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The Impact of Urban Development on Disparities in Exposures and Health in Xi'an, China

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The Impact of Urban Development on Disparities in Exposures and Health in Xi'an, China

By

Meiling Gao

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ABSTRACT

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Doctor of Philosophy in Environmental Health Sciences

Professor Catherine P. Koshland, Co-Chair
Associate Professor Edmund Y.W. Seto, Co-Chair

China's cities have been growing both in size and population at an unprecedented rate over the last three decades. The evolving urban landscape has important consequences for public health. However, the relationships among the physical environment, human behaviors, environmental exposures, and health are understudied in Chinese populations. Furthermore, more evidence from Chinese studies is needed to inform the design of urban environments and public health programs that promote and improve both mental and physical health.

This dissertation examines how urban development trends in China affect health and quality of life. I approached this question by conducting a cross-sectional socio-behavioral and health survey of 1608 adults in 20 neighborhoods in Xi'an, China in 2013. This cross-sectional study includes residents of four types of neighborhoods that represent different stages of China's urbanization: work-units, lane and courtyard housing, and two forms of commodity housing (high-density high rises and low-density high rises) neighborhoods. Although cross-sectional in design, this dissertation leverages the temporal history of the neighborhoods present in Xi'an to explore the relationships of development trends with behaviors and health. In particular, I examine the relationships between the natural and built environments and urban health. In addition, I identify neighborhood-specific factors that public health practitioners and urban planners might target to improve health.

First, I apply land use regression (LUR) methodology and the deletion/substitution/addition (DSA) algorithm to select predictive models and create concentration surfaces for four pollutants: $PM_{2.5}$, NO_2, SO_2, and O_3. The LUR models identified substantial areas of Xi'an that had annual $PM_{2.5}$, SO_2, and NO_2 concentrations exceeding current health standards set by the World Health Organization (WHO), providing more evidence for the potential health risks from ambient air pollution in Chinese cities.

Because consistent and reliable air quality monitoring networks are rarely able to keep pace with urbanization in China, new technologies are needed to complement the existing methods of environmental management in cities. Thus, I also test the validity of a new low cost particulate matter sensor (PUWP) for use in high concentration areas like Xi'an. The PUWP sensor performed well as compared to mature PM monitors and could be used to rapidly screen for air pollution "hotspots" in large areas where setting up extensive monitoring stations is challenging. The analysis also observed a sinusoidal relationship between sensor response and $PM_{2.5}$ concentrations, indicating gradual saturation in the optical sensor's ability to detect ambient concentrations in high PM environments above 300 $\mu g/m^3$.

In addition, I present the results of the cross-sectional socio-behavioral and health survey where I examine the associations between self-reported perceptions of the built environment and quality of life, and assess whether these associations differ across the four types of neighborhoods. Neighborhood built environment was strongly associated with both mental and physical-health related quality of life in the commodity housing neighborhoods (high and low-density). In particular, pedestrian infrastructure, diversity of resources, access to and from the neighborhood, and neighborhood safety had the highest positive associations with increased mental health in the high-density high-rise neighborhoods. In the work-unit neighborhoods, increased access to and from the neighborhood was found to be a significantly associated with both mental and physical health. Pedestrian infrastructure, diversity of neighborhood resources, and esthetics were found to be positively associated with mental health in lane/courtyard neighborhoods.

Finally, results from the LUR analysis are also used in an exposure assessment of ambient air pollution for the 20 surveyed neighborhoods. I examine the role of neighborhood air pollution in modifying the associations between leisure-time physical activity (LTPA) and adverse health impact and quality of life. Neighborhood ambient air pollution is included in health effects models in two ways: 1) categorical single pollutant and 2) categorical mixtures models. Increasing LTPA levels are associated with lower odds of adverse health impacts and higher reported quality of life. However, the health and quality of life benefits of physical activity are potentially lower in areas where ambient $PM_{2.5}$ and O_3 are elevated. In addition, single pollutant models are poor proxies of mixtures of pollutants, which indicate a need for considering multi-pollutant exposures in epidemiological studies.

