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Spatial patterns of air pollutants and social groups: a distributive environmental justice study in the phoenix metropolitan region of USA

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Abstract Quantifying spatial distribution patterns of air pollutants is imperative to understand environmental justice issues. Here we present a landscape-based hierarchical approach in which air pollution variables are regressed against population demographics on multiple spatiotemporal scales. Using this approach, we investigated the potential problem of distributive environmental justice in the Phoenix metropolitan region, focusing on ambient ozone and particulate matter. Pollution surfaces (maps) are evaluated against the demographics of class, age, race (African American, Native American), and ethnicity (Hispanic). A hierarchical multiple regression method is used to detect distributive environmental justice relationships. Our results show that significant relationships exist between the dependent and independent variables, signifying possible environmental inequity. Although changing spatiotemporal scales only altered the overall direction of these relationships in a few instances, it did cause the relationship to become nonsignificant in many cases. Several consistent patterns emerged: people aged 17 and under were significant predictors for ambient ozone and particulate matter, but people 65 and older were only predictors for ambient particulate matter. African Americans were strong predictors for ambient particulate matter, while Native Americans were strong predictors for ambient ozone. Hispanics had a strong negative correlation with ambient ozone, but a less consistent positive relationship with ambient particulate matter. Given the legacy conditions endured by minority racial and ethnic groups, and the relative lack of mobility of all the groups, our findings suggest the existence of environmental inequities in the Phoenix metropolitan region. The methodology developed in this study is generalizable with other pollutants to provide a multi-scaled perspective of environmental justice issues.

Keywords Environmental justice · Spatiotemporal scale · Ozone · PM_{10} · Scale effects · 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 environmental justice movement is rooted in the civil rights era and many of the historic early studies detailed the link between race and the inequitable siting of toxic industries (United Church of Christ (UCC) 1987; Bullard 1990). Based on evidence of inequitable conditions demonstrated in these and other important studies, a Presidential Executive Order (12898) mandated that federal agencies consider environmental justice issues in their policies and actions (Cutter and Solecki 1996).

Environmental justice principally addresses two types of justice: procedural and distributive. Procedural justice is

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often defined as fair application of environmental laws and policies for all groups of people. Distributive justice is the fair or equitable distribution of environmental benefits and burden across all social groups, often examined in spatial terms by neighborhoods (Rechtschaffen 2003). Studies in distributive 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, or even blighted and polluted neighborhoods (Boone et al. 2014). When these inequitable conditions are brought to light, policy makers can use that knowledge to rectify the situation or citizens can use the information to argue for improved environmental conditions.

This paper describes a novel methodology for studying distributive environmental justice by comparing demographics at the census block group level to multiple spatiotemporal scales of monitored pollution so as to determine the multi-scalar extent of environmental inequity. The methodology developed here is based on methods from landscape ecology and utilizes geographical information system (GIS) and network-based approaches to create pollution models. Landscape ecology, a discipline devoted to understand the spatial relationships between scales, patterns, and processes, offers useful methods and insight into the creation of these pollution models. The primary aim of this methodology is to explore and highlight the differences in results between multiple spatiotemporal scales in the analysis. The methodology described here is generalizable to other studies using pollution data that is multiscalar in space and time.

In this paper, we detail a case study of distributive environmental justice in Phoenix, Arizona using this multi-scalar methodology. It focuses on ambient air quality collected from government air monitoring networks and examines how distinct socioeconomic groups are exposed to ground-level ozone (O_3) and particulate matter less than 10 μ in size (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, we discuss some of the legacy conditions experienced by minority populations in the Phoenix area; but we focus mainly 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 based on neighborhood demographics.

Spatiotemporal Scale in the Environmental Justice Literature

A number of environmental justice studies 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 hazardous waste and toxics releasing facilities affect low-income minority groups at three different spatial scales: counties, census tracks, and census block groups. Associations were found at the county level, but not at finer scales. Huby et al.'s (2009) justice study in England stresses the need for multi-scale analysis, and notes that coarser scales can mask inequalities due to aggregation. Baden et al.'s (2007) review of existing empirical justice literature shows that studies span a range of scales, some employ multi-scale methods, but few use multiple units of analysis. Variation was observed across the methods, but the authors note that smaller scales tend to exhibit more statistically insignificant findings, concluding that scale and scope can strongly influence analysis and results (Baden et al. 2007).

