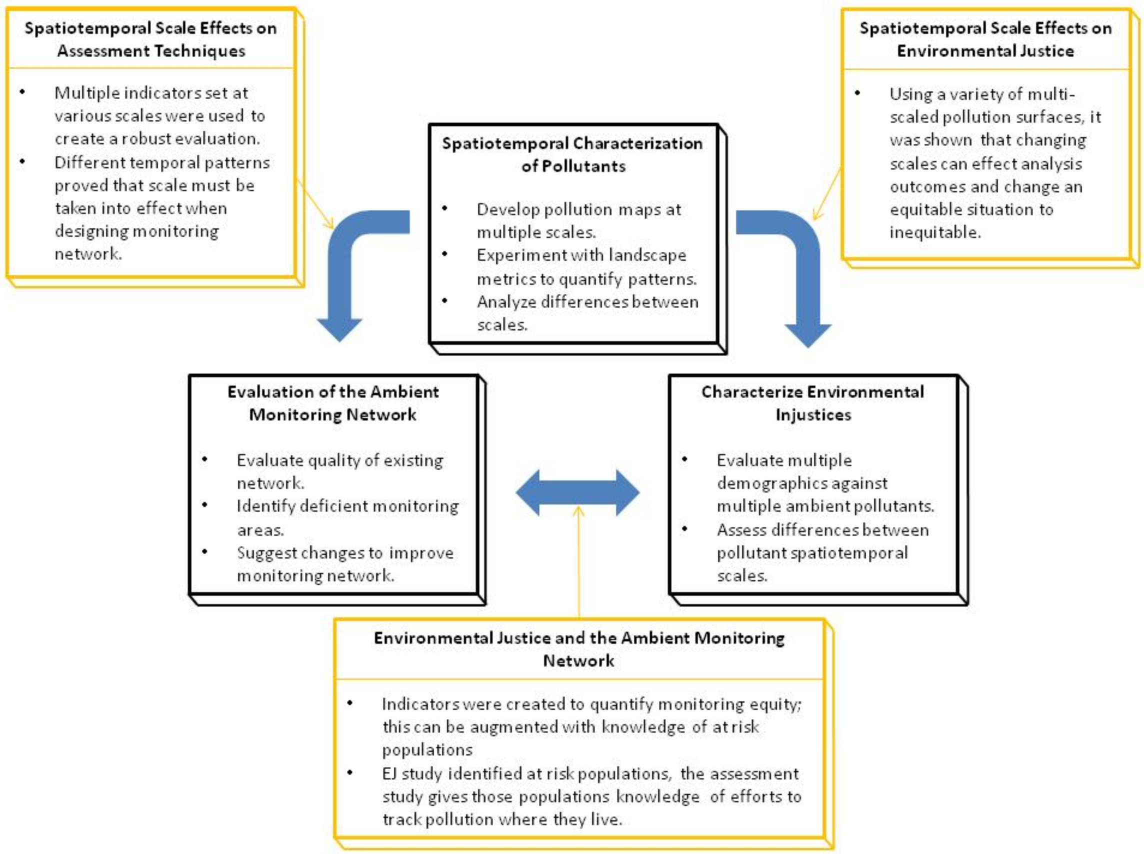

Figure 26 Diagram Displaying Major Findings Based upon the Relationship between Study Chapters in This Dissertation

An important theme underlying this dissertation research is scale in space and time. This was inspired by the widely applicable finding in landscape ecology that patterns and processes, as well as their relationships, are frequently scale-dependent (Wu and Loucks 1995, Turner et al. 2001, Wu 2007). Using interdisciplinary methods from landscape ecology, geography, sustainability assessment, and social sciences, I have addressed questions on how scale affects the patterns of air pollution, the assessment of monitoring networks used to monitor these pollutants, and how scale-dependent pollution patterns affect environmental justice. These are important questions that cut across several research fields, including urban landscape ecology, environmental justice, and air pollution research in general. This spatially explicit, multiscale approach is innovative and effective for studying air pollution problems.

To study the effects of scale on air pollution, I began this dissertation research by forming three key research questions:

1. What are the spatiotemporal patterns of air pollution and their key determinants in the Phoenix metropolitan region?
2. What implications do the spatiotemporal patterns of air pollution have for designing a monitoring network in the Phoenix metropolitan region, and is the current government ambient monitoring network adequate?
3. Using a comprehensive, multi-scale point of view, are there environmental justice problems in the Phoenix metropolitan region, and does the current ambient monitoring network adequately give representation to these vulnerable populations?

Key Research Findings

My research has addressed all the questions mentioned above, and has important implications for assessing the adequacy of air pollution monitoring systems and the potential problems of environmental injustice (Figure 26). Key findings from this research are summarized below:

1. Chapter 2 addressed research question #1, where patterns of O_3 and PM_{10} were found to change significantly with changes of spatiotemporal scale. These changes were quantified using several landscape ecological methods, and models appropriate to the pollutant were revealed. In addition, it was shown that, at longer temporal scales, O_3 is a regionally-scaled pollutant less affected by local sources, while PM_{10} is a more locally-scaled pollutant strongly affected by sources. It was also shown that the effect of season on PM_{10} was as great as the effect of scale. These results contributed to the body of urban landscape ecological science by displaying the direct attribution of scale to air pollution patterns.
2. Chapter 3 addressed research question #2. Using a novel approach of a large variety of weighted indicators at various spatiotemporal scales, the adequacy of the network in Maricopa County was quantified in a trans-disciplinary approach that involved input from various stakeholders, including academics and government policymakers (Wu 2006). Furthermore, deficiencies were spatially defined and recommendations were made on how to strengthen the design of the network. A framework utilizing a sustainability ranking system provided new insight into the strengths and weaknesses of the network. These results further scientific knowledge by demonstrating the power of a multi-objective sustainability-based method that can be used by researchers or managers in designing or assessing monitoring networks.

3. Two chapters addressed research question #3; in chapter 3 multiple indicators were used to quantify the performance of the network in monitoring air pollution in neighborhoods with high proportions of racial and ethnic minorities, and also to locate areas where additional monitors would provide benefit to these populations. In chapter 4, a novel method using multi-scalar ambient data from the air pollution monitoring network and 108 hierarchical multiple regression models revealed environmental inequities between air pollutants and race, ethnicity, age, and socioeconomic class. Though the effect was less than expected, the method nonetheless proved that changing the scale of the analysis can change the equitable relationship between pollution and demographics. This research improves the body of literature in both landscape ecology and social science by demonstrating novel, interdisciplinary methods of quantifying environmental inequity.

Concluding Remarks

The design and implementation of the Maricopa County air monitoring network was performed by various government agencies, beginning with the first site opened by the County health department in central Phoenix over fifty years ago (U.S. EPA 2009b). Since then, the network has slowly grown as sites and new pollution monitors have been added by state, local, and tribal agencies. Sites have also been moved or closed over the years as changes occurred for such reasons as environmental regulations, population demographics, new or changed pollution sources, or budget constraints. These dynamics in the physical network naturally lead to questions of whether or not the network is still representative of the pollution landscape.

This dissertation research also forms a basis for future research questions. For example, how does spatiotemporal scale affect the relationship between pollution sources and air pollution patterns, or how do differing pollutants (e.g. toxic air species or different criteria pollutants) change the scale-dependent relationships? Other future research opportunities stemming directly from this research involve using different modeling approaches, indicators, or scales to create the pollution patterns or test the related processes. For example, in lieu of geostatistical interpolation modeling to create the pollution surface, dispersion modeling could be used both for network evaluation and environmental justice research. Health indicators, e.g. an indicator focused on hotspots of asthma or respiratory disease, could be added as an additional assessment tool to ensure that vulnerable populations are properly represented. Finally, ‘human-scales’ could be implemented to research the relationship of air pollution patterns with the social demographics of where people work, go to school, and play, instead of only looking where people live with census data.

In conclusion, our citizens need a clean and healthy environment to live in, and achieving this goal requires a balance among the environmental, economic, and social dimensions underpinning urban sustainable development (Wu 2008). In respect to air pollution, a critical first step in meeting these goals is the characterization of pollution patterns. As this dissertation research has shown, a critical component of this characterization is understanding the role of scale in these pattern dynamics. By explicitly considering spatial and temporal scales, this study not only provides new insights into, but also an innovative methodology for the study of, air pollution problems in urban regions. With this knowledge brought to light, researchers, managers, and policymakers will have the ability to make informed decisions while studying or protecting the health and livelihoods of our citizens.

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APPENDIX A

SUPPLEMENTARY DATA FOR CHAPTER 2

Table 15 Table of Parameter Input Variables and Statistical Model Results in the Semivariance Analyses Conducted with the GS+ Software for the O_3 Parameter

	Temporal Extent	Data Trans-formation	Back Trans-formation	Kur-tosis	Skew-ness	Iso-tropic Model	Active Lag Distance (km)	Uniform Interval (km)	Range (km)	Nugget Variance (Intercept)	Sill (Sample Variance)	RSS	r^2
O_3	Seasonal, 2008	Log	Weighted	-0.79	0.42	Gaussian	84.722	5.651	121.4	0.0052	0.0995	5.501×10^{-4}	0.775
	Seasonal, 2009	Log	Weighted	-0.65	0.58	Gaussian	84.722	5.651	132.8	0.0048	0.1054	3.437×10^{-4}	0.823
	Seasonal, 2010	Log	Weighted	-0.65	0.30	Gaussian	84.722	5.651	171.3	0.0052	0.1398	3.508×10^{-4}	0.769
	Monthly (July), 2008	Not transformed	N/A	-0.62	0.12	Gaussian	84.722	5.651	166.4	7.0×10^{-6}	1.91×10^{-4}	7.021×10^{-10}	0.776
	Monthly (July), 2009	Log	Weighted	-0.37	0.16	Gaussian	84.722	5.651	192.4	0.0048	0.1135	1.257×10^{-4}	0.798
	Monthly (July), 2010	Not transformed	N/A	0.10	-0.28	Gaussian	84.722	5.651	194.5	4.0×10^{-6}	1.44×10^{-4}	1.281×10^{-10}	0.863
	8-hour (July 15, 15:00-22:00), 2008	Log	Weighted	-0.90	0.05	Gaussian	84.722	5.651	119.1	0.011	0.248	2.121×10^{-3}	0.857
	8-hour (July 15, 15:00-22:00), 2009	Log	Weighted	0.34	0.10	Gaussian	84.722	5.651	148.4	0.0015	0.1634	3.568×10^{-4}	0.887
	8-hour (July 15, 15:00-22:00), 2010	Not transformed	N/A	-0.44	-0.37	Gaussian	84.722	5.651	125.7	1.0×10^{-5}	3.08×10^{-4}	2.210×10^{-9}	0.884
	1-hour (July 15, 15:00), 2008	Log	Weighted	-1.00	0.08	Gaussian	84.722	5.651	40.1	0.0062	0.054	3.688×10^{-4}	0.883
	1-hour (July 15, 15:00), 2009	Square-Root	Standard	-1.06	-0.04	Gaussian	84.722	5.651	45.0	7.1×10^{-5}	6.98×10^{-4}	8.198×10^{-8}	0.891
	1-hour (July 15, 15:00), 2010	Not transformed	N/A	-0.29	-0.15	Gaussian	84.722	5.651	95.8	4.0×10^{-5}	3.4×10^{-4}	1.369×10^{-8}	0.735

Table 16 Table of Parameter Input Variables and Statistical Model Results in the Semivariance Analyses Conducted with the GS+ Software for the PM_{10} Parameters

	Temporal Extent	Data Trans-formation	Back Trans-formation	Kur-tosis	Skew-ness	Iso-tropic Model	Active Lag Distance (km)	Uniform Interval (km)	Range (km)	Nugget Variance (Intercept)	Sill (Sample Variance)	RSS	r2
PM_{10}	Annual, 2008	Log	Weighted	2.59	1.13	Spherical	61.025	4.068	25.0	1.0×10^{-4}	0.1152	0.0200	0.452
	Annual, 2009	Log	Weighted	-0.23	0.40	Spherical	61.025	4.068	34.6	0.0084	0.1268	0.0290	0.379
	Annual, 2010	Log	Weighted	-0.68	-0.11	Spherical	61.025	4.068	22.2	1.0×10^{-4}	0.0882	0.0211	0.277
	Monthly (Jan), 2008	Square-root	Standard	0.49	-0.07	Spherical	61.025	4.068	24.2	0.0010	1.509	3.66	0.472
	Monthly (Jan), 2009	Square-root	Standard	-0.58	-0.02	Spherical	61.025	4.068	28.4	0.0010	1.823	3.66	0.562
	Monthly (Jan), 2010	Square-root	Standard	-0.37	0.01	Spherical	61.025	4.068	159.2	0.1330	3.276	1.87	0.668
	Monthly (Aug), 2008	Log	Weighted	-0.84	-0.08	Spherical	61.025	4.068	23.2	6.0×10^{-4}	0.0722	6.935×10^{-3}	0.422
	Monthly (Aug), 2009	Log	Weighted	-0.50	0.42	Spherical	61.025	4.068	23.7	1.0×10^{-4}	0.0742	9.447×10^{-3}	0.421
	Monthly (Aug), 2010	Log	Weighted	-0.45	0.00	Spherical	61.025	4.068	17.5	1.0×10^{-4}	0.0662	0.0121	0.194
	24-hour (Jan 7), 2008	Square-root	Standard	0.72	0.01	Spherical	61.025	4.068	50.7	0.043	0.527	0.314	0.518
	24-hour (Jan 7), 2009	Square-root	Standard	-0.07	-0.07	Spherical	61.025	4.068	47.6	0.122	1.099	1.29	0.517
	24-hour (Jan 8), 2010	Square-root	Standard	-1.11	0.07	Spherical	61.025	4.068	24.8	0.09	3.109	14.4	0.388
	24-hour (Aug 22), 2008	Log	Weighted	-0.51	0.37	Spherical	61.025	4.068	38.1	0.0065	0.121	0.0203	0.461
	24-hour (Aug 23), 2009	Log	Weighted	1.34	0.30	Spherical	61.025	4.068	19.0	2.0×10^{-4}	0.0644	5.667×10^{-3}	0.352
	24-hour (Aug 24), 2010	Log	Weighted	-0.20	-0.44	Spherical	61.025	4.068	N/A, linear	0.028	0.743	0.0720	0.637

APPENDIX B

SUPPLEMENTARY DATA FOR CHAPTER 3

Table 17 Raw and Weighted Scores and Ranks for the Phase I O_3 Assessment. Indicator Number Labels Correspond with Those for Phase I Listed on Table 5

	Raw Indicator Scores													
Site	**1**	**2**	**3**	**4a**	**4b**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Average**	**RANK**
BE	1	1	17	5	3	3.5	12	17	4	13	1	13	7.54	15
BP	3	7	11	1.5	12	3.5	13	7	1	1	8	5	6.08	17
CC	13	8	14	4	15	5.5	15	6	6	6	3	5	8.38	11
CP	5	13	1	16	1	16.5	2.5	1	10	15	17	15.5	9.46	8
DY	2	2	15	7	11	7	14	8	11	7.5	2	9.5	8.00	13
FF	7	15	7	13	9	11	7.5	12	14	7.5	10	5	9.83	6.5
FH	15	5	4	6	13	5.5	9.5	16	5	3	6	5	7.75	14
GL	9	16	9	11	8	11	11	3	17	12	15.5	9.5	11.00	2
HM	14	6	16	3	17	1	17	15	3	4	8	1.5	8.79	10
NP	17	3	8	9	10	14	5	14	16	10	13.5	13	11.04	1
PP	10.5	11.5	10	8	14	8	16	13	7	5	11	5	9.92	5
RV	16	4	13	1.5	16	2	9.5	4.5	2	2	5	1.5	6.42	16
SP	4	9	3	15	4	9	2.5	2	8	17	13.5	13	8.33	12
SS	12	10	2	10	6	13	5	4.5	9	9	15.5	15.5	9.29	9
TE	10.5	11.5	5	14	5	16.5	5	11	12	14	4	9.5	9.83	6.5
WC	8	17	12	12	7	11	7.5	9	15	11	8	9.5	10.58	4
WP	6	14	6	17	2	15	1	10	13	16	12	17	10.75	3

	Weighted Indicator Scores													
Site	**1**	**2**	**3**	**4a**	**4b**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Average**	**RANK**
BE	0.13	0.09	1.38	0.39	0.28	0.28	0.85	1.41	0.33	0.94	0.09	0.59	0.56	16
BP	0.39	0.65	0.89	0.12	1.13	0.28	0.93	0.58	0.08	0.07	0.71	0.23	0.50	17
CC	1.69	0.75	1.14	0.31	1.41	0.45	1.07	0.50	0.50	0.43	0.26	0.23	0.73	11
CP	0.65	1.21	0.08	1.24	0.09	1.34	0.18	0.08	0.83	1.08	1.50	0.70	0.75	10
DY	0.26	0.19	1.22	0.54	1.03	0.57	1.00	0.66	0.92	0.54	0.18	0.43	0.63	14
FF	0.91	1.40	0.57	1.01	0.84	0.89	0.53	0.99	1.17	0.54	0.88	0.23	0.83	6
FH	1.95	0.47	0.32	0.47	1.22	0.45	0.68	1.32	0.42	0.22	0.53	0.23	0.69	12
GL	1.17	1.49	0.73	0.86	0.75	0.89	0.78	0.25	1.41	0.87	1.37	0.43	0.92	2
HM	1.82	0.56	1.30	0.23	1.59	0.08	1.21	1.24	0.25	0.29	0.71	0.07	0.78	8
NP	2.22	0.28	0.65	0.70	0.94	1.14	0.36	1.16	1.33	0.72	1.19	0.59	0.94	1
PP	1.37	1.07	0.81	0.62	1.31	0.65	1.14	1.07	0.58	0.36	0.97	0.23	0.85	5
RV	2.08	0.37	1.05	0.12	1.50	0.16	0.68	0.37	0.17	0.14	0.44	0.07	0.60	15
SP	0.52	0.84	0.24	1.17	0.38	0.73	0.18	0.17	0.67	1.23	1.19	0.59	0.66	13
SS	1.56	0.93	0.16	0.78	0.56	1.06	0.36	0.37	0.75	0.65	1.37	0.70	0.77	9
TE	1.37	1.07	0.41	1.09	0.47	1.34	0.36	0.91	1.00	1.01	0.35	0.43	0.82	7
WC	1.04	1.58	0.97	0.93	0.66	0.89	0.53	0.74	1.25	0.79	0.71	0.43	0.88	3
WP	0.78	1.30	0.49	1.32	0.19	1.22	0.07	0.83	1.08	1.16	1.06	0.77	0.86	4

Table 18 Raw and Weighted Indicator Scores for PM_{10}. Note That the Buckeye Station (BE) Did Not Earn A Score for Indicator #7, Removal Bias, Because Its Location on the Edge of the Map Did Not Allow It to Be Removed in the Kriging Interpolation. Indicator Number Labels Correspond with Those for Phase I Listed on Table 5