Collectively, these results suggest the built, natural, and social environments should be considered simultaneously as potential targets of intervention to improve quality of life and health in Chinese cities.

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Chapter 1 Introduction

1.1 OVERVIEW

The combination of rapid economic growth and changing physical landscapes in China is difficult to ignore. Economic development has led to dramatic changes in the physical and social environments of Chinese cities as they expand to accommodate a growing urban population. However, development trends bolstering decentralization of industries, suburbanization, and reliance on motorization raise concerns regarding the ability of the evolving cities to be healthy, sustainable, and equitable. The growing body of evidence supports a need for more health-conscious urban planning. Because more than half the Chinese population now lives in urban areas and this proportion is growing, poor urban planning can have significant downstream effects on quality of life and health by affecting how people live, travel, and access goods and services (Hvistendahl 2011). Although cities, populations, and development trends are distinct from their Western counterparts, analogous environmental quality, justice and health issues are present and should be addressed. In an ever increasingly global economy, these potential public health burdens in one country could have widespread effects.

This dissertation explores the environmental and social issues that urban communities in China are facing today by examining a cross-section of air pollution, socio-behavioral, and health data collected from an adult cohort residing in 20 neighborhoods across Xi'an, China. The exploration of these data provides insights for urban planners, environmental scientists, and public health practitioners.

1.2 BACKGROUND

The acceleration of global urbanization in the last century is one of modern society's defining characteristics. Urbanization refers to the development and expansion of cities through population growth and land use changes from rural to urban. For the first time in human history, the urban population exceeded the rural population in 2007. Recent estimates for 2014 suggest that approximately 54% of the world's population resided in urban areas. Continued population growth and urbanization is expected to add another 2.5 billion people to the urban population with China expected to contribute 11.7% (292 million) of this global growth (United Nations 2014).

1.2.1 History of Urbanization in China

China has led the world's urbanization shift in the past. Over the last 4000 years, China has been one of the primary urbanization regions around the world, and has experienced several urbanization periods (Wu, Xiang, and Zhao 2014; Friedmann 2006). In the early 19th century, Beijing was the largest city in the world, with a population of over 1 million. However, from the 1840s to 1949, China's urban population only grew by 5.5% annually while the global rate, attributed to the Industrial Revolution, was 22.8%. The Opium Wars, foreign invasions, end of Imperial China, and civil wars impeded the political stability and economic growth necessary to shift away from an agriculture-based economy to support urban growth – both in population and land area – in China (Wu, Xiang, and Zhao 2014).

After the creation of the People's Republic of China in 1949, only 58 million (11%) of the 527 million people in China lived in its 69 cities as compared the world's 29% (S. Cao et al. 2014; Bai 2008). From 1949 to 1977, the central Chinese government, viewing cities as centers of production and not consumption, focused on planned economy industrialization and ignored urban development (Friedmann 2006). The city population was organized into work units (单位 *danwei*) and physically, the city became organized around these work units with workers of the same work unit living together in organized communities. As part of the planned economy, migration was also restricted between the urban and rural areas using a household registration system (户口 *hukou*) which dictated where residents could obtain food stamps, education, healthcare, employment, etc. During this period, the economic project, the Great Leap Forward (1958-1961), which led to a famine and economic crisis, and the socio-political Cultural Revolution (1966-1976) also stunted economic and urban growth (Wu, Xiang, and Zhao 2014; Y. Zhou and Ma 2000).

The economic reforms implemented in 1978 by Deng Xiaoping shifted the country to a socialist market economy ("socialism with Chinese characteristics") by allowing foreign direct investments which boosted employment opportunities, decollectivization of agriculture, and permission for a private sector within China (Y. Zhou and Ma 2000). These reforms opened China to the global market and led to a decentralization of the government, continued industrialization, and increased internal migration to cities leading to higher urbanization. This period after 1978 focused on rapid urbanization. Urban areas experienced dramatic growth both in population size and land area as migration rules were loosened and rural areas were relabeled as urban as they became industrialization centers.