Choosing the scale of analysis is important as different scales can produce different results and using one scale to make inferences about another scale can lead to false deductions—phenomena known as the modifiable areal unit problem (MAUP) and the ecological fallacy, subjects often addressed in landscape ecology (Wu 2007). The MAUP presents two interrelated problems with spatial data analysis: the scaling problem and the zoning problem (Wu 2007; Jelinski and Wu 1996; Openshaw 1984). 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 that can create false categories of data 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; Boone 2008), with varying findings. 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 often mentioned (Jerrett et al. 2001), there is a deficit of environmental justice literature addressing multiple-scale temporal analysis methods (Noonan 2008). The methodology and case study described in this paper will address this deficit by exploring spatiotemporal patterns at multiple scales.

There have also been a number of previously conducted environmental justice studies in the Phoenix metropolitan area using different techniques and scales. These techniques typically find environmental inequities, 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 many high-tech industries, implicated with emissions of greater toxicity, are located in more affluent areas of Phoenix away from the higher density locations of minority populations. 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, nitrous oxides (NO_x), and O_3, modeled in a 1 h time resolution, and analyzed the pollutant levels to the race and class composition of associated neighborhoods. They found equity issues for Latinos and Native Americans, but not African Americans. Grineski (2007) used the same pollution model, along with the Toxics Release Inventory 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. The case study detailed in this paper does address both the spatial and temporal dimensions of environmental justice by 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.

Methods

Case Study Area, Monitoring Stations, and Pollution Data

The case study covers the Phoenix metropolitan statistical area (MSA) in South-Central Arizona, a modern, thriving metropolitan area with more than 20 self-governing municipalities with over 4.2 million residents in 2010 (Wu et al. 2011) (Fig. 1). There are two distinct study areas in this project, one representing the O_3 pollution 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 2015). The O_3 study area is ~2.3 million hectares in size, and the PM_{10} study area is ~1 million hectares in size. Both of these areas are based upon Pope and Wu's (2014a) 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 2014a).

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 1), and pollution monitoring complied with all federal regulations (Pope and Wu 2014a). Air pollution data for the study were obtained from the United States Environmental Protection Agency's Air Quality System (AQS) database.

O_3 data were collected for the time period of 2008–2010; the finest temporal resolution (or grain size) was 1 h (i.e., raw data were 1 h averages). Four temporal extents (i.e., time durations over which average values of measurements were derived) were utilized: 1 h (at 15:00 on 15 July), 8 h (15:00–22:00 on 15 July), 1 month (July), and seasonal (April–October) (Table 2). The seasonal average was chosen instead of an annual average because many of the O_3 monitoring sites only operated during this time period. The rationale used in these selections was to pick a random date during the height of the summer O_3 season and then to scale this out from the hourly to the seasonal scales. A requirement was that no unusual weather or exceptionally high pollution event occurred on this date across the 3 years of the study period.

PM_{10} data were also collected from 2008–2010, though the temporal resolution for PM_{10} was a 24 h average measured 1 day out of every 6 (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-h or 1-h averages; however, all finer averages were rolled into a 24-h 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 2). As with the O_3 data, a date was selected at random with the qualifying criteria that no unusual weather or high pollution event occurred. Due to significant seasonal differences in pollution patterns (Pope and Wu 2014a), we