	Raw Indicator Scores												
Site	**1**	**2**	**3**	**4a**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Average**	**RANK**
BE	13	2	14	4	1	11	-	3	8	1	10	6.70	12
CP	8	13	3	9	14	4	4	6	10.5	13.5	12.5	8.86	1
DC	12	3	1	14	7.5	3	7	1	12.5	5	1	6.09	13
DY	5	9	13	5	2	6.5	6	9	1	2	6	5.86	14
GL	4	8	10	11	7.5	6.5	5	14	7	11.5	6	8.23	4
GR	9	12	2	13	13	1.5	3	2	14	6.5	6	7.45	7
HI	11	6	9	2	6	13	11	8	2	4	2.5	6.77	11
ME	2	5	6	12	12	14	10	12	9	8.5	6	8.77	2
NP	1	4	12	3	5	12	8	13	3	8.5	10	7.23	9
SP	10	11	7	8	4	6.5	2	5	10.5	13.5	10	7.95	5
SS	3	7	5	6	10	6.5	9	7	4	11.5	12.5	7.41	8
WC	6	10	8	1	9	9	13	11	6	6.5	6	7.77	6
WF	14	1	11	10	3	10	12	4	5	3	2.5	6.86	10
WP	7	14	4	7	11	1.5	1	10	12.5	10	14	8.36	3

	Weighted Indicator Scores												
Site	**1**	**2**	**3**	**4a**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Average**	**RANK**
BE	1.80	0.19	1.19	0.46	0.09	0.70	-	0.30	0.74	0.10	0.49	0.60	12
CP	1.10	1.23	0.25	1.04	1.19	0.25	0.31	0.59	0.97	1.36	0.61	0.81	1
DC	1.66	0.28	0.09	1.62	0.64	0.19	0.55	0.10	1.15	0.50	0.05	0.62	10
DY	0.69	0.85	1.10	0.58	0.17	0.41	0.47	0.88	0.09	0.20	0.29	0.52	14
GL	0.55	0.76	0.85	1.27	0.64	0.41	0.39	1.37	0.65	1.16	0.29	0.76	4
GR	1.24	1.14	0.17	1.51	1.10	0.10	0.24	0.20	1.29	0.66	0.29	0.72	6
HI	1.52	0.57	0.76	0.23	0.51	0.82	0.86	0.79	0.18	0.40	0.12	0.62	11
ME	0.28	0.47	0.51	1.39	1.02	0.88	0.79	1.18	0.83	0.86	0.29	0.77	2
NP	0.14	0.38	1.02	0.35	0.42	0.76	0.63	1.28	0.28	0.86	0.49	0.60	13
SP	1.38	1.04	0.59	0.93	0.34	0.41	0.16	0.49	0.97	1.36	0.49	0.74	5
SS	0.41	0.66	0.42	0.70	0.85	0.41	0.71	0.69	0.37	1.16	0.61	0.64	9
WC	0.83	0.95	0.68	0.12	0.76	0.57	1.02	1.08	0.55	0.66	0.29	0.68	7
WF	1.93	0.10	0.93	1.16	0.26	0.63	0.94	0.39	0.46	0.30	0.12	0.66	8
WP	0.97	1.32	0.34	0.81	0.93	0.10	0.08	0.98	1.15	1.01	0.68	0.76	3

Individual Indicator Results

Indicator #1: Measured Concentrations

Table 19 O_3 Measured Concentrations

O_3	Design value (3-Yr Average of 4^{th} High)						
Site	**2005**	**2006**	**2007**	**2008**	**2009**	**Average**	**Score**
BE	0.06	0.06	0.07	0.07	0.07	0.064	1
BP	0.08	0.07	0.07	0.07	0.07	0.071	3
CC	0.08	0.08	0.08	0.08	0.08	0.078	13
CP	0.08	0.08	0.08	0.07	0.07	0.074	5
DY	0.07	0.07	0.07	0.07	0.07	0.068	2
FF	0.08	0.08	0.08	0.08	0.07	0.075	7
FH	0.08	0.08	0.08	0.08	0.07	0.080	15
GL	0.08	0.08	0.08	0.07	0.07	0.075	9
HM	0.08	0.08	0.08	0.08	0.07	0.080	14
NP	0.08	0.08	0.08	0.08	0.08	0.081	17
PP	0.08	0.08	0.08	0.08	0.07	0.076	10.5
RV	0.08	0.08	0.08	0.08	0.08	0.080	16
SP	0.08	0.07	0.07	0.07	0.07	0.073	4
SS	0.08	0.08	0.08	0.08	0.08	0.077	12
TE	0.08	0.08	0.08	0.08	0.07	0.076	10.5
WC	0.07	0.08	0.08	0.08	0.07	0.075	8
WP	0.07	0.07	0.08	0.08	0.07	0.074	6

Table 20 PM_{10} Measured Concentrations

PM_{10}	Design value (Max 24hr Avg)						
Site	**2005**	**2006**	**2007**	**2008**	**2009**	**Average**	**Score**
BE	169	272	195	223	439	259.6	13
CP	116	190	267	133	153	171.8	8
DC	206	253	155	247	277	227.6	12
DY	76	67	111	75	227	111.2	5
GL	84	60	92	80	196	102.4	4
GR	173	212	124	133	229	174.2	9
HI	142	274	230	133	275	210.8	11
ME	86	75	110	71	87	85.8	2
NP	81	79	78	88	69	79	1
SP	147	132	171	230	250	186	10
SS	121	76	73	92	135	99.4	3
WC	94	77	104	67	220	112.4	6
WF	233	313	227	278	317	273.6	14
WP	155	178	124	113	210	156	7

Indicator #2: Deviation from the NAAQS

Table 21 O_3 Deviation from the NAAQS

O_3	Design value (3-Yr Average of 4th High)									
Site	**2005**	**2006**	**2007**	**2008**	**2009**	**Avg**	**NAAQS**	**Deviant**	**ABS**	**Score**
BE	0.0620	0.0630	0.0650	0.0660	0.0650	0.0642	0.075	-0.0108	0.0108	1
BP	0.0810	0.0730	0.0670	0.0650	0.0670	0.0706	0.075	-0.0044	0.0044	7
CC	0.0800	0.0790	0.0800	0.0780	0.0750	0.0784	0.075	0.0034	0.0034	8
CP	0.0760	0.0760	0.0750	0.0740	0.0700	0.0742	0.075	-0.0008	0.0008	13
DY	0.0680	0.0680	0.0680	0.0680	0.0670	0.0678	0.075	-0.0072	0.0072	2
FF	0.0750	0.0750	0.0760	0.0760	0.0710	0.0746	0.075	-0.0004	0.0004	15
FH	0.0820	0.0820	0.0820	0.0790	0.0740	0.0798	0.075	0.0048	0.0048	5
GL	0.0790	0.0770	0.0750	0.0740	0.0710	0.0752	0.075	0.0002	0.0002	16
HM	0.0840	0.0810	0.0810	0.0780	0.0740	0.0796	0.075	0.0046	0.0046	6
NP	0.0830	0.0830	0.0820	0.0810	0.0770	0.0812	0.075	0.0062	0.0062	3
PP	0.0780	0.0760	0.0780	0.0750	0.0730	0.0760	0.075	0.0010	0.0010	11.5
RV	0.0810	0.0810	0.0830	0.0800	0.0750	0.0800	0.075	0.0050	0.0050	4
SP	0.0750	0.0720	0.0720	0.0720	0.0720	0.0726	0.075	-0.0024	0.0024	9
SS	0.0760	0.0770	0.0780	0.0780	0.0750	0.0768	0.075	0.0018	0.0018	10
TE	0.0760	0.0750	0.0770	0.0780	0.0740	0.0760	0.075	0.0010	0.0010	11.5
WC	0.0740	0.0750	0.0760	0.0770	0.0730	0.0750	0.075	0.0000	0.0000	17
WP	0.0720	0.0740	0.0750	0.0780	0.0730	0.0744	0.075	-0.0006	0.0006	14

Table 22 PM_{10} Deviation from the NAAQS

PM_{10}	Design value (Max 24hr Avg)									
Site	**2005**	**2006**	**2007**	**2008**	**2009**	**Avg**	**NAAQS**	**Deviant**	**ABS**	**Score**
BE	169	272	195	223	439	260	150	109.6	109.6	2
CP	116	190	267	133	153	172	150	21.8	21.8	13
DC	206	253	155	247	277	228	150	77.6	77.6	3
DY	76	67	111	75	227	111	150	-38.8	38.8	9
GL	84	60	92	80	196	102	150	-47.6	47.6	8
GR	173	212	124	133	229	174	150	24.2	24.2	12
HI	142	274	230	133	275	211	150	60.8	60.8	6
ME	86	75	110	71	87	85.8	150	-64.2	64.2	5
NP	81	79	78	88	69	79	150	-71	71	4
SP	147	132	171	230	250	186	150	36	36	11
SS	121	76	73	92	135	99.4	150	-50.6	50.6	7
WC	94	77	104	67	220	112	150	-37.6	37.6	10
WF	233	313	227	278	317	274	150	123.6	123.6	1
WP	155	178	124	113	210	156	150	6	6	14

Indicator #3: Area Served

Table 23 O_3 Area Served

O_3 Site	Area Served (km^2)	Score
BE	12,565	17
BP	441	11
CC	1617	14
CP	80	1
DY	2,690	15
FF	228	7
FH	139	4
GL	318	9
HM	7,767	16
NP	273	8
PP	414	10
RV	940	13
SP	123	3
SS	118	2
TE	147	5
WC	511	12
WP	190	6

Table 24 PM_{10} Area Served

PM_{10} Site	Area Served (km2)	Score
BE	15,100	14
CP	86	3
DC	15	1
DY	4,845	13
GL	379	10
GR	20	2
HI	376	9
ME	148	6
NP	857	12
SP	207	7
SS	136	5
WC	344	8
WF	638	11
WP	112	4

Indicator #4a: Emissions Inventory

Table 25 O_3 (VOC) Emissions Inventory

O_3 Site	Sum of VOC Emissions (lbs)	Mean	Max emission-section	Area of Polygon (km^2)	Density: Sum/Area (lbs/km2)	Score
BE	258,594	9,235	51,590	9,902	26	5
BP	0	0	0	441	0	1.5
CC	16,699	3,340	7,815	985	17	4
CP	447,686	22,384	106,506	83	5,394	16
DY	161,902	6,746	51,863	2,333	69	7
FF	200,057	16,671	94,343	228	877	13
FH	6,121	3,060	5,915	139	44	6
GL	240,333	10,924	92,160	318	756	11
HM	18	18	18	668	0.03	3
NP	162,441	12,495	32,645	273	595	9
PP	28,811	4,116	13,729	414	70	8
RV	0	0	0	850	0	1.5
SP	832,811	43,832	202,998	168	4,957	15
SS	73,843	10,549	34,738	118	626	10
TE	702,033	26,001	113,404	147	4,776	14
WC	356,114	13,189	73,189	442	806	12
WP	2,303,800	50,083	430,755	249	9,252	17

Table 26 PM_{10} Emissions Inventory

PM_{10} Site	Sum of PM_{10} Emissions (lbs)	Mean	Max emission-section	Area of Polygon (km2)	Density: Sum/Area (lbs/km2)	Score
BE	321,961	18,939	232,691	8,179	39	4
CP	39,517	2,325	11,188	86	460	9
DC	291,007	58,201	195,492	15	19,400	14
DY	209,309	7,475	14,202	3,081	68	5
GL	201,152	11,175	56,032	379	531	11
GR	95,471	11,934	71,659	20	4,774	13
HI	138	69	87	349	0.4	2
ME	80,546	5,034	30,970	148	544	12
NP	32,177	1,788	5,994	837	38	3
SP	50,062	5,006	22,774	206	243	8
SS	14,984	2,141	7,793	136	110	6
WC	0	0	0	342	0	1
WF	295,379	10,185	57,469	607	487	10
WP	18,427	1,417	7,620	112	165	7

Indicator #4b: Predicted Ozone

Table 27 Predicted O_3

O_3 Site	Min Predicted O_3 (ppm)	Max predicted O_3 concentration (ppm)	Mean predicted O_3 (ppm)	Score (based on mean)
BE	0.0296	0.0433	0.0322	3
BP	0.0376	0.0443	0.0404	12
CC	0.0401	0.0496	0.0457	15
CP	0.0299	0.0336	0.0316	1
DY	0.0314	0.046	0.0392	11
FF	0.0355	0.0381	0.037	9
FH	0.0381	0.0438	0.0411	13
GL	0.032	0.0403	0.0348	8
HM	0.0463	0.052	0.0491	17
NP	0.0318	0.0424	0.0376	10
PP	0.0398	0.049	0.0453	14
RV	0.0402	0.0498	0.0459	16
SP	0.031	0.0344	0.0331	4
SS	0.0323	0.0396	0.0346	6
TE	0.032	0.0353	0.0333	5
WC	0.0336	0.0361	0.0347	7
WP	0.0297	0.0333	0.032	2

Indicator#5: Traffic Counts

Table 28 O_3 Traffic Counts

O_3 Site	Freeway Sum of AWT Counts	Arterial Sum of AWT Counts	Area of Polygon (km^2)	Length of Roads (m)	Traffic Count Density (Sum/Area)	Road Density (Length/Area)	Traffic Density Score	Road Density Score	Average Score
BE	441,881	559,413	9902	2,152,160	101	217	4	3	3.5
BP	0	23,718	441	98,003	54	222	3	4	3.5
CC	405,562	653,505	985	416,285	1,075	423	6	5	5.5
CP	4,075,333	1,531,085	83	181,510	67,809	2,195	17	16	16.5
DY	780,091	2,786,684	2,333	1,185,701	1,529	508	7	7	7
FF	1,272,800	4,179,774	228	261,969	23,892	1,148	13	10	11
FH	0	114,946	139	59,387	829	428	5	6	5.5
GL	2,206,427	3,312,061	317.5	426,544	17,381	1,343	11	12	11
HM	0	1,668	668.12	89,156	2	133	1	1	1
NP	4,085,750	3,201,204	272.86	376,181	26,706	1,379	14	13	14
PP	1,030,877	925,787	413.69	250,215	4,730	605	8	8	8
RV	0	8,349	850.08	144,614	10	170	2	2	2
SP	467,456	1,527,054	168.46	137,799	11,840	818	9	9	9
SS	810,010	1,205,076	118.36	170,788	17,025	1,443	10	14	13
TE	5,259,616	2,951,145	147.09	357,331	55,821	2,429	16	17	16.5
WC	2,548,856	5,278,548	441.65	547,268	17,723	1,239	12	11	11
WP	3,478,558	3,686,963	249.33	362,031	28,739	1,452	15	15	15

Table 29 PM_{10} Traffic Counts

PM_{10} Site	Freeway Sum of AWT Counts	Arterial Sum of AWT Counts	Area of Polygon (km^2)	Length of Roads (m)	Traffic Count Density (Sum/Area)	Road Density (Length/Area)	Traffic Density Score	Road Density Score	Average Score
BE	441,881	541,860	8,179	2,242,300	120	274	1	1	1
CP	4,681,440	1,474,336	86	215,563	71,938	2,519	13	14	14
DC	118,668	266,203	15	11,732	25,008	762	10	5	7.5
DY	997,355	2,937,941	3,081	1,333,503	1,277	433	2	2	2
GL	2,394,725	3,322,245	379	447,363	15,097	1,181	7	8	7.5
GR	1,774,353	413,467	20	39,263	110,384	1,981	14	12	13
HI	1,150,509	4,115,465	349	344,946	15,096	989	6	7	6
ME	4,145,383	3,723,345	148	320,602	53,024	2,160	12	13	12
NP	4,541,914	4,239,517	838	685,792	10,485	819	5	6	5
SP	117,988	1,396,107	206	125,655	7,338	609	4	4	4
SS	1,202,720	1,443,388	136	222,159	19,421	1,631	9	10	10
WC	2,672,268	3,621,075	342	423,711	18,376	1,237	8	9	9
WF	0	1,455,885	607	264,137	2,400	435	3	3	3
WP	1,984,895	2,280,263	112	189,279	38,242	1,697	11	11	11

Indicator#6: Monitor-to-Monitor Correlations

Table 30 O_3 Correlations

O_3 Sites	Max Correlation	Score
BE	0.79	12
BP	0.78	13
CC	0.69	15
CP	0.9	2.5
DY	0.76	14
FF	0.86	7.5
FH	0.83	9.5
GL	0.81	11
HM	0.59	17
NP	0.89	5
PP	0.64	16
RV	0.83	9.5
SP	0.9	2.5
SS	0.89	5
TE	0.89	5
WC	0.86	7.5
WP	0.94	1

Table 31 PM_{10} Correlations

PM_{10} Sites	Max Correlation	Score
BE	0.82	11
CP	0.9	4
DC	0.91	3
DY	0.89	6.5
GL	0.89	6.5
GR	0.92	1.5
HI	0.78	13
ME	0.72	14
NP	0.81	12
SP	0.89	6.5
SS	0.89	6.5
WC	0.87	9
WF	0.86	10
WP	0.92	1.5

Indicator#7: Removal Bias

Table 32 O_3 Removal Bias

O_3 Sites	2005-2009 Average	Removal Bias	Difference	Absolute Value	Score
BE	0.0295	0.0391	0.0096	0.0096	17
BP	0.0373	0.0386	0.0013	0.0013	7
CC	0.0471	0.0459	-0.0012	0.0012	6
CP	0.0311	0.0312	0.0001	0.0001	1
DY	0.0336	0.035	0.0014	0.0014	8
FF	0.0389	0.0362	-0.0027	0.0027	12
FH	0.0443	0.0367	-0.0076	0.0076	16
GL	0.034	0.0333	-0.0007	0.0007	3
HM	0.0526	0.0464	-0.0062	0.0062	15
NP	0.0367	0.0321	-0.0046	0.0046	14
PP	0.0472	0.0442	-0.003	0.003	13
RV	0.0437	0.0426	-0.0011	0.0011	4.5
SP	0.0327	0.0321	-0.0006	0.0006	2
SS	0.0344	0.0333	-0.0011	0.0011	4.5
TE	0.0317	0.0338	0.0021	0.0021	11
WC	0.0353	0.0338	-0.0015	0.0015	9
WP	0.0317	0.0301	-0.0016	0.0016	10

Table 33 PM_{10} Removal Bias. Note That a Removal Bias Could Not Be Calculated for the Buckeye Site (BE), As It Is the Furthest West PM_{10} Site and Located on the Edge of the Map

PM_{10} Sites	2005-2009 Average	Removal Bias	Difference	Absolute Value	Score
BE	48.1	N/A	N/A	N/A	N/A
CP	38.3	41	2.7	2.7	4
DC	57.52	51.9	-5.62	5.62	7
DY	29.3	34.7	5.4	5.4	6
GL	31	34.9	3.9	3.9	5
GR	47.6	46.3	-1.3	1.3	3
HI	48.7	37.3	-11.4	11.4	11
ME	27.6	37.9	10.3	10.3	10
NP	29.1	34.8	5.7	5.7	8
SP	50.9	49.7	-1.2	1.2	2
SS	29.6	39.2	9.6	9.6	9
WC	31	47.8	16.8	16.8	13
WF	66.6	52.1	-14.5	14.5	12
WP	42.9	43.4	0.5	0.5	1