At the start of the reforms the late 1970s, only 17.9% of the population lived in its 223 cities. By 1979, a quarter – 969 million - of the world's population was living in China on only 7% of the world's arable land area. The government saw slowing population growth as key to continued economic growth. In 1979, the Chinese government introduced the one child policy to curb population growth by limiting the family size, encouraging late marriage, and controlling childbearing. Despite these restrictions by the 2000 Census, the actual population of 1.27 billion exceeded that of the targeted 1.2 billion goal (Hesketh, Lu, and Xing 2005). By 2011, total population had reached 1.34 billion and urbanization had reached 51.3% (World Bank 2015). While China's urbanization lagged behind the rest of the world's in the early 20th century, by 2050 China is projected to have 77.5% of its population in cities as compared to 67.2% of the rest of the world's population (Wu, Xiang, and Zhao 2014). Currently, 25 of the world's largest 100 cities are in China, all with populations over 2 million (City Mayors 2011) and more than half the population lives in urban areas (National Bureau of Statistics 2011).

1.2.2 Trends in Modern Chinese Cities

Post-2000 urbanization has altered urban form, land use, transportation sectors, and energy consumption in China. With a focus on economic growth as measured through gross domestic product (GDP), emphasis was placed on industries or sectors that would help boost GDP estimates such as real estate development and manufacturing (Bai 2008).

The economic reforms gave more autonomy to local governments, allowed foreign investments to enter and compete in the Chinese markets and also increased competition among domestic state-owned enterprises (SOE). To attract both domestic and foreign investments, local governments created development zones and industrial parks whose construction helped increase local GDP. In 2003, over 3,800 parks were created and this number increased to 6,015 in 2006 (Y. Li 2010). The creation of industrial and technology parks also helped cities expand in size as the parks were built in the urban fringes bordering rural land and grow in population as employment opportunities grew (Pucher et al. 2007). Because local governments controlled the land, additional revenue from land sales to real estate developers became a significant part of a local government's income, with much of the land coming from converting existing farmland to new plots of urban land for development (S. Cao et al. 2014). In extreme cases, governments have leveled mountains to make more land available for urban expansion (Clark 2014).

Recent urbanization has also been strongly tied to changes in transportation. Government support for increasing private vehicle ownership also influenced the form of the new redesigned cities. A few decades ago, China was known as the bicycle kingdom (China Daily 2004) but starting in the 1990s, the car industry in China became a "pillar industry" that would help China industrialize (Kenworthy and Hu 2002). In 2009, China passed the United States and became the world's largest car market, with over 50,000 vehicles sold per day and planning policies became car-centric to accommodate this boom in private vehicle ownership (J. Zhou et al. 2014). As private car ownership increased, China more than doubled its length of roads (Z.-R. Peng, Zhu, and Song 2006), while bicycle lanes were converted to parking or eliminated as roads were widened to accommodate increased vehicular traffic (Schipper 2006). However, car ownership rates are still lower than that in the US (69 versus 786 cars every 1,000 persons in 2011) (The World Bank 2011).

Urbanization has also profoundly changed energy consumption patterns in residential households. From 1980 to 2011, urban residential energy consumption (REC) more than tripled from 110.2 to 374.1 million tons coal equivalent (Mtce) when urbanization increased 2.6 times to 51.3% of the population. REC of coal decreased to 8% over this period while petroleum was the fastest growing fuel type in residential households, as motorization increased (Qiang Wang 2014). Construction of new residential and commercial buildings and urban infrastructure in cities also increased industrial energy consumption, primarily by the energy-intensive steel and cement industries that manufacture products used in construction. From 1991 to 2005, output from cement and steel industries grew at annual rates averaging 11% and 12%, respectively (W. Zhou et al. 2012). Increased energy consumption is directly affecting the natural environment by increasing emissions of air pollutions and greenhouse gases, which have significant implications for urban health.