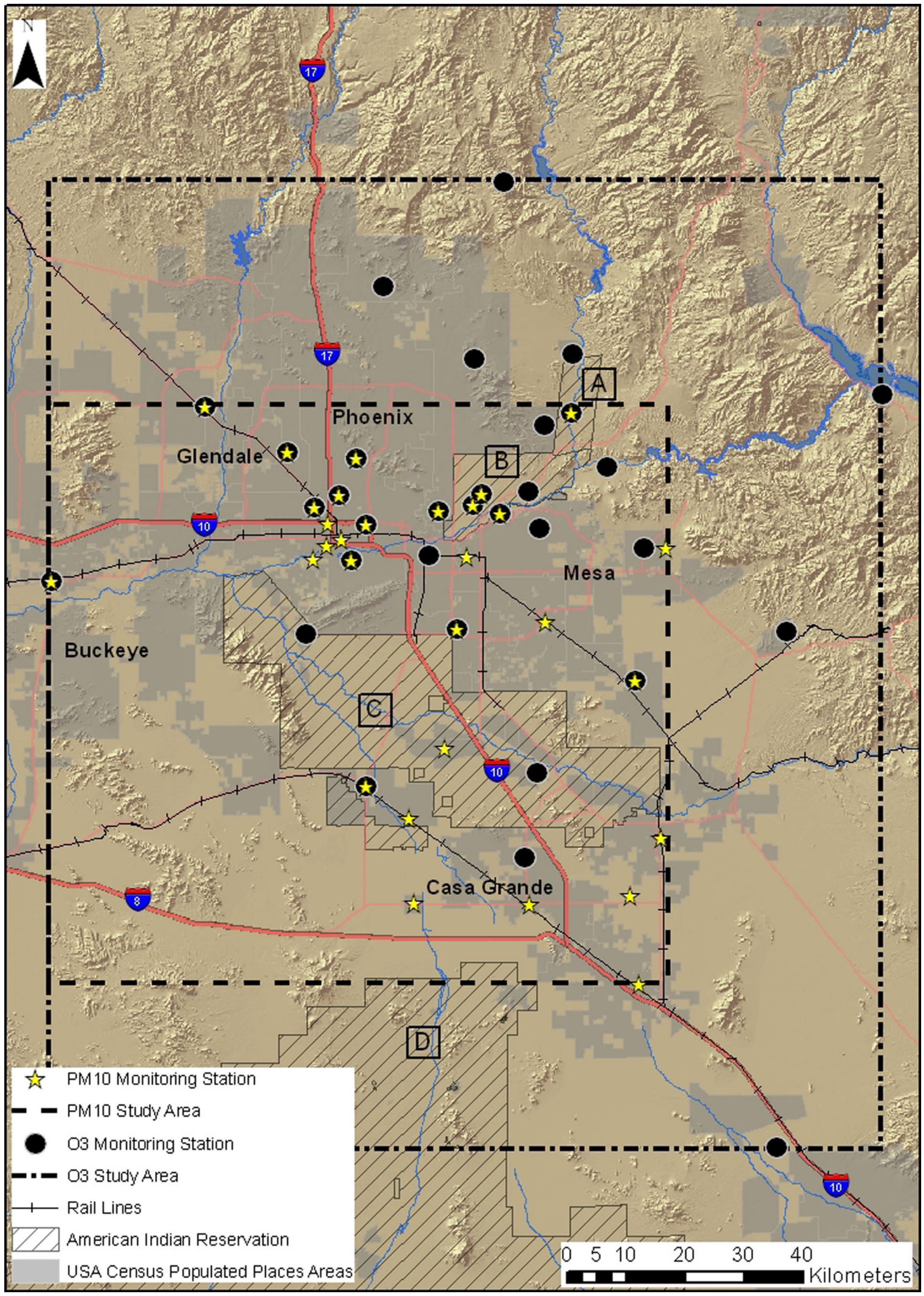


Fig. 1 Map of Central Arizona including the Phoenix metropolitan area. The map includes the location of O_3 and PM_{10} monitoring stations, note that some stations contain both monitor types. American Indian Reservations are labeled on the map: **a** Ft. McDowell Yavapai Nation, **b** Salt River Pima-Maricopa Indian Community, **c** Gila River Indian Community, and **d** Tohono O'odham Nation

chose to scale up from two dates, one in summer and one in winter. The 1-in-6 day sampling period complicated date selection, but of the final six selected dates (across 3 years), five were weekdays and one was a weekend.

Pollution Surfaces

Pollution surfaces were modeled using the landscape ecological methods in Pope and Wu (2014a). 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). The data 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 (2014a) for further details).

Following the semivariance analysis, a universal kriging interpolation map of the pollution surface was created at a spatial resolution of 250 m. Kriging is a geostatistical

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

Table 2 Details on the temporal scales used within this study

Pollutant	Temporal resolution	Study years	Temporal extents				
Ozone	1-h averages, continuous sample grain	2008–2010	Seasonal (Apr–Oct)	Monthly (July)	8-h (15 July, 15:00–22:00)	1-h (15 July, 15:00)	
PM_{10}	24-h averages, 1-in-6 day sample grain	2008–2010	Annual	Monthly (Jan)	Monthly (Aug)	Daily (Jan) [7 Jan, 2008, 7 Jan, 2009, 8 Jan, 2010]	Daily (Aug) [22 Aug, 2008, 23 Aug, 2009, 24 Aug, 2010]

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

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). Our 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 our semivariance analysis. Thematic maps were created at each temporal scale, for both O_3 and PM_{10} (Fig. 2; also see Online Resource Supplementary Figs. S1–S9).