Indicator#8: Population Served

Table 34 O_3 Population Served

O_3 Sites	Population Served	Score
BE	31,132	4
BP	3	1
CC	46,772	6
CP	153,630	10
DY	174,019	11
FF	248,082	14
FH	34,926	5
GL	457,740	17
HM	14,197	3
NP	387,993	16
PP	67,517	7
RV	2,414	2
SP	90,333	8
SS	130,327	9
TE	236,002	12
WC	321,428	15
WP	246,076	13

Table 35 PM_{10} Population Served

PM_{10} Sites	Population Served	Score
BE	35,459	3
CP	144,345	6
DC	12,348	1
DY	179,961	9
GL	467,204	14
GR	31,503	2
HI	166,608	8
ME	293,977	12
NP	452,859	13
SP	126,432	5
SS	148,186	7
WC	266,220	11
WF	38,150	4
WP	211,122	10

Indicator#9: Environmental Justice

Table 36 O_3 Environmental Justice

O_3 Sites	Population Served	Minority Population Served	% Minority	Score
BE	31,132	11,231	36%	13
BP	3	0	0%	1
CC	46,772	4,856	10%	6
CP	153,630	100,866	66%	15
DY	174,019	28,312	16%	7.5
FF	248,082	39,184	16%	7.5
FH	34,926	2,461	7%	3
GL	457,740	134,973	29%	12
HM	14,197	1,115	8%	4
NP	387,993	86,371	22%	10
PP	67,517	6,006	9%	5
RV	2,414	78	3%	2
SP	90,333	84,455	93%	17
SS	130,327	24,482	19%	9
TE	236,002	87,838	37%	14
WC	321,428	84,768	26%	11
WP	246,076	196,670	80%	16

Table 37 PM_{10} Environmental Justice

PM_{10} Sites	Population Served	Minority Population Served	% Minority	Score
BE	35,459	12,559	35%	8
CP	144,345	90,392	63%	10.5
DC	12,348	8,775	71%	12.5
DY	179,961	29,581	16%	1
GL	467,204	136,339	29%	7
GR	31,503	25,542	81%	14
HI	166,608	29,375	18%	2
ME	293,977	109,276	37%	9
NP	452,859	91,983	20%	3
SP	126,432	80,046	63%	10.5
SS	148,186	30,938	21%	4
WC	266,220	74,082	28%	6
WF	38,150	8,775	23%	5
WP	211,122	150,192	71%	12.5

Indicator#10: Trends Impact

Table 38 O_3 Trends Impact

O_3 Sites	Length of Continuous Monitoring Record (Years as of 2009)	Score
BE	6	1
BP	17	8
CC	9	3
CP	43	17
DY	7	2
FF	21	10
FH	14	6
GL	36	15.5
HM	17	8
NP	35	13.5
PP	22	11
RV	13	5
SP	35	13.5
SS	36	15.5
TE	10	4
WC	17	8
WP	26	12

Table 39 PM_{10} Trends Impact

PM_{10} Sites	Length of Continuous Monitoring Record (Years as of 2009)	Score
BE	6	1
CP	25	13.5
DC	11	5
DY	7	2
GL	23	11.5
GR	17	6.5
HI	10	4
ME	20	8.5
NP	20	8.5
SP	25	13.5
SS	23	11.5
WC	17	6.5
WF	8	3
WP	22	10

Indicator#11: Number of Parameters Monitored

Table 40 O_3 Number of Parameters Monitored

O_3 Sites	Number of Parameters Monitored	Score
BE	6	13
BP	3	5
CC	3	5
CP	7	15.5
DY	5	9.5
FF	3	5
FH	3	5
GL	5	9.5
HM	1	1.5
NP	6	13
PP	3	5
RV	1	1.5
SP	6	13
SS	7	15.5
TE	5	9.5
WC	5	9.5
WP	8	17

Table 41 PM_{10} Number of Parameters Monitored

PM_{10} Sites	**Number of Parameters Monitored**	**Score**
BE	6	10
CP	7	12.5
DC	3	1
DY	5	6
GL	5	6
GR	5	6
HI	4	2.5
ME	5	6
NP	6	10
SP	6	10
SS	7	12.5
WC	5	6
WF	4	2.5
WP	8	14

Phase I Indicator Radar Charts Results

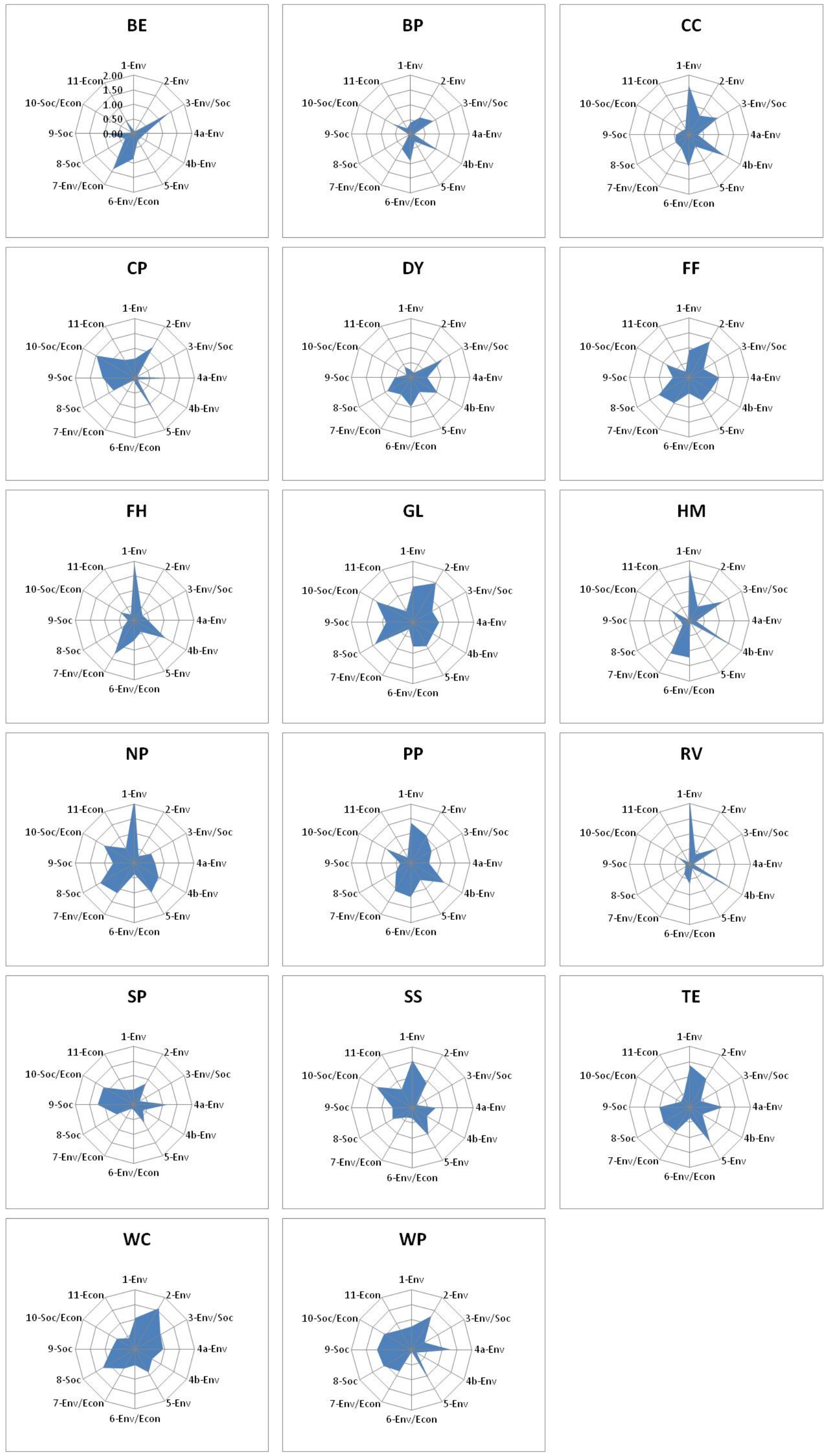

Figure 27 Results by Site from the O_3 Phase I Assessment. Number Labels Correspond to the Indicator Numbers of Table 5. Graph Gridlines Each Represent 0.5 Points of Score, from 0-2.0

Figure 28 Results by Site from the PM_{10} Phase I Assessment. Number Labels Correspond to the Indicator Numbers of Table 5. Graph Gridlines Each Represent 0.5 Points of Score, from 0-2.0

Phase I Sustainability Radar Chart Results

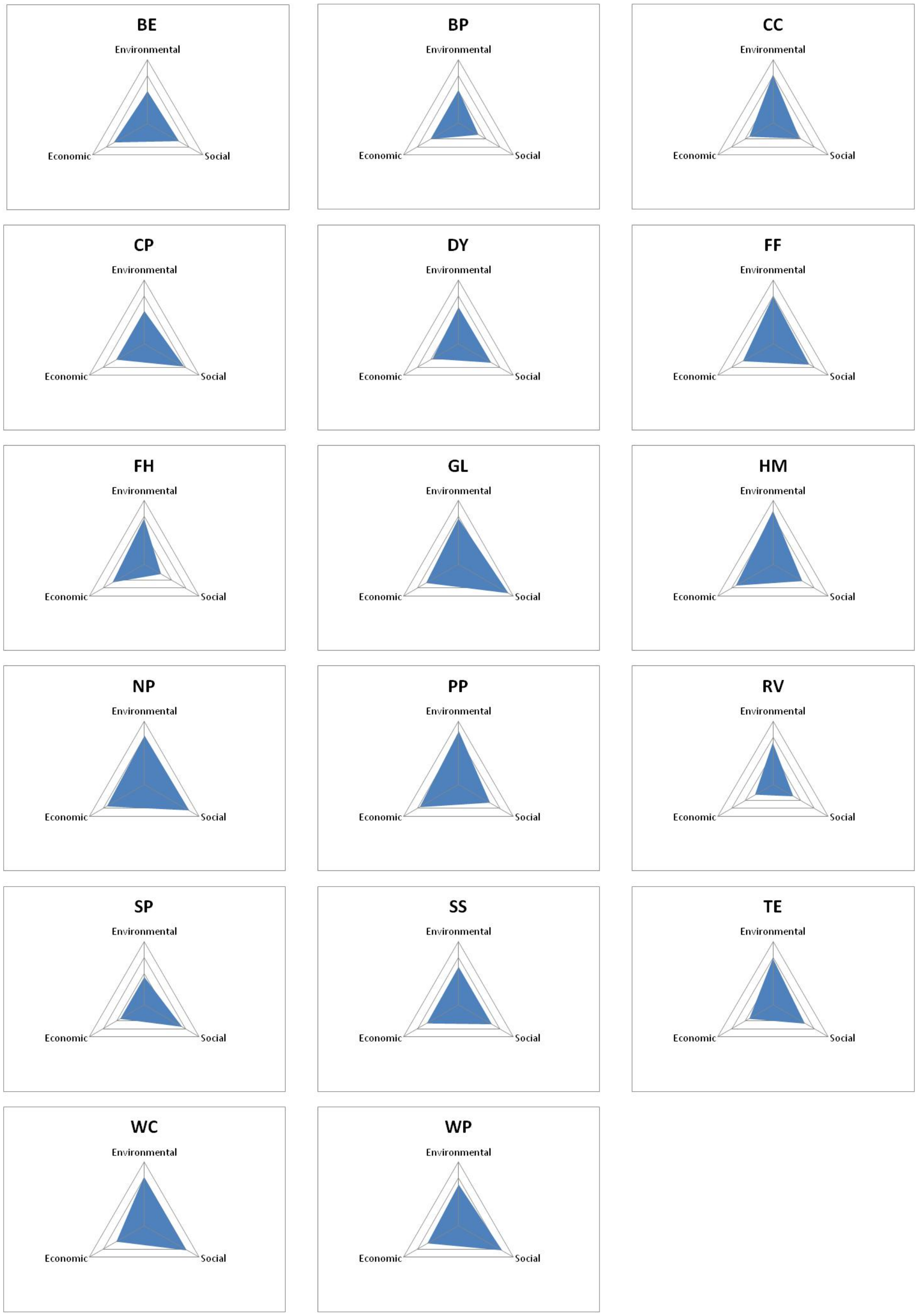

Figure 29 Results by Site from the Aggregation of O_3 Phase I Sustainability Indicators. Sustainability Labels Correspond to the Groups on Table 5. Graph Gridlines Each Represent 0.3 Points of Score, from 0-1.2

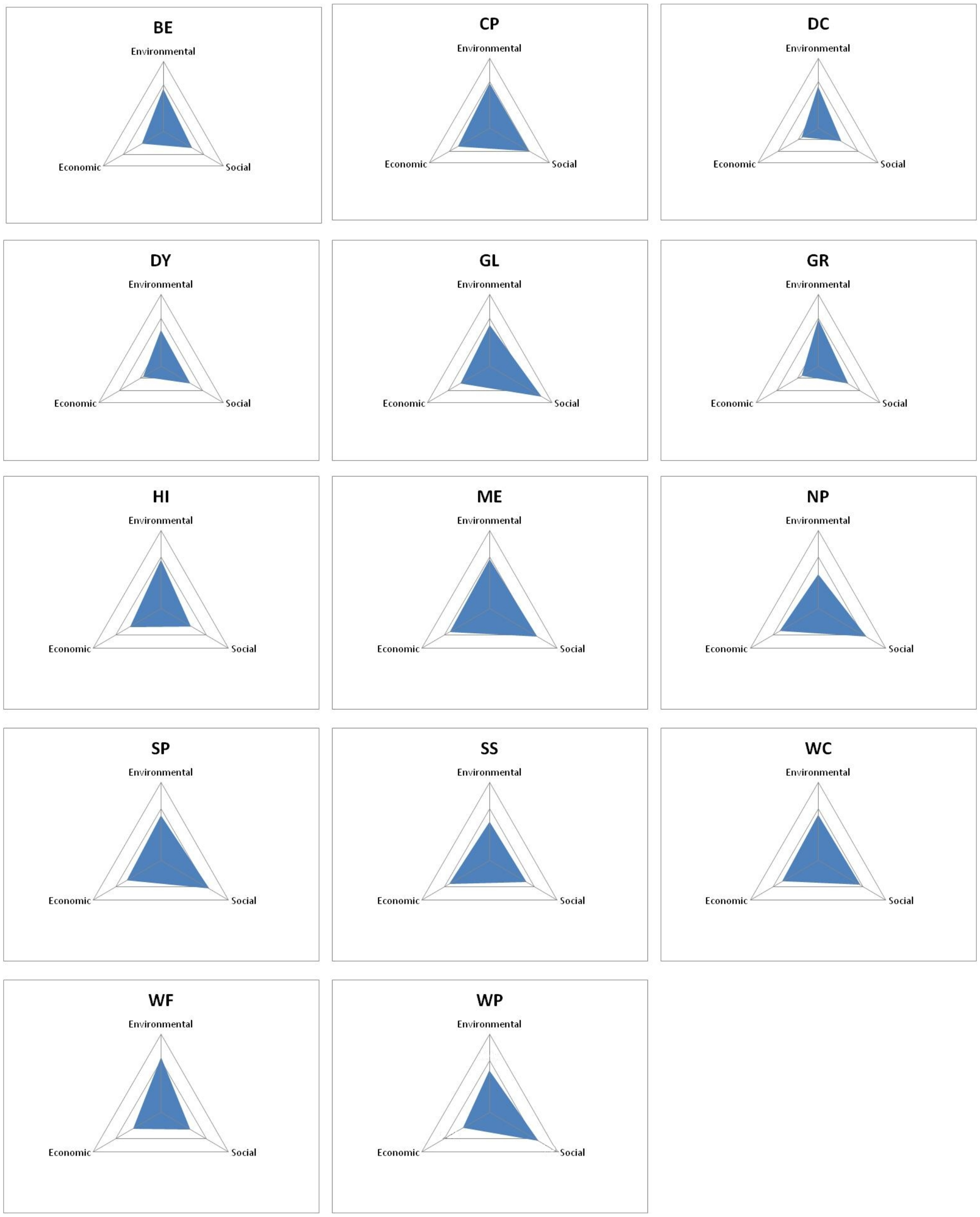

Figure 30 Results by Site from the Aggregation of PM_{10} Phase I Sustainability Indicators. Sustainability Labels Correspond to the Groups on Table 5. Graph Gridlines Each Represent 0.3 Points of Score, from 0-1.2

APPENDIX C

SUPPLEMENTARY DATA FOR CHAPTER 4

Table 42 Regression Results for the O_3 Parameter

					Median HH Income		Age ≤17		Age ≥65		Proportion African American		Proportion Native American		Proportion Hispanic	
		Model#	**R2**	**F***	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**
O_3 Seasonal Averaged Data	**Raw Data**	1	0.11	310.5	**0.332**	0.000										
		2	0.16	177.4	**0.325**	0.000	**-0.223**	0.000	-0.001	0.970						
		3	0.27	240.5	**0.198**	0.000	**-0.233**	0.000	**-0.161**	0.000	**-0.411**	0.000	**0.051**	0.009		
		4	0.37	326.7	**-0.059**	0.043	**0.116**	0.000	**-0.103**	0.000	**-0.404**	0.000	**0.101**	0.000	**-0.532**	0.000
	Deciles	1	0.11	303.8	**0.330**	0.000										
		2	0.16	177.7	**0.323**	0.000	**-0.222**	0.000	0.011	0.696						
		3	0.27	218.7	**0.197**	0.000	**-0.233**	0.000	**-0.147**	0.000	**-0.397**	0.000	**0.044**	0.026		
		4	0.37	313.4	**-0.073**	0.011	**0.135**	0.000	**-0.085**	0.002	**-0.389**	0.000	**0.096**	0.000	**-0.561**	0.000
	Quartiles	1	0.09	258.3	**0.185**	0.000										
		2	0.15	162.2	**0.182**	0.000	**-0.197**	0.000	**-0.069**	0.000						
		3	0.25	194.1	**0.133**	0.000	**-0.196**	0.000	**-0.142**	0.000	**-0.243**	0.000	**0.081**	0.000		
		4	0.33	260.1	-0.016	0.361	0.007	0.742	**-0.108**	0.000	**-0.238**	0.000	**0.110**	0.000	**-0.309**	0.000
O_3 Monthly Averaged Data	**Raw Data**	1	0.09	249.1	**0.301**	0.000										
		2	0.14	152.1	**0.296**	0.000	**-0.291**	0.000	**-0.092**	0.001						
		3	0.24	186.8	**0.198**	0.000	**-0.296**	0.000	**-0.224**	0.000	**-0.383**	0.000	**0.089**	0.000		
		4	0.28	214.8	0.022	0.468	-0.056	0.093	**-0.184**	0.000	**-0.378**	0.000	**0.123**	0.000	**-0.365**	0.000
	Deciles	1	0.08	246.9	**0.363**	0.000										
		2	0.16	186.4	**0.335**	0.000	**-0.576**	0.000	**-0.410**	0.000						
		3	0.21	113.7	**0.217**	0.000	**-0.563**	0.000	**-0.508**	0.000	**-0.343**	0.000	0.004	0.904		
		4	0.25	172.2	0.001	0.986	**-0.295**	0.000	**-0.484**	0.000	**-0.335**	0.000	-0.030	0.351	**-0.418**	0.000
	Quartiles	1	0.05	110.7	**0.109**	0.000										
		2	0.09	79.2	**0.108**	0.000	**-0.155**	0.000	**-0.079**	0.000						
		3	0.14	70.8	**0.106**	0.000	**-0.147**	0.000	**-0.097**	0.000	**-0.131**	0.000	**0.093**	0.000		
		4	0.16	69.5	**0.046**	0.004	**-0.065**	0.000	**-0.083**	0.000	**-0.129**	0.000	**0.105**	0.000	**-0.125**	0.000