1.2.3 Public Health Issues in Chinese Cities

As with many developing economies, China has made substantial public health improvements by decreasing infant mortality and limiting the spread of communicable diseases through improved infrastructure, healthcare, and sanitation. The life expectancy of men and women increased from 60.4 and 63.5 years, respectively, in 1970 to 72.9 and 79.0 years, respectively, in 2010 (G. Yang et al. 2013a). However, the current wave of urbanization in China has raised some concerns for creating healthy and sustainable cities. Several public health issues are especially pressing:

Increasing Chronic Disease

While urbanization increases access to healthcare, rising household incomes and longer lifespans of urban populations are changing China's health profile through exposure to environmental risk factors such as ambient air pollution and behavior risks factors such as smoking, poor diet (increased consumption of sugar and salt), and a more sedentary lifestyle, which all can contribute to non-communicable diseases (NCD) (G. Yang et al. 2013b; The World Bank Human Development Unit 2011). The prevalence of NCD is increasing in China, especially in urban areas. Of the 8.2 million deaths per year in China, about 7 million are due to non-communicable diseases. The leading causes of death are stroke, ischemic heart disease, and chronic obstructive pulmonary disease (Yuanli Liu et al. 2013). NCDs also contribute almost 70% of the total disease burden with 50% of the burden occurring in people under 65 (The World Bank Human Development Unit 2011). Diabetes prevalence has increased from 0.67% in the 1980s to 9.7% in 2008. With about 200 million people estimated to be overweight or obese, overweight and obesity prevalence reached 22.8% and 7.1%, respectively, in the population in 2002 (The World Bank Human Development Unit 2011).

Changing Social Environments

Rapid economic growth has also led to significant changes in social relationships. With increased mobility and the shift away from the relative stability of the work-unit communities into new commodity housing high-rise neighborhoods, even residents of the same neighborhoods are frequently distrustful of one another (Hazelzet and Wissink 2012). In 2012, trust among people was a record low with only 30% saying strangers can be trusted (J. Wang and Yang 2013).

China's Gini coefficient, a measure of income inequality, is estimated to be 0.53-0.55, higher than that in the United States, despite having low income inequality up until the late 1980s (Xie and Zhou 2014). This shift is partly attributed to regional disparities, as economic development started earlier along the geographically accessible and densely populated coastal region; and partly attributed to the rural-urban divide in the population. Urban residents, who have access to better educational and employment opportunities, broader social networks and are more socially mobile, had incomes that were 45 times that of rural residents in 2011. Even in cities, this income disparity persists where urban *hukou* residents on average make 1.3 times than of their rural *hukou* counterparts living in the same city (Démurger et al. 2009). Further, 95% of China's total wealth belongs to only 5% of its population (S. Cao et al. 2014). The widening income gap and concentrated wealth have serious implications for happiness, social cohesion, trust, crime, and social stability across the country (C. Wang, Wan, and Yang 2014).

Widening Social Inequities

Economic development, while improving living standards and quality of life for the population as a whole, has also created marginalized groups in China. As labor demands increased in the cities, restrictions placed on rural residents were loosened to allow rural to urban migration. From 1978 to 2004, an estimated 300 million rural residents migrated to cities (Y. Li 2010). Migrant workers are relatively young, predominantly male, and poorly educated (L. Shi 2008a). Because of their low educational attainment, migrant workers often accept undesirable manual jobs that permanent urban residents avoid.

Migrant workers also face social stigmas, exploitation, and discrimination due to their *hukou* status (Human Rights Watch 2008). A migrant worker's wages can be a quarter of that of local urban workers; they often work seven days a week and work more hours per day than urban residents (L. Shi 2008a). Long hours, stressful work conditions, and low pay increase the vulnerability of this group to experiencing higher health risks. In addition, surveys have shown migrants are less aware of and have less access to social and health services in the cities (L. Shi 2008a). They often live in urban villages[1] (城中村*cheng zhong cun*) where low-cost housing exists (Y. Li 2010). Migrant workers, along with the urban poor, could be further marginalized through inequitable development.