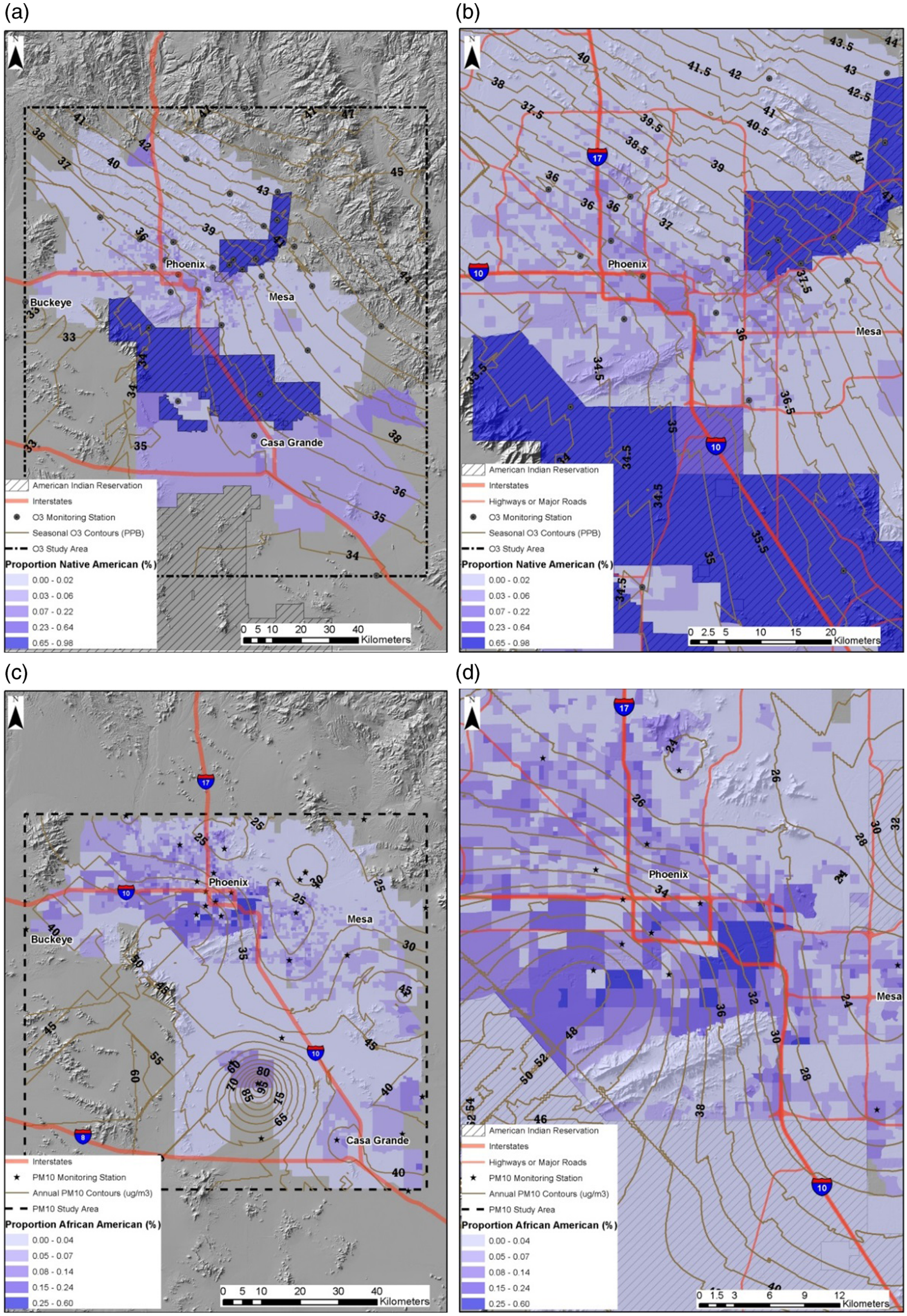
To quantify error, prediction error maps were created and a removal bias analysis was performed to quantify the modeled error in the kriging interpolations. The removal bias analysis involves creating the interpolated pollution surface, and then systematically removing each input point (i.e., monitoring station) and recreating the interpolation. The difference, or bias, between the actual monitored value and the predicted value after removing the station is recorded to obtain an estimate of error in the interpolation (Pope and Wu 2014b) (see Online Resource Supplementary Figs. S10, S11).