*All F scores are significant at $p<0.000$. ***Bold*** BETAs are significant at $p<0.05$

Table 42 Continued

		Model#	R2	F*	Median HH Income		Age ≤17		Age ≥65		Proportion African American		Proportion Native American		Proportion Hispanic	
					BETA	SIG.	BETA	SIG.	BETA	SIG.	BETA	SIG.	BETA	SIG.	BETA	SIG.
O_3 8-hour Averaged Data	Raw Data	1	0.06	213.4	**0.238**	0.000										
		2	0.08	100.6	**0.235**	0.000	**-0.170**	0.000	-0.048	0.116						
		3	0.18	158.0	**0.220**	0.000	**-0.152**	0.000	**-0.107**	0.000	**-0.367**	0.000	**0.242**	0.000		
		4	0.25	195.4	-0.003	0.912	**0.152**	0.000	-0.056	0.064	**-0.361**	0.000	**0.285**	0.000	**-0.463**	0.000
	Deciles	1	0.06	214.3	**0.240**	0.000										
		2	0.08	101.5	**0.237**	0.000	**-0.158**	0.000	-0.038	0.218						
		3	0.17	154.2	**0.218**	0.000	**-0.141**	0.000	**-0.100**	0.001	**-0.359**	0.000	**0.227**	0.000		
		4	0.24	193.6	-0.007	0.803	**0.165**	0.000	-0.049	0.111	**-0.353**	0.000	**0.270**	0.000	**-0.466**	0.000
	Quartiles	1	0.05	199.9	**0.186**	0.000										
		2	0.06	82.8	**0.184**	0.000	**-0.082**	0.000	-0.006	0.812						
		3	0.15	130.1	**0.171**	0.000	**-0.069**	0.002	**-0.052**	0.045	**-0.273**	0.000	**0.175**	0.000		
		4	0.24	149.5	-0.028	0.206	**0.201**	0.000	-0.006	0.808	**-0.267**	0.000	**0.214**	0.000	**-0.413**	0.000
O_3 1-hour Averaged Data	Raw data	1	0.05	186.4	**0.223**	0.000										
		2	0.07	95.9	**0.221**	0.000	**-0.211**	0.000	**-0.098**	0.001						
		3	0.17	152.4	**0.200**	0.000	**-0.195**	0.000	**-0.161**	0.000	**-0.361**	0.000	**0.226**	0.000		
		4	0.22	175.2	0.006	0.823	**0.069**	0.042	**-0.117**	0.000	**-0.355**	0.000	**0.263**	0.000	**-0.403**	0.000
	Deciles	1	0.05	177.5	**0.218**	0.000										
		2	0.07	90.4	**0.216**	0.000	**-0.206**	0.000	**-0.100**	0.001						
		3	0.16	148.1	**0.194**	0.000	**-0.190**	0.000	**-0.164**	0.000	**-0.359**	0.000	**0.222**	0.000		
		4	0.22	170.0	0.006	0.833	**0.067**	0.049	**-0.120**	0.000	**-0.353**	0.000	**0.258**	0.000	**-0.392**	0.000
	Quartiles	1	0.06	219.0	**0.273**	0.000										
		2	0.09	107.8	**0.271**	0.000	**-0.296**	0.000	**-0.184**	0.000						
		3	0.18	157.0	**0.268**	0.000	**-0.273**	0.000	**-0.236**	0.000	**-0.388**	0.000	**0.280**	0.000		
		4	0.25	177.2	0.023	0.418	0.060	0.101	**-0.180**	0.000	**-0.381**	0.000	**0.327**	0.000	**-0.508**	0.000

*All F scores are significant at $p<0.000$. ***Bold*** BETAs are significant at $p<0.05$

Table 43 Regression Results for the PM_{10} Parameter

					Median HH Income		Age ≤17		Age ≥65		Proportion African American		Proportion Native American		Proportion Hispanic	
		Model#	**R2**	**F***	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**
PM_{10} Annual Average Data	**Raw data**	1	.00	**4.68**	**-0.043**	0.031										
		2	.18	**126.37**	**-0.033**	0.077	**0.506**	0.000	**0.138**	0.000						
		3	.24	**125.53**	**-0.041**	0.077	**0.497**	0.000	**0.184**	0.000	**0.266**	0.000	**-0.195**	0.000		
		4	.26	**124.30**	**0.090**	0.004	**0.340**	0.000	**0.175**	0.000	**0.270**	0.000	**-0.201**	0.000	**0.250**	0.000
	Deciles	1	.00	**5.15**	**-0.048**	0.023										
		2	.17	**118.93**	**-0.036**	0.070	**0.464**	0.000	**0.089**	0.005						
		3	.22	**121.04**	**-0.042**	0.079	**0.456**	0.000	**0.130**	0.000	**0.239**	0.000	**-0.174**	0.000		
		4	.24	**124.85**	**0.094**	0.003	**0.292**	0.000	**0.121**	0.000	**0.244**	0.000	**-0.180**	0.000	**0.260**	0.000
	Quartiles	1	.01	**21.05**	**-0.061**	0.000										
		2	.13	**95.08**	**-0.054**	0.000	**0.273**	0.000	**0.062**	0.000						
		3	.17	**71.52**	**-0.048**	0.002	**0.271**	0.000	**0.098**	0.000	**0.158**	0.000	**-0.093**	0.000		
		4	.18	**72.32**	0.010	0.664	**0.202**	0.000	**0.094**	0.000	**0.160**	0.000	**-0.095**	0.000	**0.110**	0.001

*All ***Bold*** F scores are significant at $p<0.05$. ***Bold*** BETAs are significant at $p<0.05$

Table 43 Continued

					Median HH Income		Age ≤17		Age ≥65		Proportion African American		Proportion Native American		Proportion Hispanic	
		Model#	**R2**	**F***	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**	**BETA**	**SIG.**
PM_{10} January Monthly Average Data	**Raw Data**	1	.05	**111.49**	**-0.217**	0.000										
		2	.21	**168.29**	**-0.199**	0.000	**0.356**	0.000	-0.058	0.066						
		3	.28	**181.93**	**-0.141**	0.000	**0.366**	0.000	0.050	0.122	**0.315**	0.000	**-0.092**	0.001		
		4	.37	**230.18**	**0.132**	0.000	0.038	0.310	0.031	0.311	**0.325**	0.000	**-0.104**	0.000	**0.521**	0.000
	Deciles	1	.05	**112.33**	**-0.220**	0.000										
		2	.19	**156.54**	**-0.203**	0.000	**0.347**	0.000	-0.043	0.167						
		3	.26	**167.43**	**-0.150**	0.000	**0.355**	0.000	**0.061**	0.061	**0.311**	0.000	**-0.099**	0.000		
		4	.35	**218.69**	**0.125**	0.000	0.024	0.530	0.042	0.180	**0.321**	0.000	**-0.112**	0.000	**0.525**	0.000
	Quartiles	1	.06	**149.80**	**-0.213**	0.000										
		2	.20	**161.79**	**-0.203**	0.000	**0.357**	0.000	**0.059**	0.014						
		3	.26	**126.33**	**-0.161**	0.000	**0.364**	0.000	**0.139**	0.000	**0.234**	0.000	**-0.071**	0.002		
		4	.37	**174.50**	**0.103**	0.000	0.046	0.161	**0.120**	0.000	**0.244**	0.000	**-0.083**	0.000	**0.504**	0.000
PM_{10} January Daily Average Data	**Raw data**	1	.03	**66.25**	**-0.170**	0.000										
		2	.23	**179.80**	**-0.154**	0.000	**0.488**	0.000	0.049	0.138						
		3	.28	**157.47**	**-0.139**	0.000	**0.486**	0.000	**0.111**	0.002	**0.255**	0.000	**-0.141**	0.000		
		4	.33	**176.42**	0.062	0.050	**0.244**	0.000	**0.097**	0.005	**0.262**	0.000	**-0.150**	0.000	**0.384**	0.000
	Deciles	1	.03	**65.01**	**-0.163**	0.000										
		2	.21	**159.01**	**-0.149**	0.000	**0.470**	0.000	0.063	0.056						
		3	.26	**136.87**	**-0.134**	0.000	**0.468**	0.000	**0.124**	0.000	**0.251**	0.000	**-0.138**	0.000		
		4	.30	**154.01**	**0.065**	0.042	**0.229**	0.000	**0.110**	0.001	**0.258**	0.000	**-0.147**	0.000	**0.379**	0.000
	Quartiles	1	.03	**70.58**	**-0.130**	0.000										
		2	.16	**114.51**	**-0.123**	0.000	**0.352**	0.000	**0.099**	0.000						
		3	.19	**86.65**	**-10.430**	0.000	**0.353**	0.000	**0.150**	0.000	**0.180**	0.000	**-0.081**	0.002		
		4	.26	**105.25**	**0.084**	0.001	**0.126**	0.000	**0.137**	0.000	**0.187**	0.000	**-0.090**	0.001	**0.359**	0.000

*All ***Bold*** F scores are significant at $p<0.05$. ***Bold*** BETAs are significant at $p<0.05$

Table 43 Continued

		Model#	R2	F*	Median HH Income BETA	Median HH Income SIG.	Age ≤17 BETA	Age ≤17 SIG.	Age ≥65 BETA	Age ≥65 SIG.	Proportion African American BETA	Proportion African American SIG.	Proportion Native American BETA	Proportion Native American SIG.	Proportion Hispanic BETA	Proportion Hispanic SIG.
PM_{10} August Monthly Average Data	**Raw Data**	1	.00	**2.79**	**0.034**	0.095										
		2	.15	**93.38**	**0.034**	0.083	**0.554**	0.000	**0.315**	0.000						
		3	.21	**99.79**	**-0.050**	0.029	**0.525**	0.000	**0.275**	0.000	**0.145**	0.000	**-0.272**	0.000		
		4	.21	**83.86**	**-0.052**	0.088	**0.527**	0.000	**0.275**	0.000	**0.145**	0.000	**-0.272**	0.000	-0.004	0.909
	Deciles	1	.00	**9.73**	**0.065**	0.002										
		2	.11	**71.55**	**0.066**	0.001	**0.464**	0.000	**0.252**	0.000						
		3	.15	**75.28**	0.007	0.789	**0.443**	0.000	**0.231**	0.000	**0.140**	0.000	**-0.218**	0.000		
		4	.15	**63.43**	0.018	0.584	**0.429**	0.000	**0.230**	0.000	**0.141**	0.000	**-0.219**	0.000	0.021	0.574
	Quartiles	1	.00	0.05	0.003	0.822										
		2	.10	**69.13**	0.009	0.472	**0.264**	0.000	**0.062**	0.000						
		3	.12	**49.80**	0.005	0.727	**0.261**	0.000	**0.080**	0.000	**0.106**	0.000	**-0.079**	0.000		
		4	.13	**43.00**	**-0.501**	0.039	**0.327**	0.000	**0.084**	0.000	**0.104**	0.000	**-0.077**	0.000	**-0.106**	0.002
PM_{10} August Daily Average Data	**Raw data**	1	.00	0.24	0.010	0.628										
		2	.14	**88.09**	0.023	0.244	**0.404**	0.000	0.051	0.098						
		3	.16	**74.16**	0.035	0.156	**0.402**	0.000	**0.099**	0.005	**0.194**	0.000	**-0.105**	0.001		
		4	.17	**69.07**	**0.083**	0.015	**0.345**	0.000	**0.096**	0.007	**0.196**	0.000	**-0.108**	0.000	**0.092**	0.021
	Deciles	1	.00	0.28	-0.011	0.598										
		2	.13	**97.08**	0.000	0.998	**0.421**	0.000	**0.081**	0.010						
		3	.15	**75.20**	0.011	0.641	**0.421**	0.000	**0.121**	0.001	**0.155**	0.000	**-0.080**	0.007		
		4	.15	**70.37**	0.037	0.266	**0.390**	0.000	**0.119**	0.001	**0.156**	0.000	**-0.082**	0.006	0.049	0.193
	Quartiles	1	.00	0.32	0.007	0.570										
		2	.09	**69.02**	0.012	0.295	**0.221**	0.000	**0.051**	0.001						
		3	.11	**48.49**	0.023	0.117	**0.222**	0.000	**0.076**	0.000	**0.084**	0.000	-0.035	0.085		
		4	.11	**41.56**	-0.016	0.482	**0.268**	0.000	**0.078**	0.000	**0.083**	0.000	-0.033	0.099	**-0.073**	0.012

*All ***Bold*** F scores are significant at $p<0.05$. ***Bold*** BETAs are significant at $p<0.05$

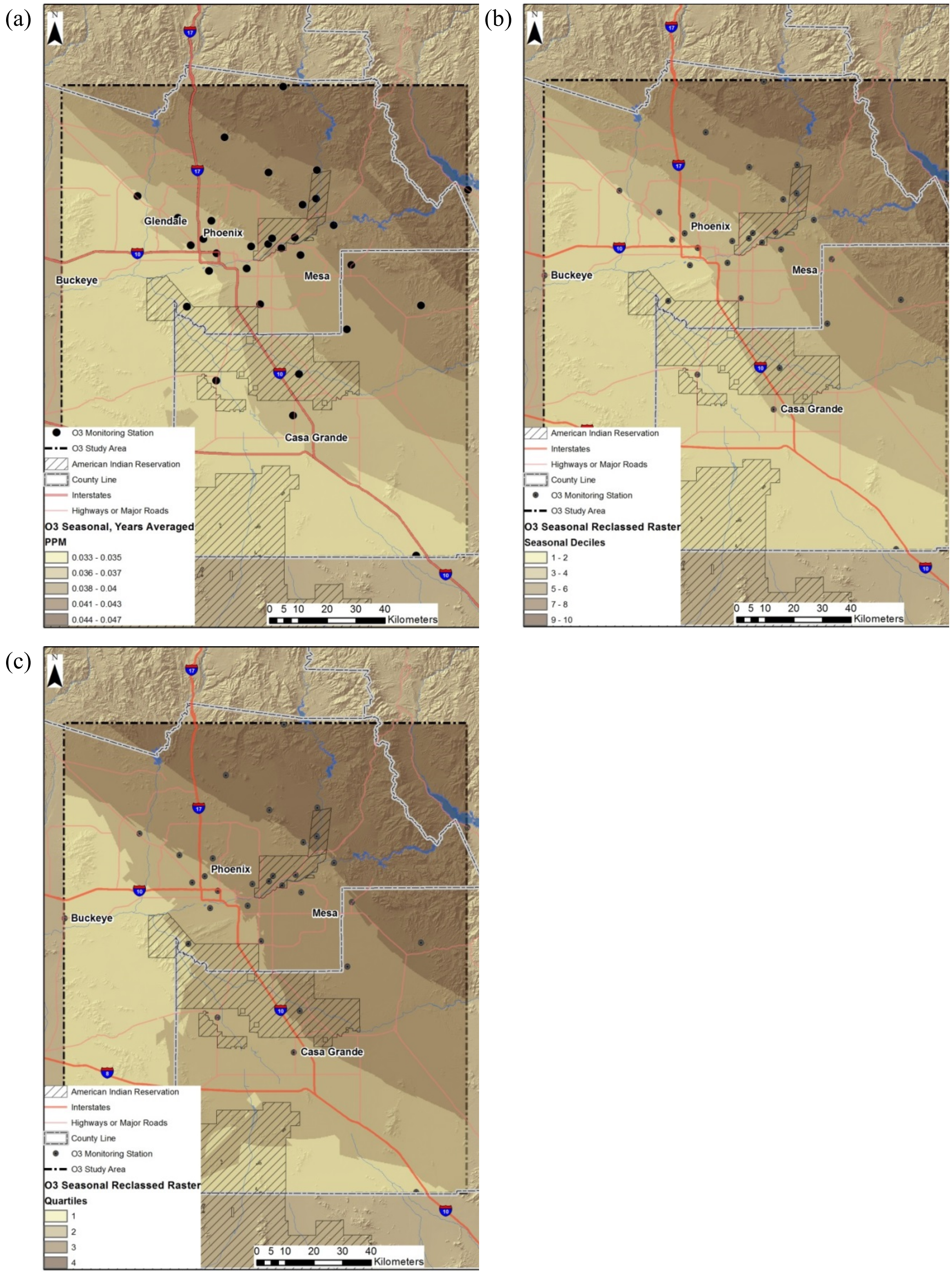

Figure 31 O_3 Pollution Surface Maps for the Seasonally-Averaged Temporal Extents. Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