Worsening Air Pollution

Decentralized cities and growth in vehicle ownership are major contributors to China's poor air quality. The "getting rich first" approach prioritized economic development at the expense of environmental degradation (C. Fan 2010). Twenty of the thirty most polluted cities around the world are in China with annual concentrations of SO_2 (50 µg/m^3) and PM_{10} (30-200 µg/m^3) exceeding both World Health Organization (WHO) and US Environmental Protection Agency's (EPA) air quality guidelines (HEI 2010). However, China's current air quality guidelines, although acceptable limits have been lowered since they were first set in 1989, are usually more lenient than those set by the U.S. EPA and WHO in part to account for its status as an industrializing country (Fang, Chan, and Yao 2009). Growing car ownership also increased emissions of nitrous oxides (NO_x), particulate matter (PM), black carbon (BC), and carbon monoxide (CO) in cities (Vennemo et al. 2009; He, Huo, and Zhang 2002).

China's asthma prevalence increased 40% from 2000 to 2005 and has been attributed to worsening environmental conditions from economic development (Watts 2006). Epidemiology studies in China found health effect estimates similar to those in Western populations (HEI, 2010). Short-term exposures to $PM_{2.5}$ were found to be significantly associated with increased rate of mortality: 0.37% increase in total mortality, 0.51% in respiratory mortality, 0.44% in cardiovascular mortality, for every 10 µg/m^3 increase in $PM_{2.5}$ (Shang et al. 2013). Chinese populations of lower socioeconomic status face higher health risks from air pollution, hinting at disproportionate burdens of air pollution risks on already disadvantaged populations (Haidong Kan et al. 2008).

[1] Urban villages are previously rural villages surrounding the periphery of the city whose administrative classification was changed from "rural" to "urban" as the land was expropriated for urban expansion. However, the villagers retain their residential areas/housing which prevents the need for relocation (Liu et al. 2010)

1.3 RESEARCH OBJECTIVES

My research aims to better understand the current status of the built environment, human behaviors, social interactions, and air quality, and their associations with health indicators in an urban Chinese urban population.

Specific objectives include the following:

1. Quantify spatial and seasonal patterns in $PM_{2.5}$, NO_2, ozone (O_3), and SO_2 across the six urban districts of Xi'an, China. (Chapter 2)
2. Calibrate and validate a new low cost particulate matter sensor alongside mature $PM_{2.5}$ monitors to determine if the low cost sensor can provide additional information that can be used for human health exposure assessment. (Chapter 3)
3. Assess the associations between residential neighborhood built environment and health-related quality of life (HRQOL) across four types of urban neighborhoods. (Chapter 4)
4. Assess how multi-pollutant exposures modify the associations between leisure-time physical activity levels and adverse health impacts and health-related quality of life (HRQOL) across four types of urban neighborhoods. (Chapter 5)

1.4 STUDY SITE

The research presented in the following chapters relies on primary data collected from Xi'an, China in 2013. As the capital of Shaanxi province with almost 8.1 million residents and an average gross domestic product growth above 10% every year since 2000, Xi'an is a sub-provincial city in central China and a major city in the expansion and development of central and western China (Statistical Bureau of Shaanxi Province 2010). Xi'an also has one of the worst air pollution records in China (HEI 2010) driven by a heavy reliance on coal burning and coal mining industries, development projects, unique topography, and environmental conditions for accumulation of air pollutants (J. Cao 2014).

Chapter 2 Development of Multi-Pollutant Air Quality Maps

2.1 OVERVIEW

This chapter models the spatial variability of air pollutants ($PM_{2.5}$, NO_2, O_3, and SO_2) across Xi'an, China and assesses the feasibility of using land-use regression to understand city-wide air quality and exposures in large cities. Results from this chapter will be used in approximating exposure to air pollutants in the population of adults surveyed within 20 neighborhoods.