Census Data

Census data were selected at the block group level, as this was the finest resolution available for all variables (Table 3 and Fig. 3; also see Online Resource Supplementary Figs. S12–S18 for demographic summaries). We selected the fine resolution of census block groups as this represents best neighborhood boundaries in a nationally consistent manner and because neighborhood is the primary unit of analysis in environmental justice studies (Williams 1999; Mohai and Saha 2007). There were six variables in four groups: socioeconomic status, age, race, and ethnicity (Table 4). Our 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 (Tecer et al. 2008; Andersen et al. 2007).

GIS Model

Rasters for the 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 250 m 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 in a one-to-one relationship with the census data using the pollution score at the centroid of each block group; thus each census block group had its centroid-associated pollution value listed. The spatially explicit tables were then exported for statistical analysis (Fig. 4).


(a)
(b)
(c)
(d)
Phoenix
Mesa
Buckeye
Casa Grande
American Indian Reservation
Interstates
Highways or Major Roads
O3 Monitoring Station
Seasonal O3 Contours (PPB)
O3 Study Area
Proportion Native American (%)
0.00 - 0.02
0.03 - 0.06
0.07 - 0.22
0.23 - 0.64
0.65 - 0.98
PM10 Monitoring Station
Annual PM10 Contours (ug/m3)
PM10 Study Area
Proportion African American (%)
0.00 - 0.04
0.05 - 0.07
0.08 - 0.14
0.15 - 0.24
0.25 - 0.60
Kilometers

◀ **Fig. 2** 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 μg/m^3) at the annual temporal extent overlaying the population proportion of African Americans and **d** is a finer resolution in the urban metropolitan area. See Supplementary materials, Figs. S1–S9, for complete maps from all temporal extents

Statistical Model

We 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 5; also see Supplementary Tables S1, S2 in the Supplementary Materials for complete details).

The models were created in SPSS Version 22.0 (IBM Corp 2013). Input data were transformed as necessary, and homoskedasticity was tested for with Breusch-Pagan and 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.

Results

The hierarchical multiple regression models did find significant relationships between the dependent pollution and independent demographic variables (see Online Resources Supplementary Tables S1, S2 for complete statistical results). These relationships are summarized in Table 6, 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 few instances where changing the temporal scale or spatial aggregation changed significant relationships between the dependent and independent variables (Table 6). The examples of this were O_3 with the variables median household income and proportion aged ≤ 17, and PM_{10} with income and proportion Hispanic; in all other cases the direction of the effects were the same when significant relationships were found.

There were many examples where changing scale resulted in the model 4 relationship becoming non-significant (Table 6). 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 (Supplementary results Supplementary Tables S1, S2).

There were several distinct consistent patterns that emerged in the data. At most scales, the proportion of people aged 17 and under was a significant predictor for both O_3 and PM_{10}; however, the proportion of people aged 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

Table 3 Spatial and population statistics for the census block groups located within the O_3 and PM_{10} study areas

Study area	Census block groups spatial statistics					Census block groups population statistics				
	N	Min. size (km^2)	Max. size (km^2)	Mean size (km^2)	SD (km^2)	Population *N*	Min. pop.	Max. pop.	Mean pop.	SD
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

Note that only block groups that were completely inside the respective study areas were included