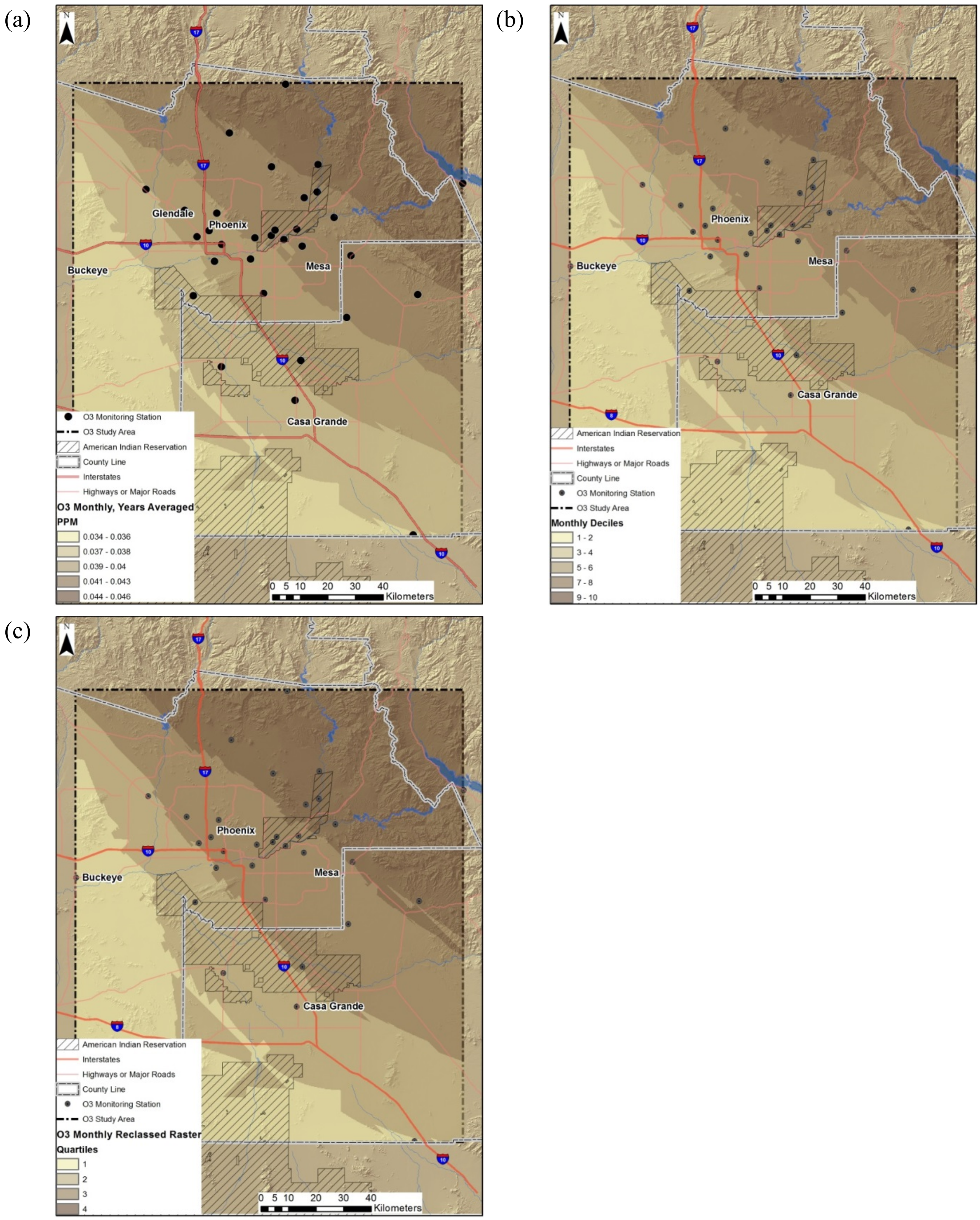

Figure 32 O_3 Pollution Surface Maps for the Monthly-Averaged Temporal Extents (July). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

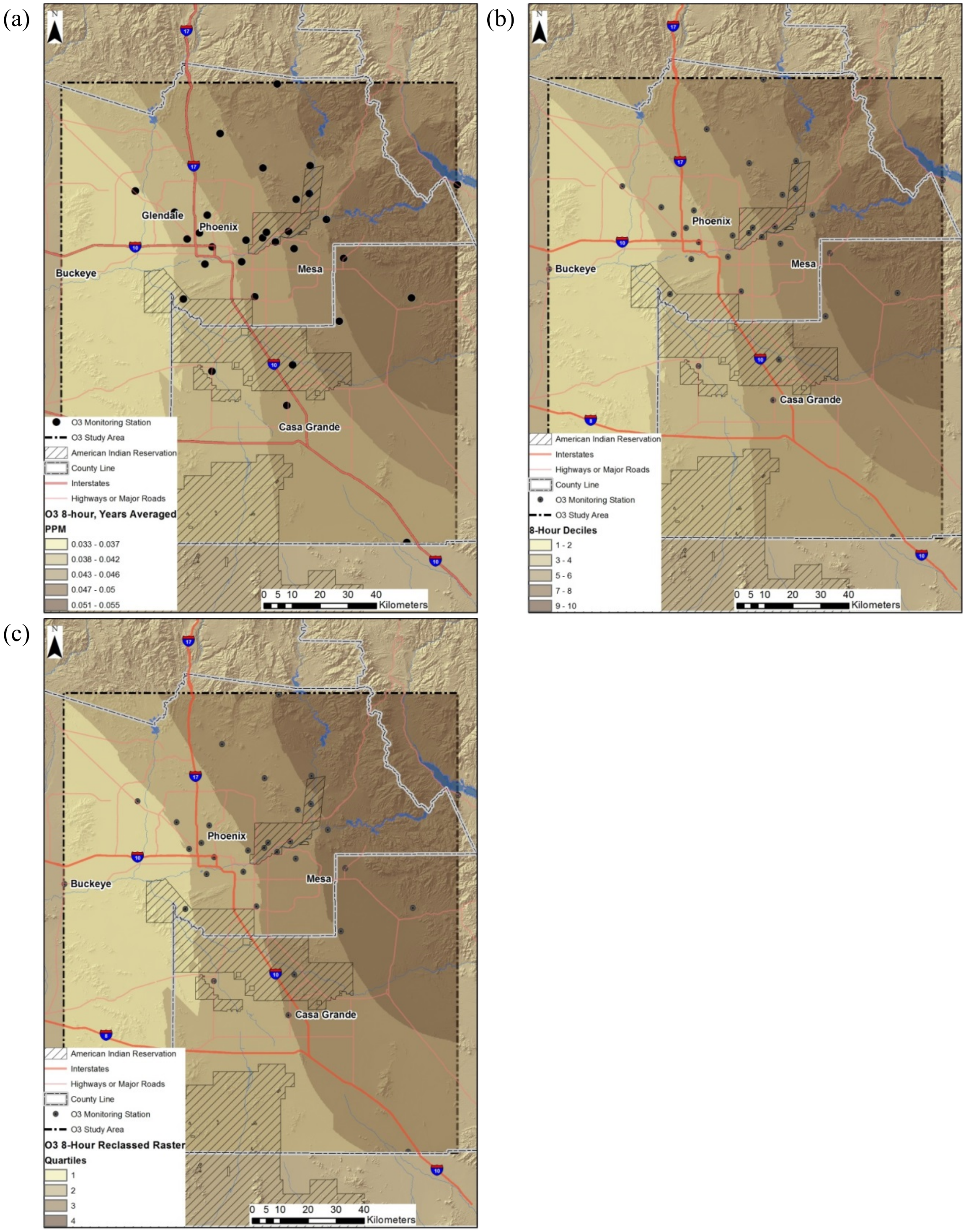

Figure 33 O_3 Pollution Surface Maps for the 8-Hour Averaged Temporal Extents (July 15). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

(a) (b) (c)

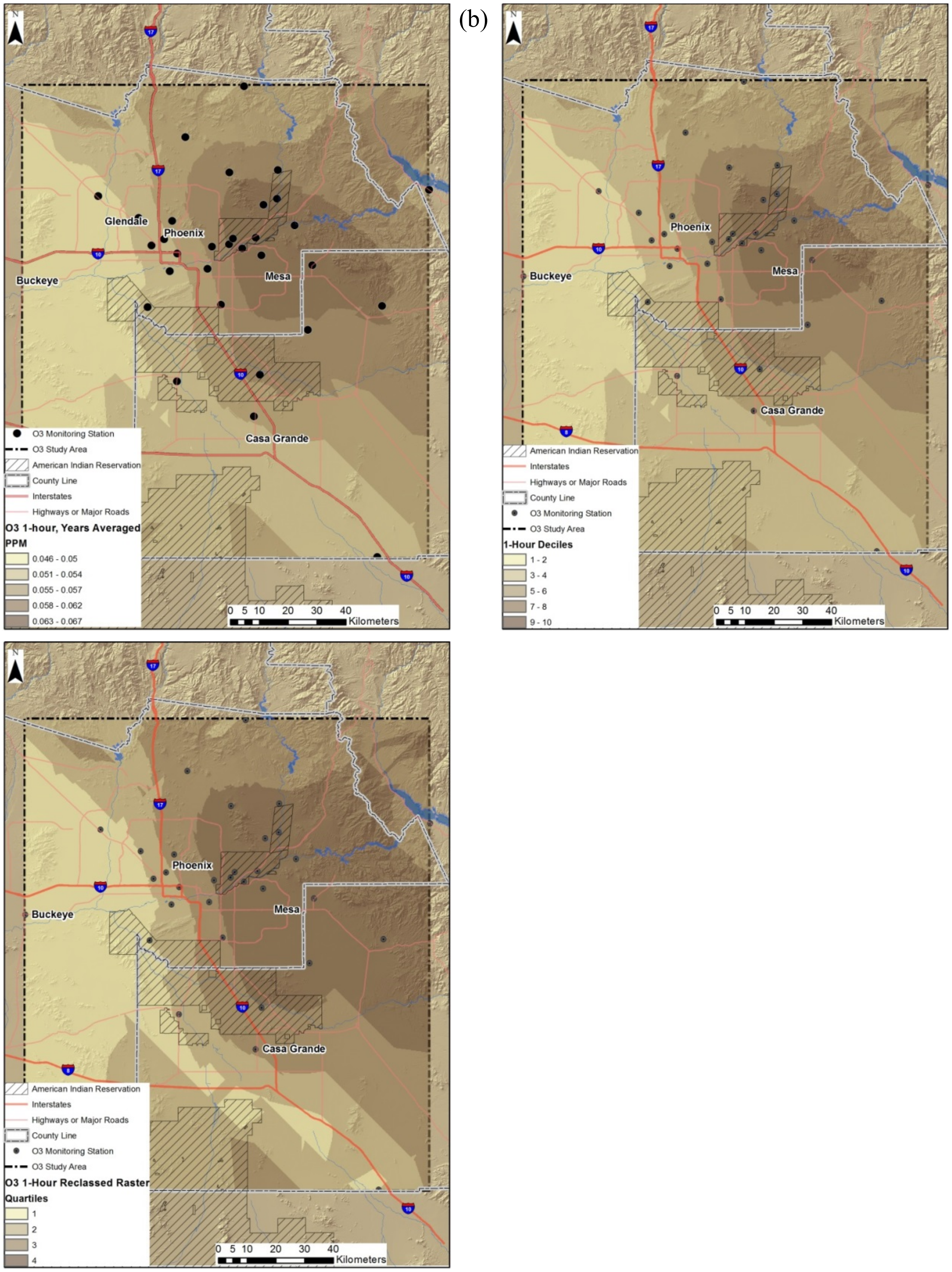

Figure 34 O_3 Pollution Surface Maps for the 1-Hour Averaged Temporal Extents (July 15, 15:00). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

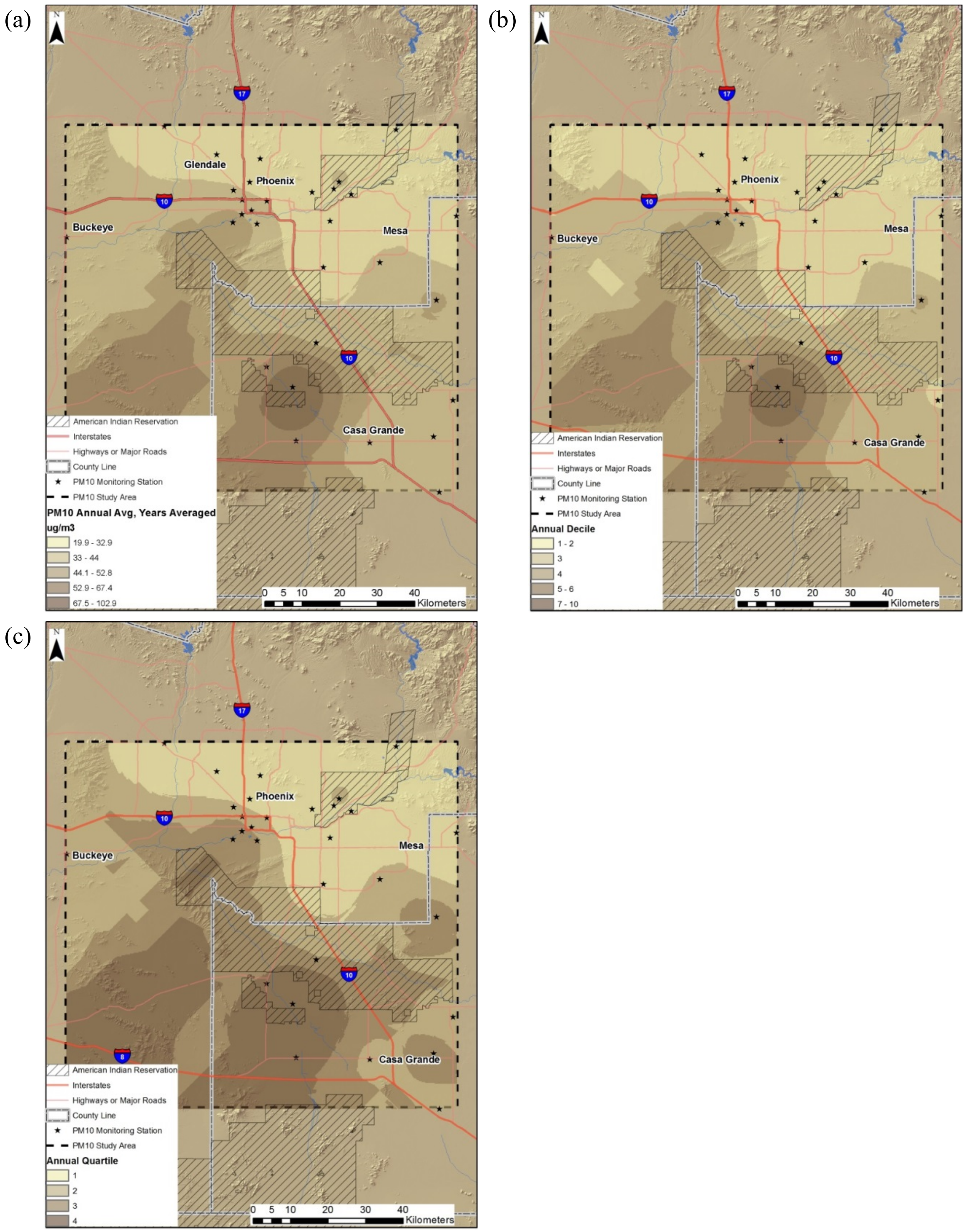

Figure 35 PM_{10} Pollution Surface Maps for the Annually-Averaged Temporal Extents. Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

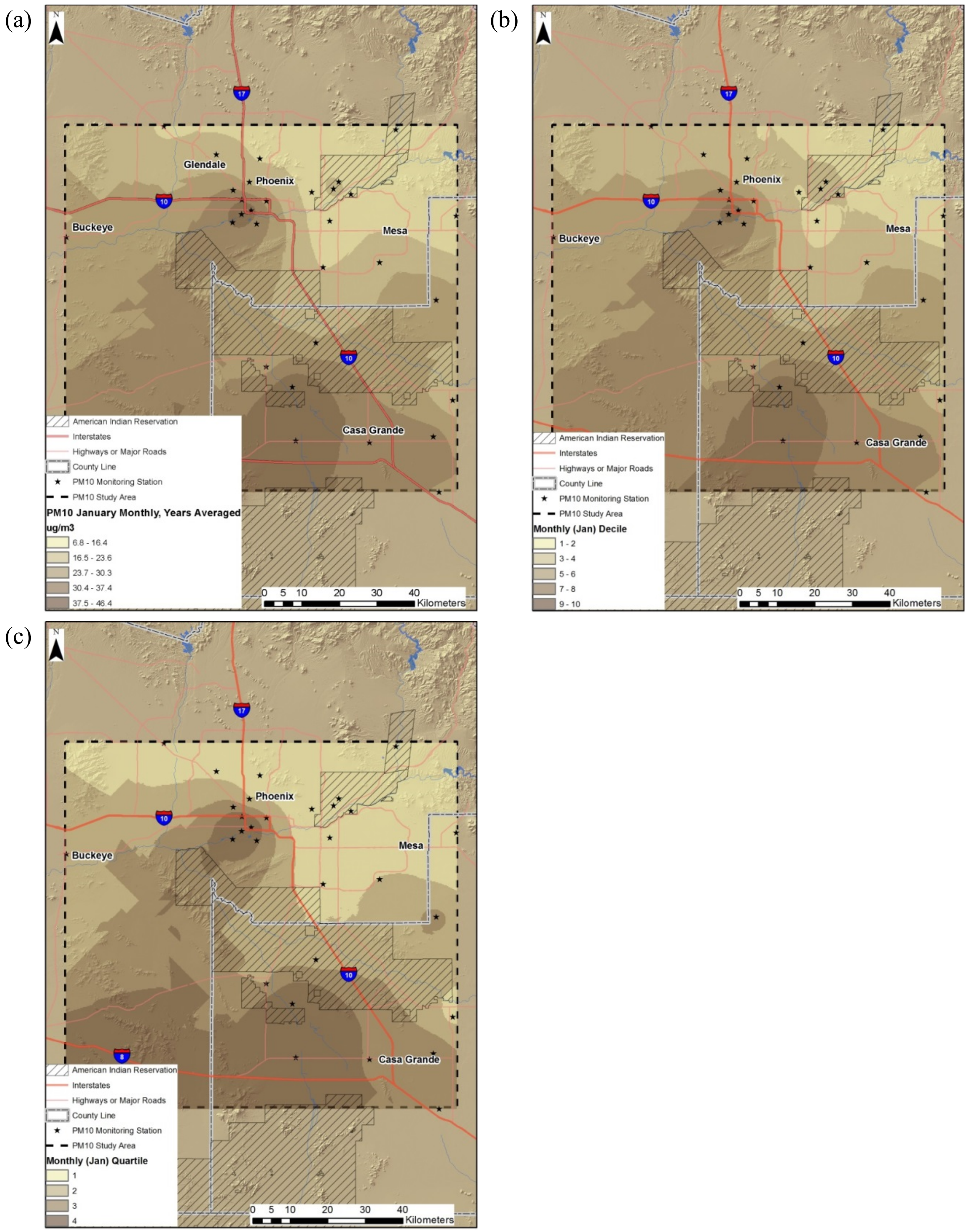

Figure 36 PM_{10} Pollution Surface Maps for the Monthly-Averaged Temporal Extents (January). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