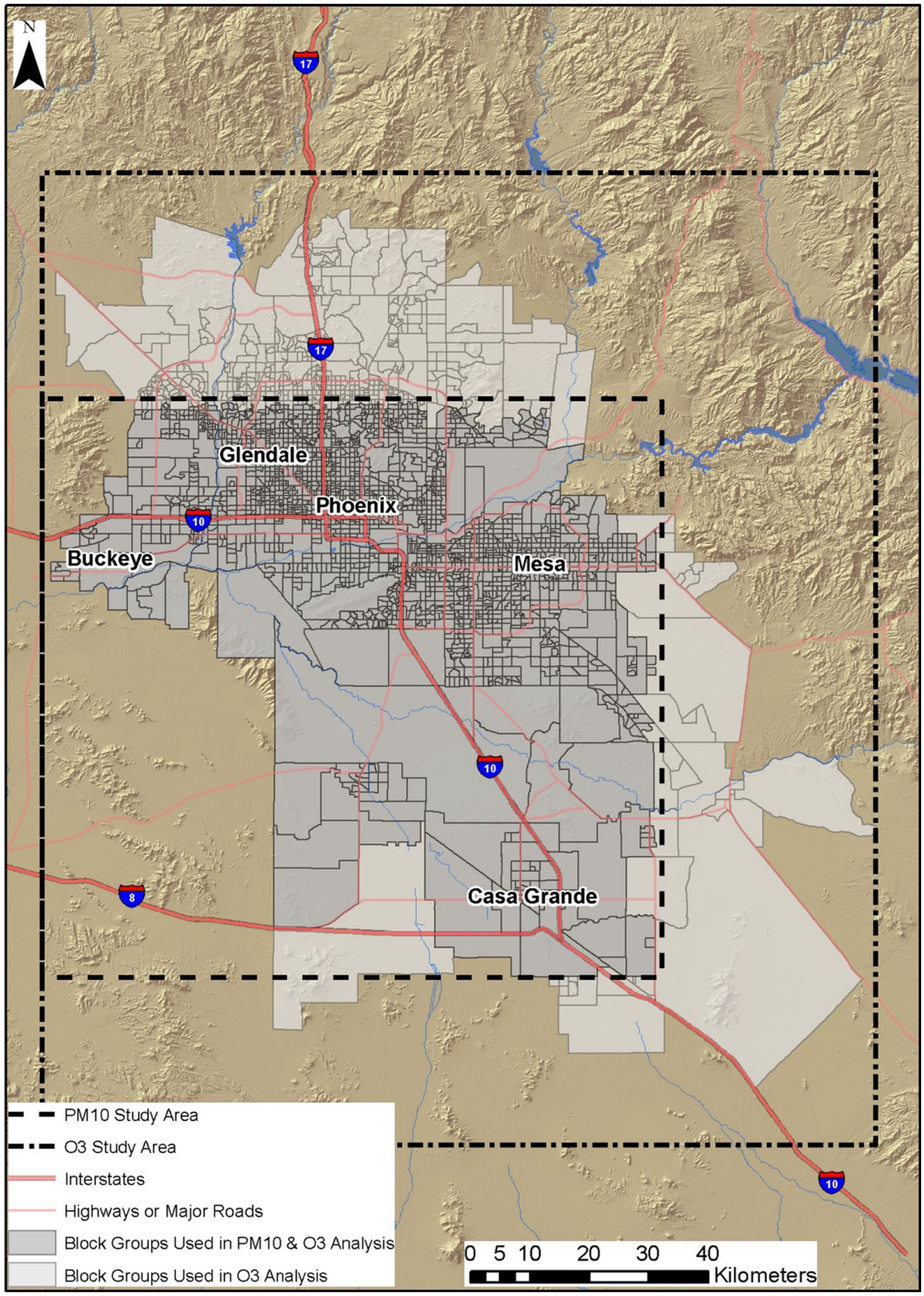


Fig. 3 Map of the census block groups that were used within the PM_{10} and O_3 portions of the study. Note that only those block groups that were fully contained within the respective study areas were included. The very large, sparsely populated block groups in rural areas that crossed the studies' boundaries were excluded. Block groups that are colored *light gray* were used in the O_3 study, those that are colored dark gray were used for both the O_3 and PM_{10} studies

monthly and daily temporal scales varying between positive, negative, and non-significant beta scores (Table 6).

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 less than anticipated (Table 6). 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 indicates 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. Another interesting result was the change between the PM_{10} winter and summer scales, especially in relation to

Table 4 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-h O_3 (ppb)	2646	19.6	33.2	52.8	41.8	4.0	16.3
1-h 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} (μg/m^3)	2172	74.0	20.7	94.6	30.4	6.9	47.5
Monthly (Jan) PM_{10} (μg/m^3)	2172	34.3	8.2	42.5	20.2	6.4	40.8
Monthly (Aug) PM_{10} (μg/m^3)	2172	57.0	24.0	81.0	31.3	5.3	28.4
Daily (Jan) PM_{10} (μg/m^3)	2172	35.8	10.0	45.8	21.3	6.0	36.1
Daily (Aug) PM_{10} (μg/m^3)	2172	50.3	17.9	68.2	24.7	4.8	23.4

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 2014a).