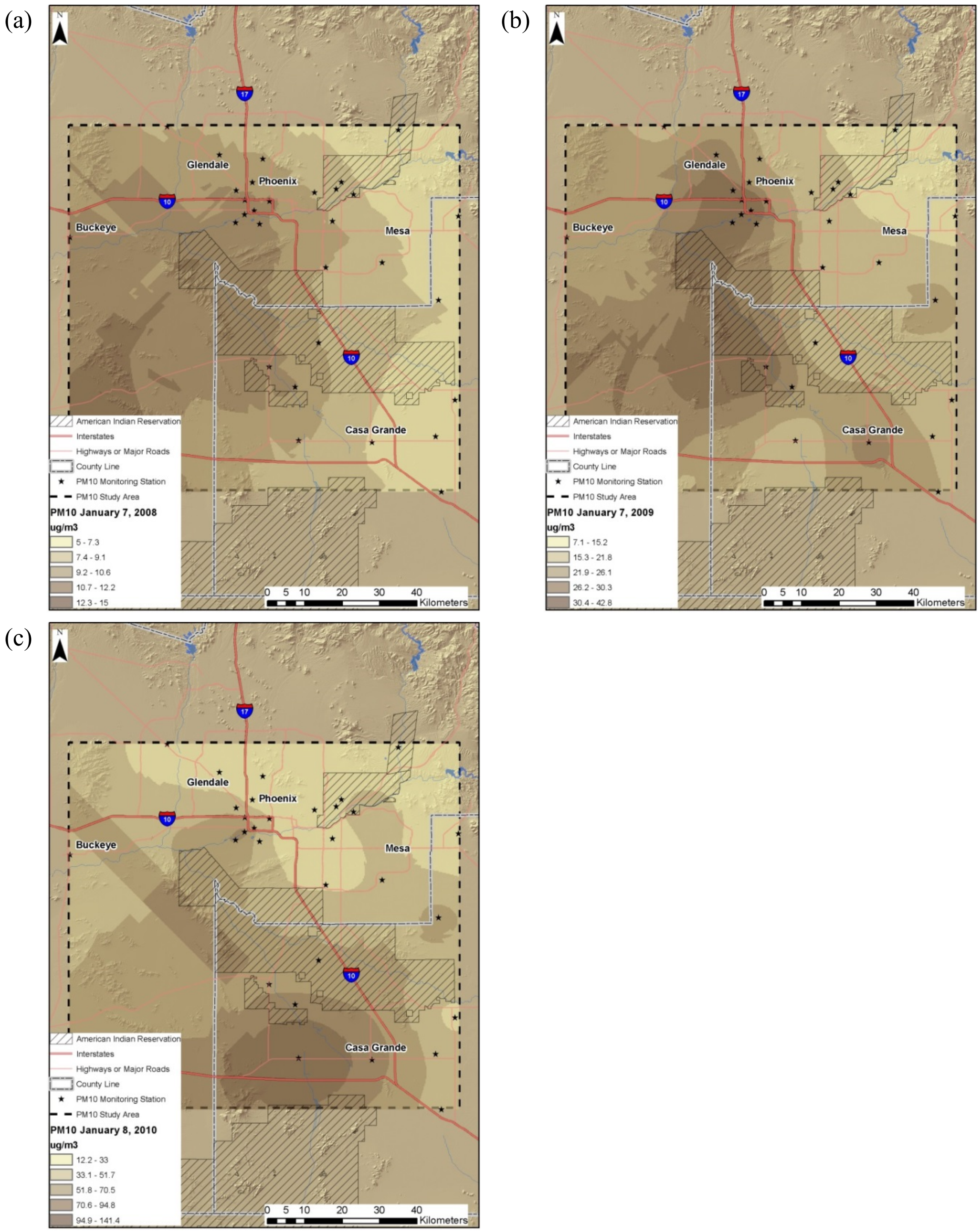

Figure 37 PM_{10} Pollution Surface Maps for the Daily-Averaged Temporal Extents (January 7, 2008-2009, January 8, 2010). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

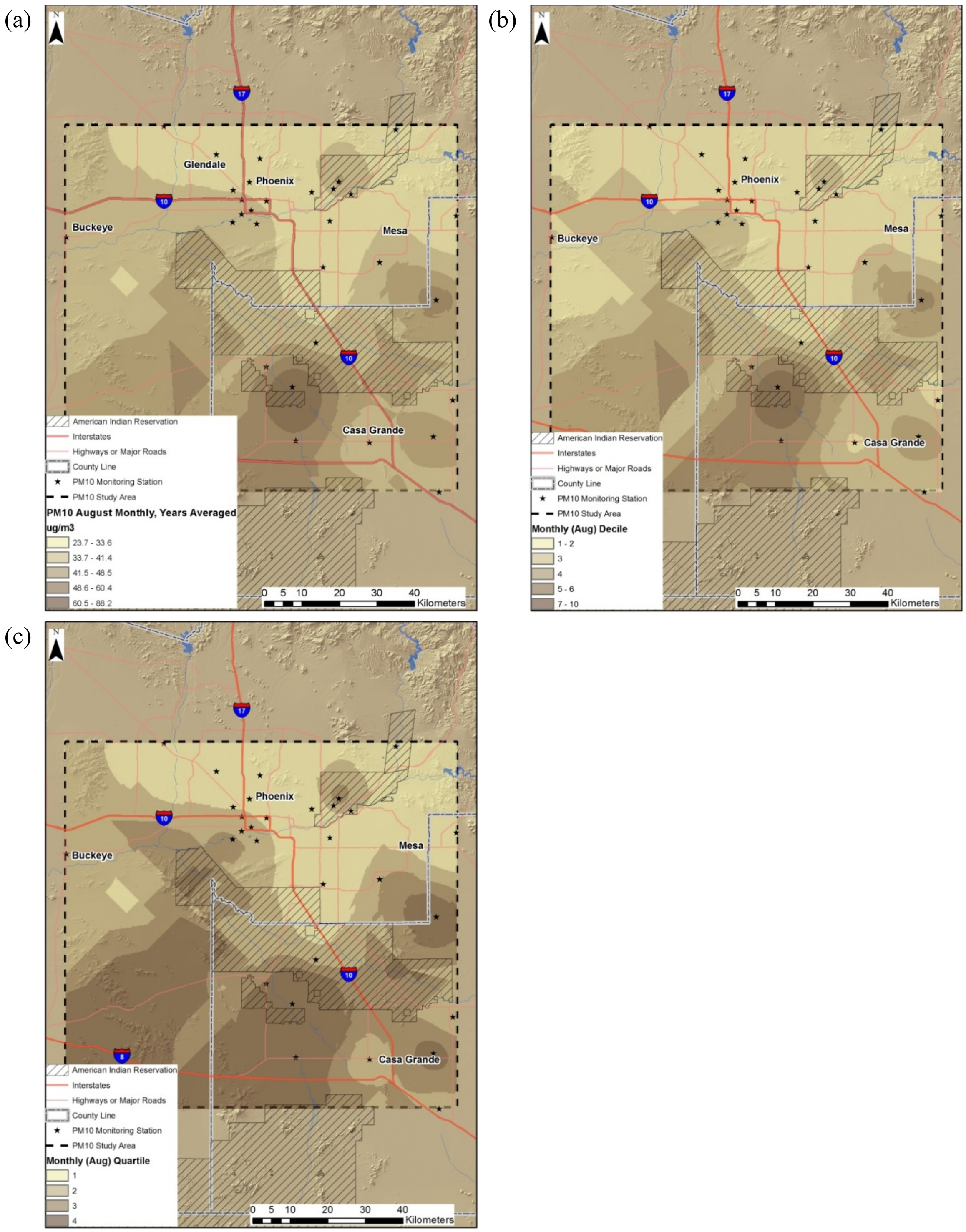

Figure 38 PM_{10} Pollution Surface Maps for the Monthly-Averaged Temporal Extents (August). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

(a) (b) (c)

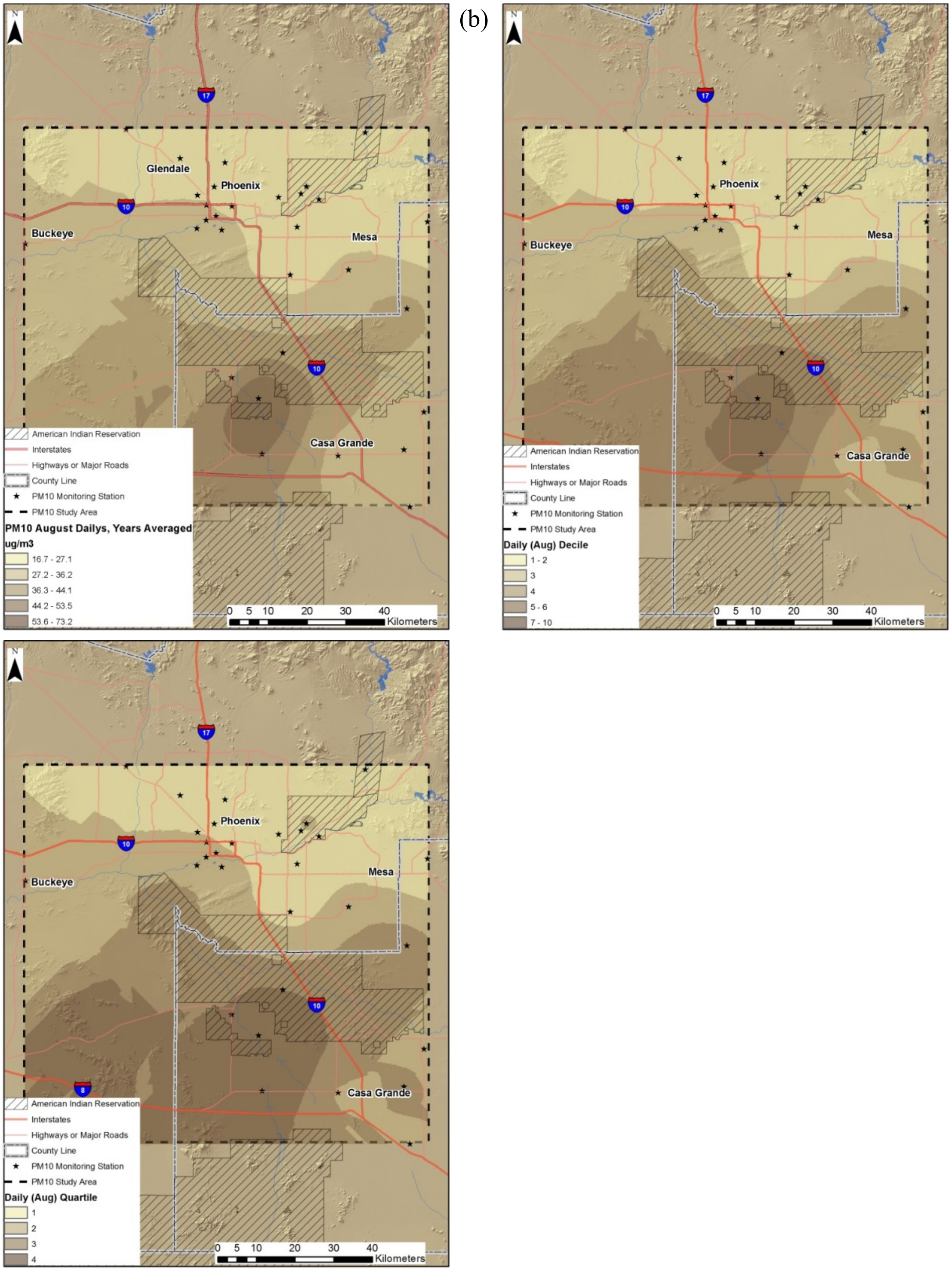

Figure 39 PM_{10} Pollution Surface Maps for the Daily-Averaged Temporal Extents (Aug 22, 2008; Aug 23, 2009; Aug 24, 2010). Includes Averaged Data from 2008-2010. (a) Raw Concentration Data. (b) Concentrations Aggregated into Deciles. (c) Concentrations Aggregated into Quartiles

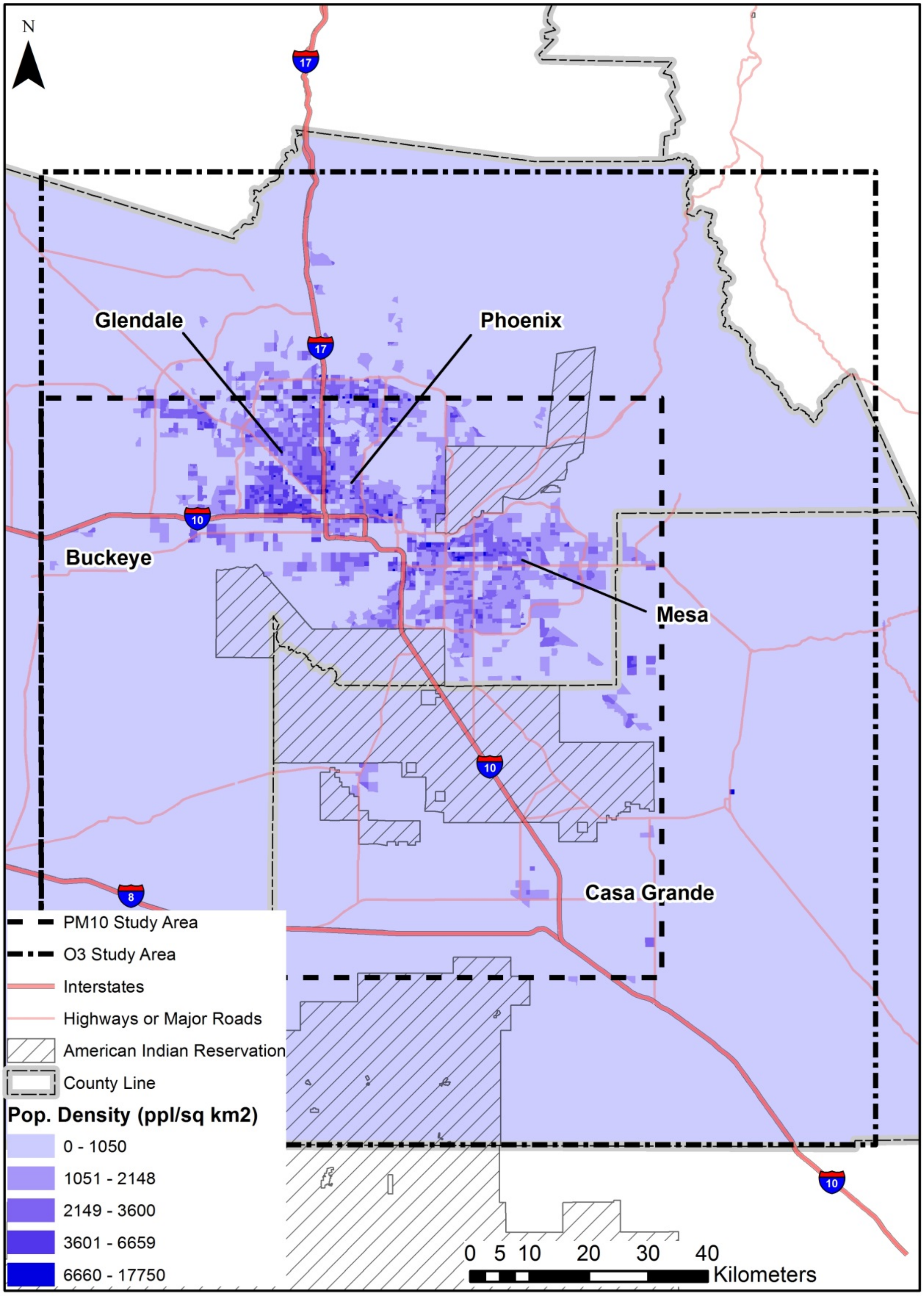

Figure 40 Total Population Density, Aggregated by Census Block Group, within Maricopa and Pinal Counties. Units Are People/Km^2

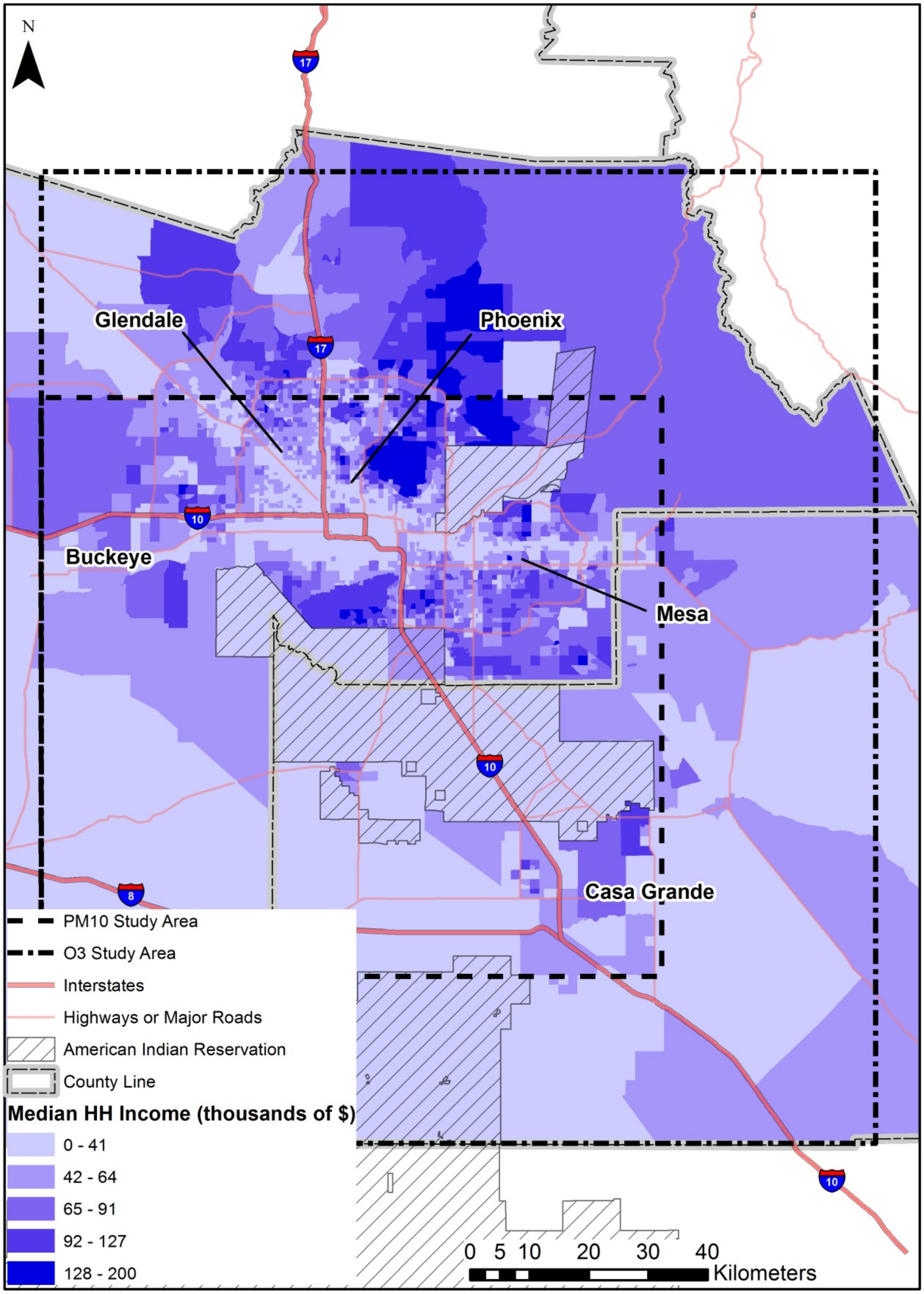

Figure 41 Median Household Income, by Census Block Group, within Maricopa and Pinal Counties. Units Are Thousands of Dollars