In many of these cases we do not have definitive proof about the reasons for the change, or lack thereof, of the relationships between demographics and the pattern of pollutants at differing temporal scales. The spatial patterns of pollutants often do change between the differing time periods, so the reasons could range from the new patterns affecting differing population groups to a blurring heterogeneity of demographics. However, apparent associations between demographics and the pollution patterns are noted where appropriate.

Changes in spatial aggregation of pollutant also resulted in less effect than expected. We 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 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 6).

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

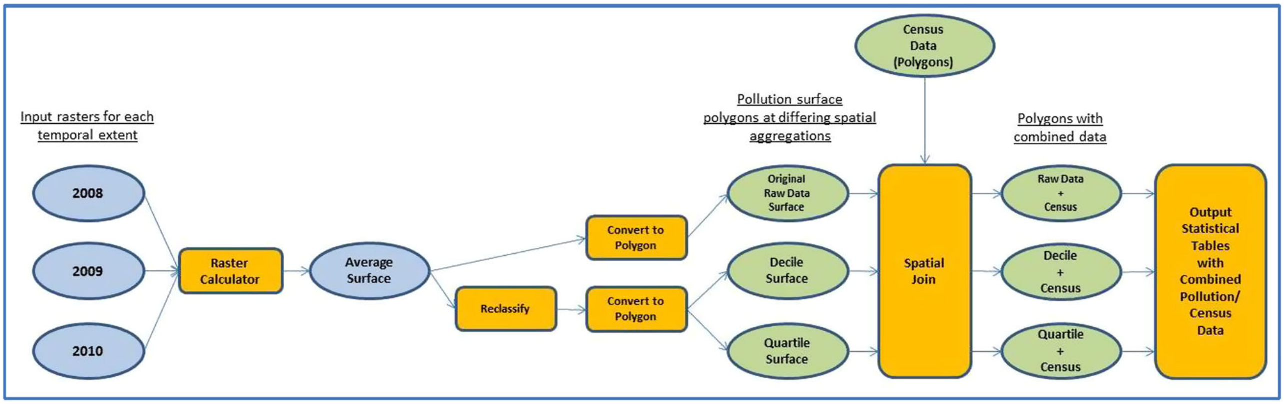


Fig. 4 The model used to generate spatial files combining pollution surface data and census data. Ovals represent map data files, either rasters (*blue*) or polygons (*green*). Rectangles represent tools or processes within the GIS. The spatial join added the pollution value at the centroid of each block group to the census files. The spatially explicit table was then exported for statistical analysis

Table 5 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 65 and over
3	Median household income, Age 17 and under, Age 65 and over, Proportion African American, Proportion Native American
4	Median household income, Age 17 and under, Age 65 and over, Proportion African American, Proportion Native American, Proportion Hispanic

scales), and to a limited extent, with lower median household incomes (Table 6). 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 2014a, also see Supplementary figures S1–S4 in the supplementary information). 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 (Pope and Wu 2014a; Ellis et al. 1999). Furthermore, O_3 within the urban area is destroyed, or scavenged, during the night by 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, we 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 that Native Americans have endured, such as forced segregation and economic hardship on the reservations (Meeks 2007), the pattern of environmental injustice is clear.

It should also be noted that our findings differ from earlier Phoenix area environmental justice studies using O_3. Grineski et al. (2007) 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 1-h temporal scale, 27 August, 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 block groups with higher proportions of young people are scattered into rural areas and American Indian reservations (see Supplementary Figs. S17, S22 in the supplementary information). Furthermore, the relationships were less consistent, with the regression models always showing negative correlations, until the

Table 6 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-h	**NS**	**NS**	**NS**	+	+	+	**NS**	**NS**	**NS**
	1-h	**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 h	–	–	–	+	+	+	–	–	–
	1 h	–	–	–	+	+	+	–	–	–
PM_{10}	Annual	+	+	+	–	–	–	+	+	+
	Jan monthly	+	+	+	–	–	–	+	+	+
	Jan daily	+	+	+	–	–	–	+	+	+
	Aug monthly	+	+	+	–	–	–	**NS**	**NS**	–
	Aug daily	+	+	+	–	–	**NS**	+	**NS**	–

NS = No significant relationships found; – = Negative correlation suggesting unlikely inequitable relationship; + = Positive correlation suggesting possible inequitable relationship

Hispanic demographics were added in model 4 (Supplementary Table S1 in the supplementary information). 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 6). 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 show patterns that are often directly opposite to 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 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 (Supplementary Table S2 in the Supplementary information).

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 mining and material handling industries in South Phoenix (Dimitrova et al. 2012; Fernando et al. 2009; 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 more spatially distributed throughout the study area, and this is likely to account 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 (Supplementary Fig. S22 in Online Resource). 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) (Supplementary Fig. S23 in the Online Resource). 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 alongside industrial source zoning, clarifies the origin of these long-term inequities with minority population in these areas (Bolin et al. 2005).

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 are small enough and the spatial units are as small as possible, as in the case of census block groups for this study (Gilbert and Chakraborty 2011; Páez 2004; Grineski and Collins 2008). 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, we believe that stationarity bias in our regression model is low. However, future studies could be improved by using regression techniques that control for spatial dependence, such as geographically weighted regression or simultaneous autoregressive models (Brunsdon et al. 1999; Kissling and Carl 2008; Chakraborty 2009).

It should also be noted that there is inherent spatial error involved in using kriging interpolation to create the pollution surfaces, especially when the density of the input network is sparse. Although alternatives have been suggested to minimize this error, e.g., using linear regression models to improve the interpolation (Diem 2003; Diem and Comrie 2002), these methods have their own drawbacks including the need for significant high-resolution data resources; and thus are best suited to smaller scales.

Though we recognize the inherent problems with kriging interpolation, we contend that since this study focuses primarily on the regional scale pattern and its changes between temporal scales, our pollution surfaces are adequately robust for the purposes. To further test this contention, we created error prediction surfaces and performed a removal bias analysis on the interpolated surface (see Online Resources Supplementary Figs. S10, S11). This analysis showed estimated average bias for O_3 at 2 ppb (Range: 7–0 ppb; SD: 2 ppb). PM_{10} exhibited more error than O_3, with an average bias of 11.8 $\mu g/m^3$ (Range: 91.5–0.1; SD: 18.7). The highest bias existed in sparsely populated rural areas where stations are farther apart in distance, and is especially associated with PM_{10} hotspots located in rural areas south of metropolitan Phoenix. PM_{10} bias in the metropolitan area, where monitoring stations, and population, are more densely located, was considerably lower (see Online Resource Supplementary Fig. 11).

Conclusions

Distributive environmental inequities exist in the Phoenix area across spatial scales for the two ambient pollutants of most concern—O_3 and PM_{10}. These inequities affect different social groups to varying degrees, based on their location and population proportion in the metropolitan area. These populations have various legacy stories behind them: Native Americans were forcibly confined to reservations in the nineteenth century where the greater part of their freedom and livelihood was denied them (Meeks 2007). African Americans and Hispanic people, arriving after the nineteenth century Anglo settlers, were excluded from living in privileged areas reserved for Whites, including by restrictive deeds and covenants, and instead were segregated into South and West Phoenix, where city planners placed heavy industries and waste handling facilities (Bolin et al. 2013). The observed patterns between air pollution and demographics today are in part a persistent legacy of past segregation.

Youth and elder populations, most 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 to say about the environment where 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 differing population groups because of excessive exposure to

O_3 or PM_{10} has not been confirmed with this study, although serious health complications can be implied from frequent acute or long-term chronic exposure to these pollutants (Pope and Dockery 2006; Lippmann 1989). The case to be made here is that conditions, either historical or current, are such that populations of limited mobility are located in areas where they bear a larger burden of criteria pollutant exposure. Our findings can help policy makers and regulating agencies in the Phoenix area to make more informed decisions to protect the health of its communities.

Our case study has shown the usefulness of using a multi-scaled spatiotemporal methodology for investigating environmental justice issues. This methodology is generalizable to other studies where pollution data, especially ambient air pollution data, from a network or model exists across multiple scales of space and time. As shown in this case study, air pollution patterns are spatially heterogeneous and temporally dynamic, so the utilization of a multi-scaled spatiotemporal methodology is important to discover the full extent of distributive environmental inequity.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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