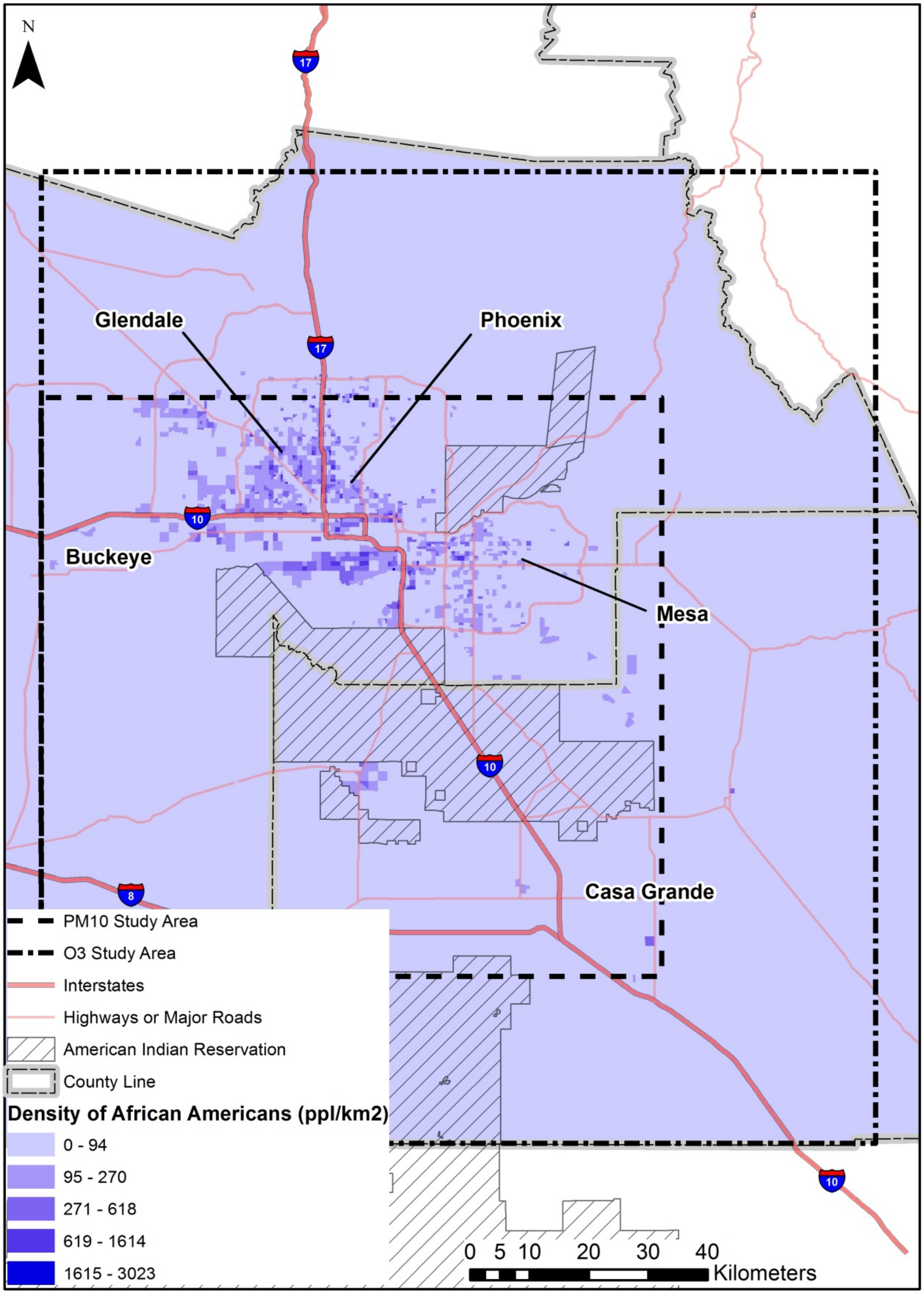

Figure 42 Population Density of African Americans within Maricopa and Pinal Counties by Census Block Group. Units Are People/Km^2

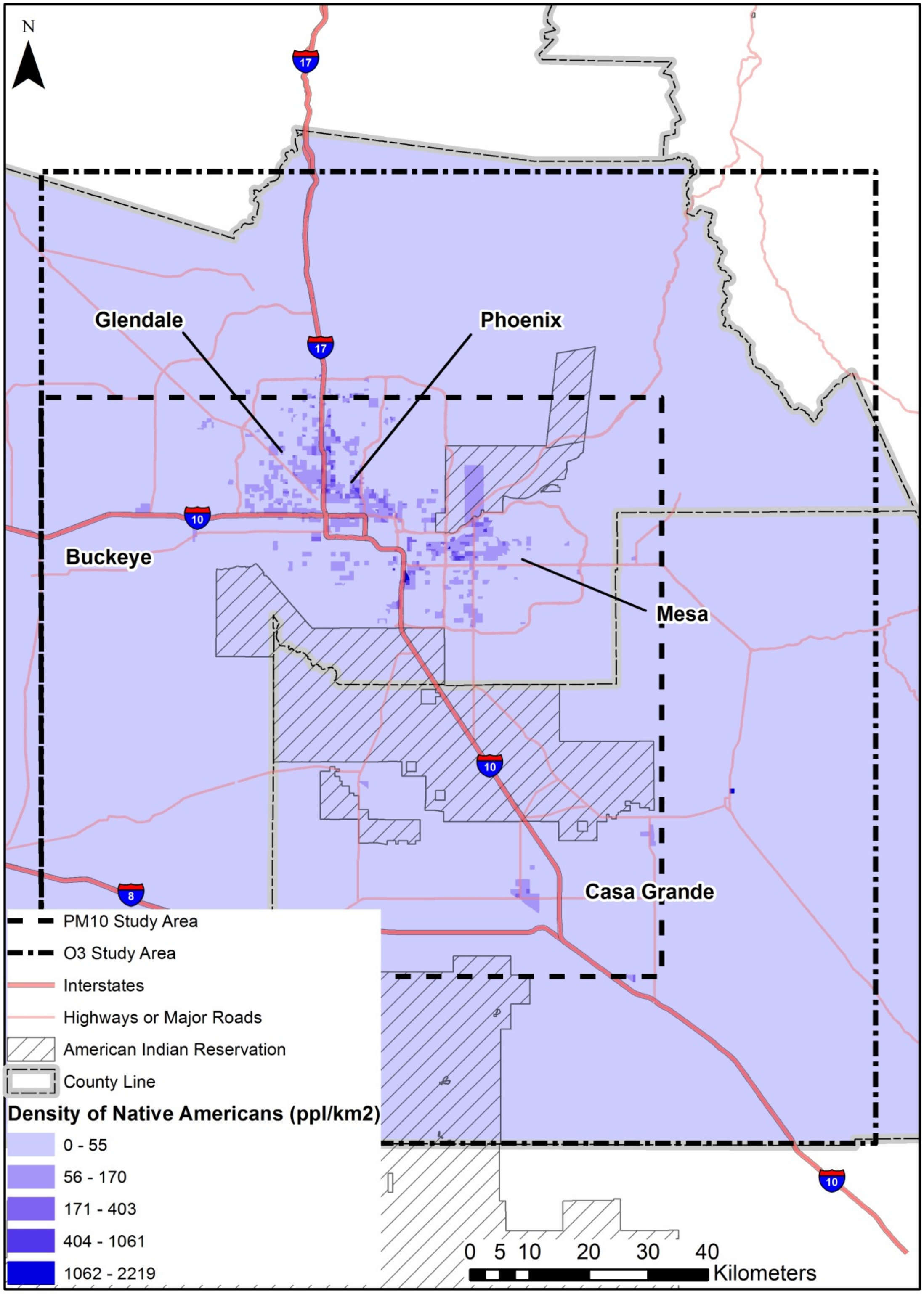

Figure 43 Population Density of Native Americans in Maricopa and Pinal Counties by Census Block Group. Units Are People/Km^2

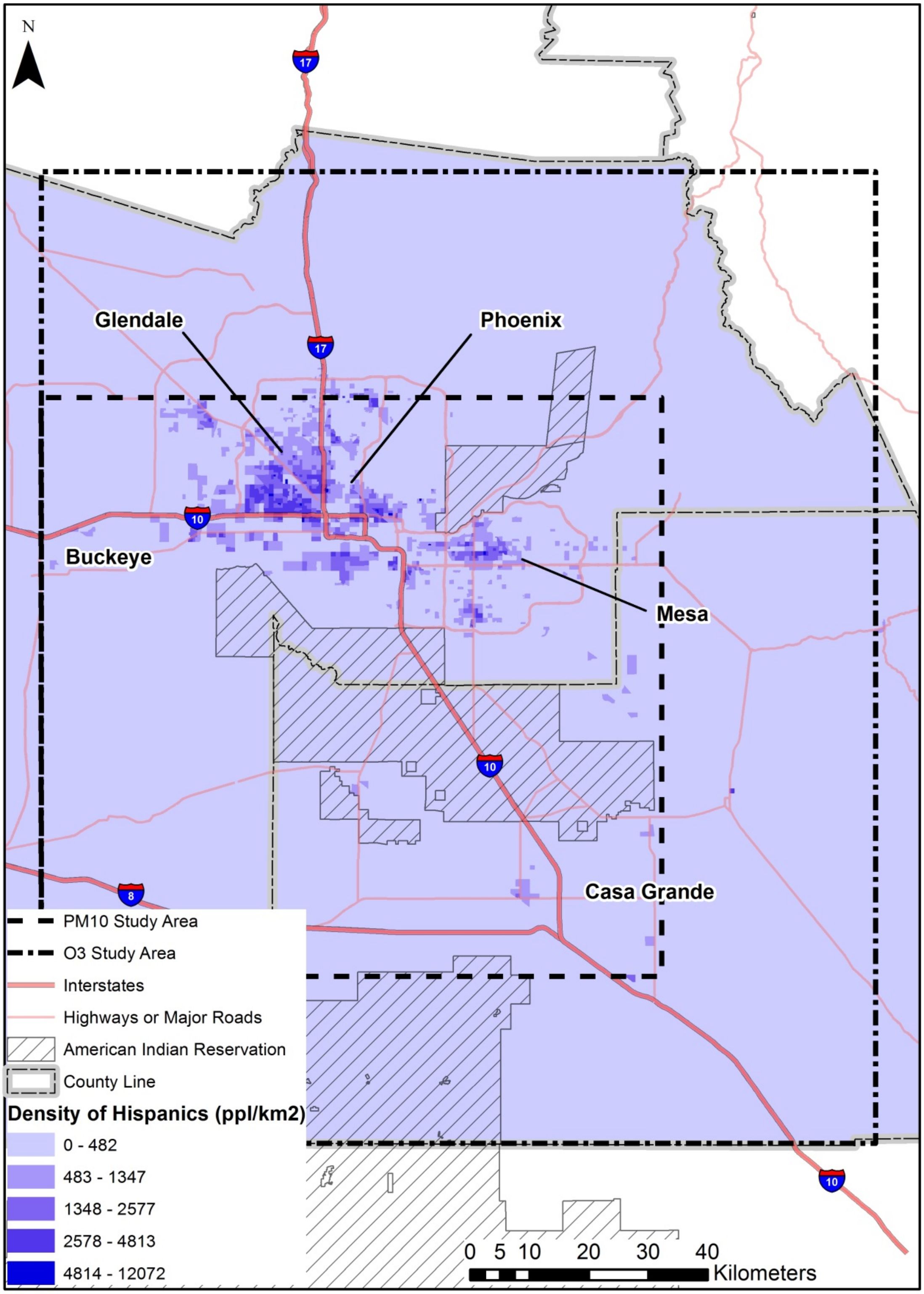

Figure 44 Population Density of Hispanics within Maricopa and Pinal Counties by Census Block Group. Units Are People/Km^2

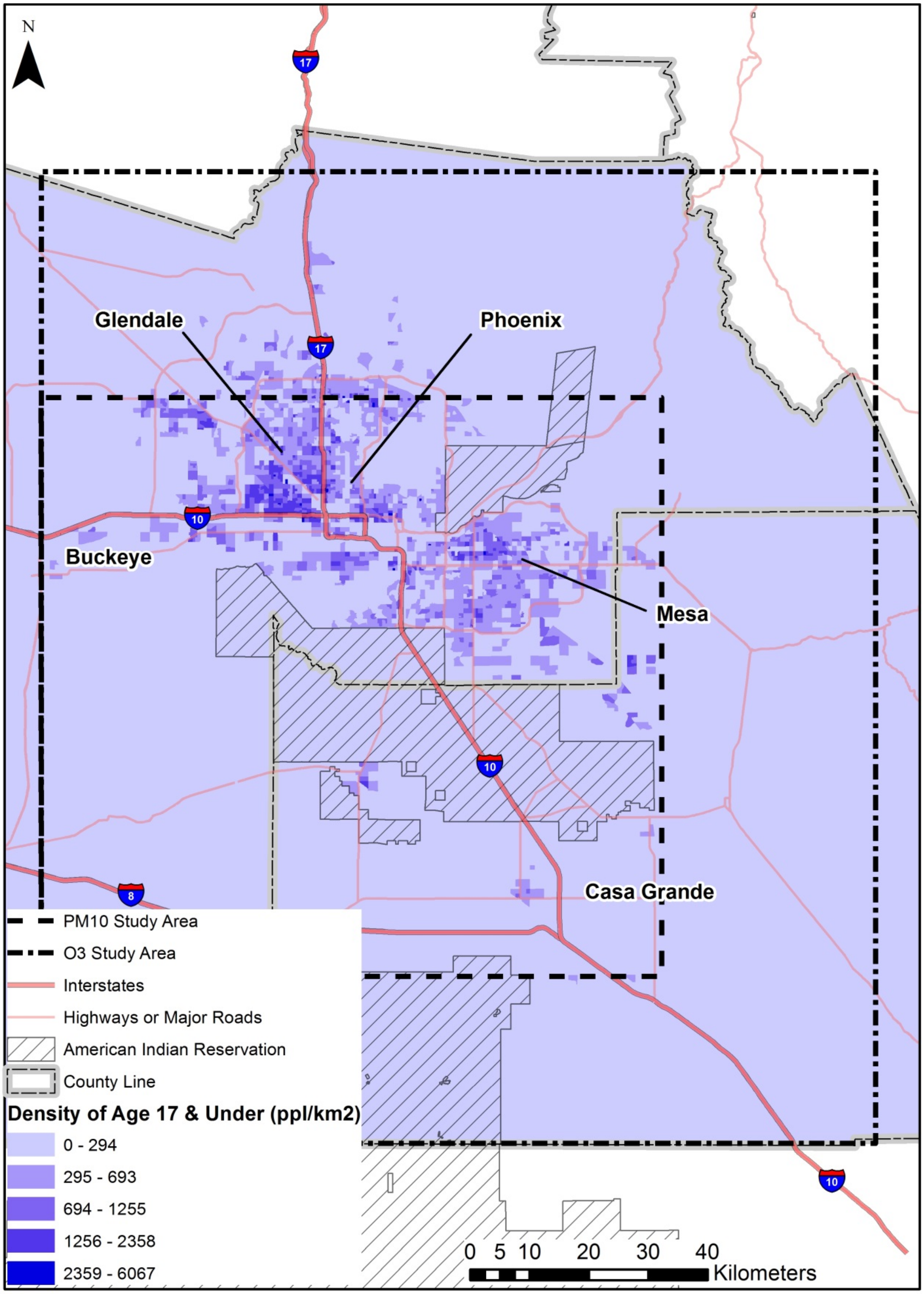

Figure 45 Population Density of People Aged 17 and Under within Maricopa and Pinal Counties by Census Block Group. Units Are People/Km^2

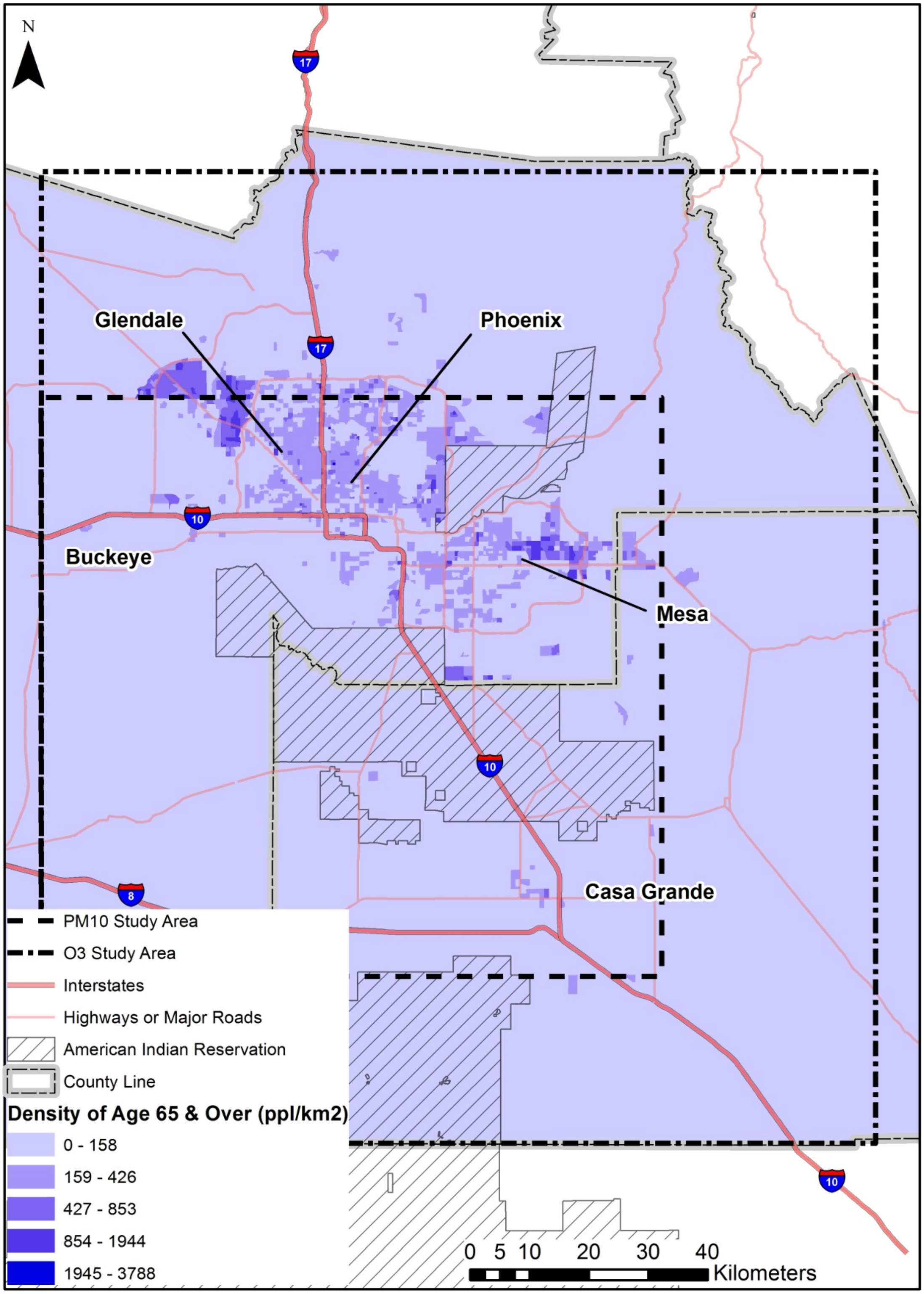

Figure 46 Population Density of People Aged 65 and Over within Maricopa and Pinal Counties by Census Block Group. Units Are People/Km^2

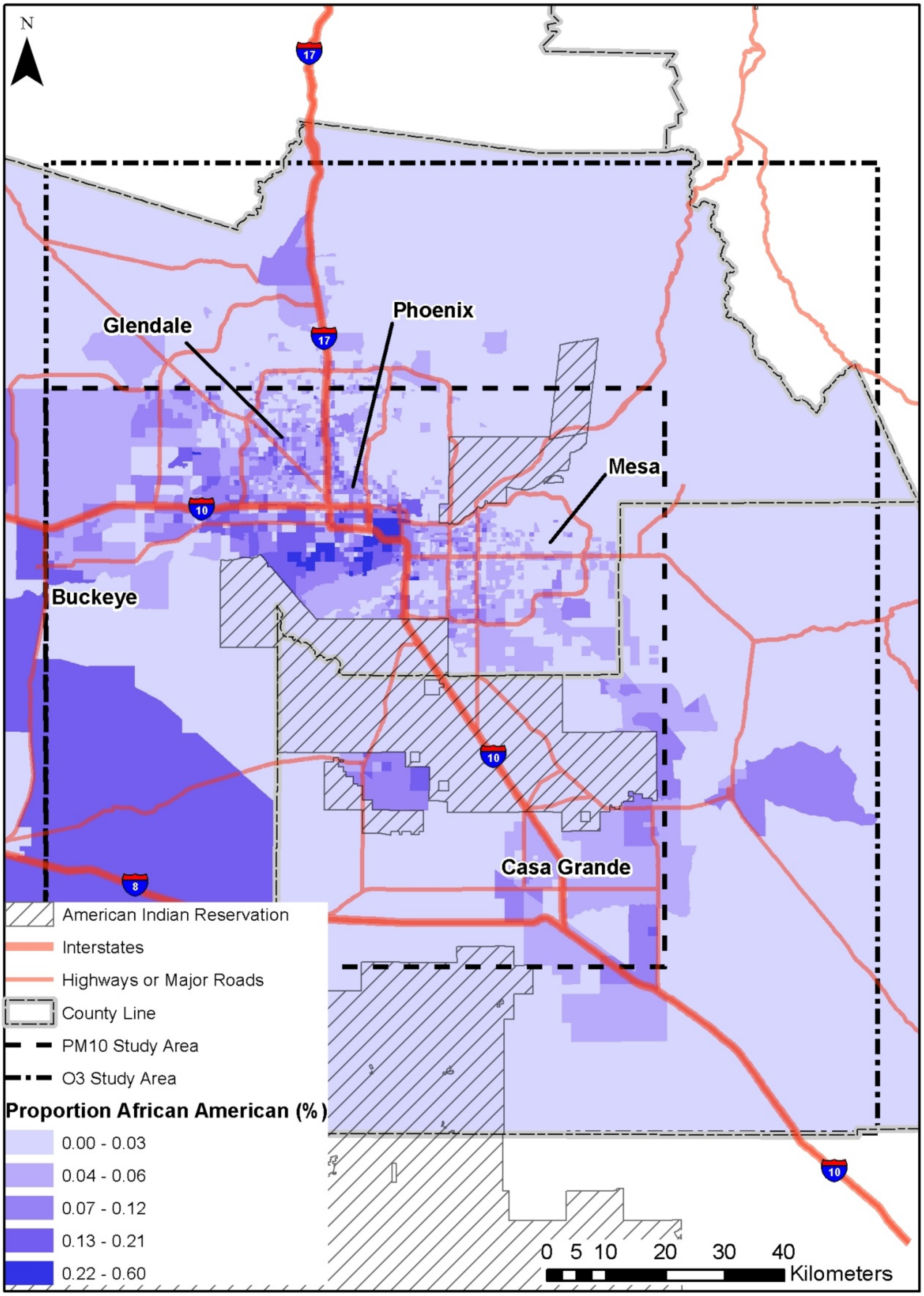

Figure 47 Population Proportion of African Americans within Maricopa and Pinal Counties by Census Block Group. Units Are Percentage

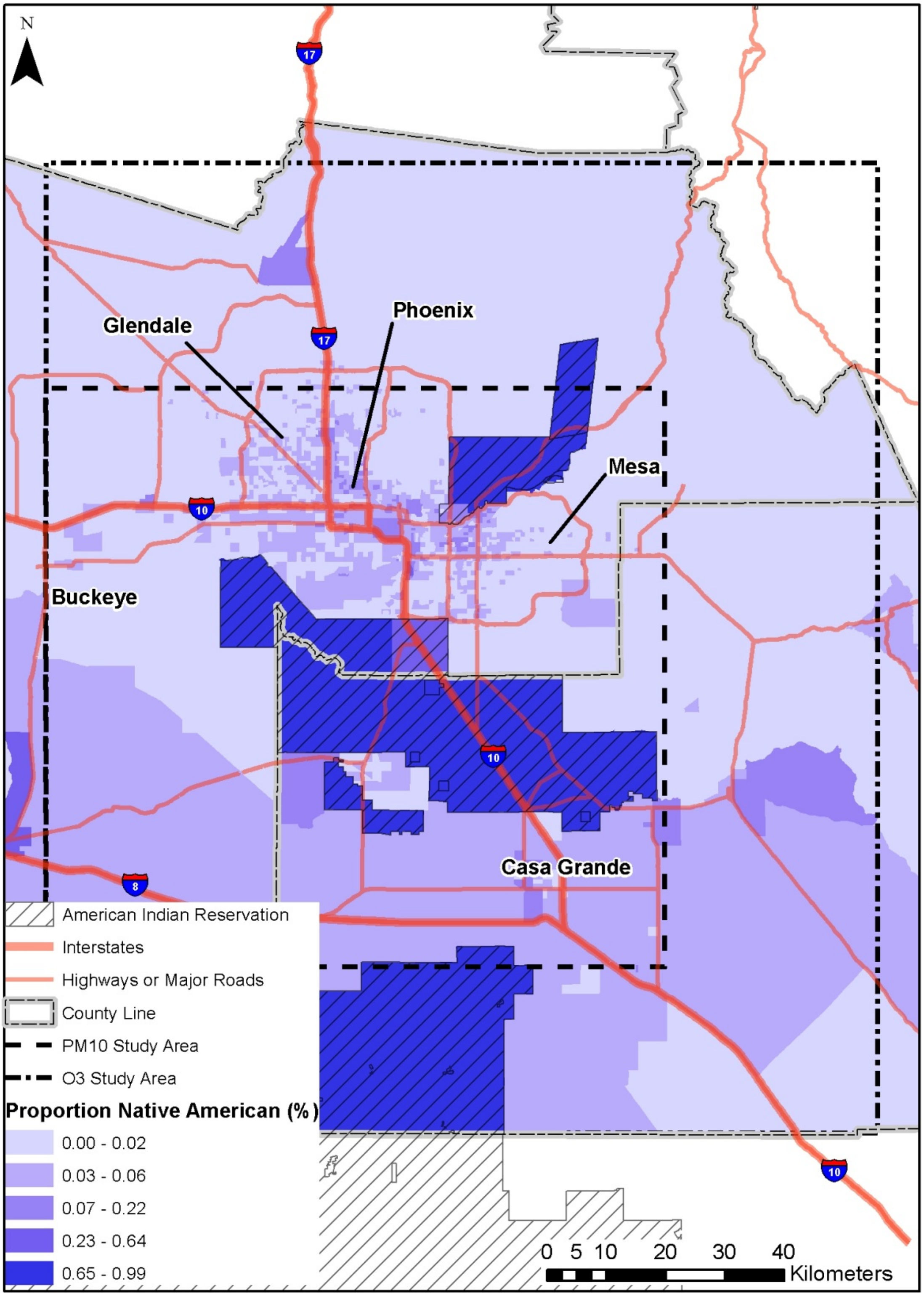

Figure 48 Population Proportion of Native Americans within Maricopa and Pinal Counties by Census Block Group. Units Are Percentage

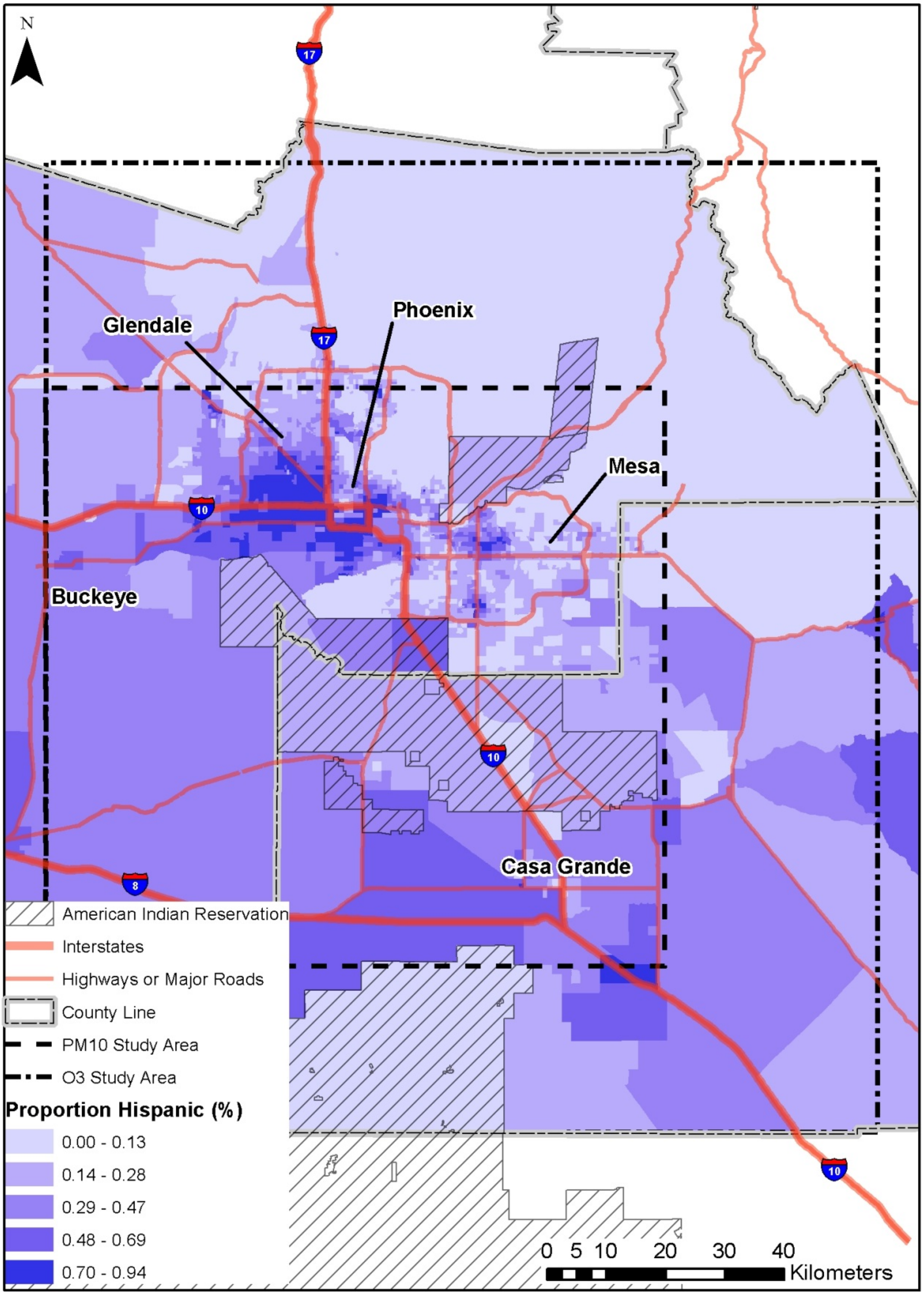

Figure 49 Population Proportion of Hispanics within Maricopa and Pinal Counties by Census Block Group. Units Are Percentage

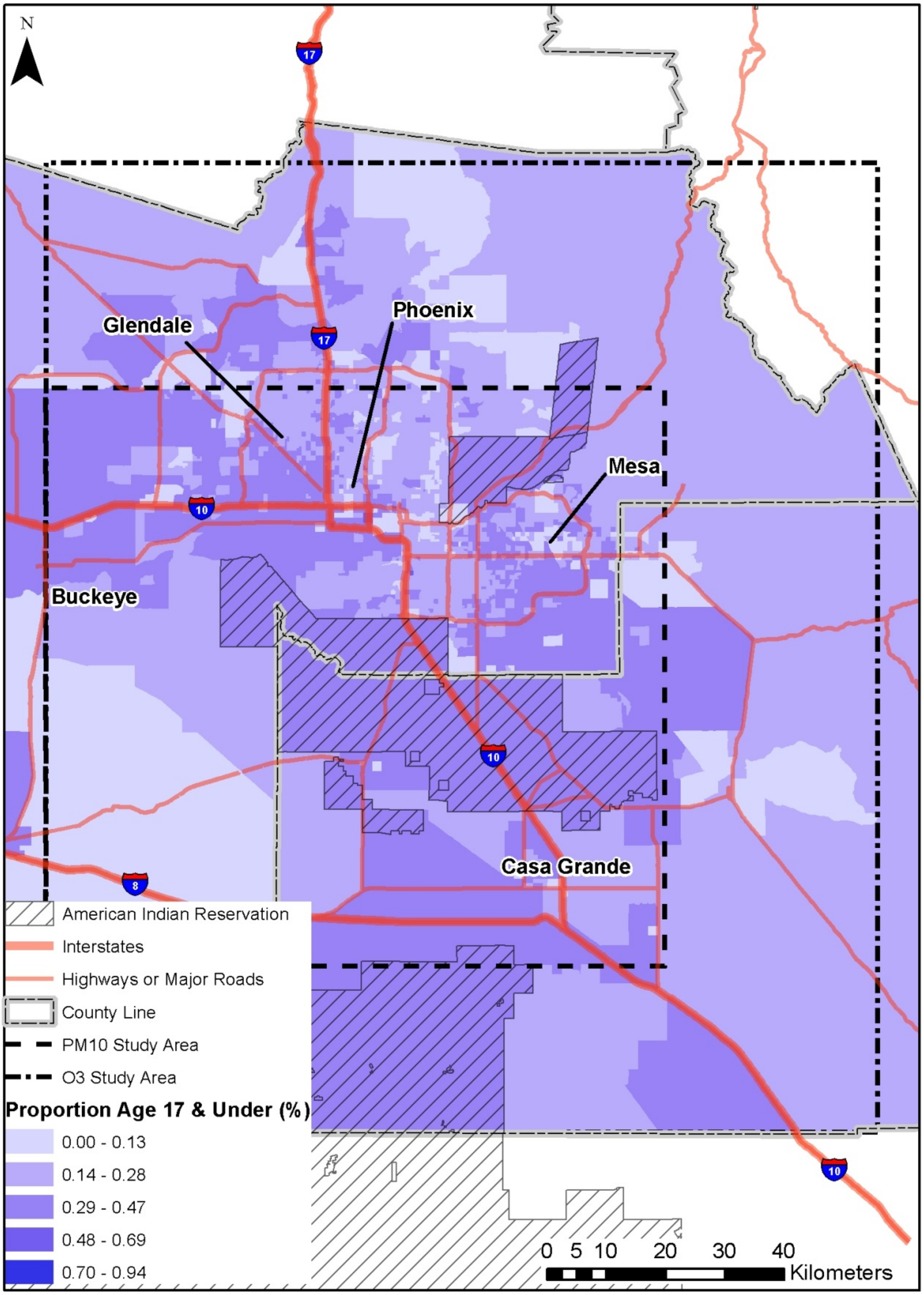

Figure 50 Population Proportion of People Age 17 and Under within Maricopa and Pinal Counties by Census Block Group. Units Are Percentage

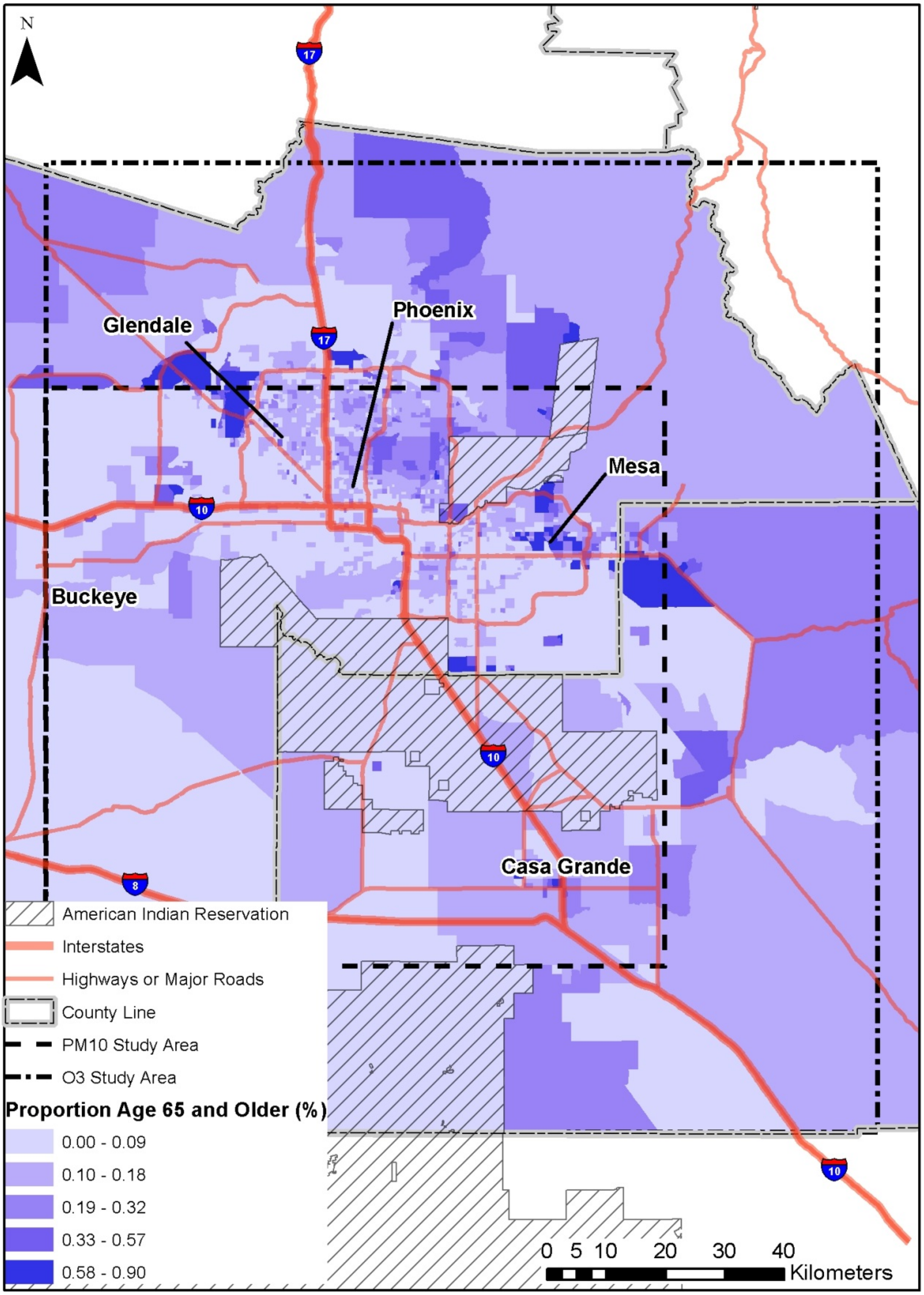

Figure 51 Population Proportion of People Age 65 and Older within Maricopa and Pinal Counties by Census Block Group. Units Are Percentage