2.2 BACKGROUND

2.2.1 China's urban air quality problems

The rise in China's environmental problems correlates with its economic development trajectory. The economic reforms that began in 1978 had a goal of modernizing China's primarily agricultural economy by strengthening industry, agriculture, national defense, and science and technology (Xu 2011). As a result, from 1978 to the early 2000s, China's economy grew at an unprecedented annual rate of 11.4% or more (H. Shi and Zhang 2006). While improving the quality of life for millions of Chinese, economic development also intensified fossil fuel consumption and pollutant emissions.

Although China's Environmental Protection Leadership Group (now the Ministry of Environmental Protection), created in 1973, was able to slow down the environmental degradation stemming from the rapid growth in the last three decades, industry continues to be a major emitter of sulfur oxides (SO_x), nitrogen oxides (NO_x), carbon dioxide (CO_2), and particulate matter (PM) as energy consumption increases (H. Shi and Zhang 2006). Coal remains China's main energy source and in 2012, China accounted for 50% of the world's total coal consumption (Z. Chen et al. 2013). Cities are growing larger in both population and size leading to increased infrastructure and real estate development. A growing and motorizing middle class is also changing consumption patterns of both goods produced and energy consumed (Haidong Kan, Chen, and Tong 2012).

In 2010 as a result of the government's emphasis on installing emission control technologies, SO_2 emissions were estimated to be 11 to 14% lower than levels in 2005 (Y. Zhao, Zhang, and Nielsen 2013; S. Wang and Hao 2012). NO_x controls, however, still lagged behind in implementation and emissions grew with construction of new power plants and increased motorization. From 2000 to 2010, NO_x emissions from power plants doubled while that from the transportation sector tripled (S. Wang and Hao 2012). With increasing emissions of ozone precursors such as NO_x and volatile organic compounds (VOCs), increasing tropospheric ozone formation has been observed in both cities and rural areas where concentrations have exceeded health guidelines (S. Wang and Hao 2012).

China also has one of the highest $PM_{2.5}$ levels in the world (van Donkelaar et al. 2010) but both PM_{10} and $PM_{2.5}$ emissions have steadily decreased over the last decade with increased use of emission control technologies (Cheng et al. 2013; Y. Zhao, Zhang, and Nielsen 2013; B. Zhao et al. 2013). In general, northern parts of China have higher levels of PM than in the south because of increased coal use, especially in the winter for heating (Cheng et al. 2013; Haidong Kan, Chen, and Tong 2012). Cities like Beijing and Xi'an in the arid and semiarid northern regions also experience dust events with increasing frequency in the spring that reduce visibility, increase air pollution, and increase soil erosion. Desertification from cropland expansion has contributed to this phenomenon (Y. Chen, Cai, and Tang 2003).

Stricter ambient and emission standards, adoption of cleaner fuels, relocation of polluting industries, and land-use rezoning efforts have led to some improvements in air quality in Chinese cities, as the decreases in SO_2 and PM10 levels have demonstrated (Z. Chen et al. 2013; Haidong Kan, Chen, and Tong 2012). However, the Ministry of Environmental Protection (MEP) is frequently unable to provide sufficient monitoring to ensure compliance across the country (Junfeng Zhang et al. 2010). Therefore, China still ranks as one of the countries with the worst air pollution as continued economic development competes with a growing concern for environmental protection.

2.2.2 Public health relevance of air pollution

Ambient air pollution is a growing health burden for China's population of 1.35 billion. The 2010 Global Burden of Disease has listed $PM_{2.5}$ as the country's fourth largest health risk (Cheng et al. 2013), resulting in an estimated 1.2 million premature deaths in 2010 (G. Yang et al. 2013b). Of the air pollutants in the atmosphere, four are of interest in this study: $PM_{2.5}$, NO_2, SO_2, and O_3.

Particulate matter (PM), liquid and solid particles suspended in the air, can be emitted directly (primary pollutant) or formed in the atmosphere (secondary pollutant). Anthropogenic sources include soot generated from fuel combustion. Secondary PM can form in the atmosphere through reactions of NO_x, VOCs, SO_x, and ammonia (NH_3). The spatial variability of PM depends on its aerodynamic diameter with ultrafine (PM_1) and coarse ($PM_{2.5\text{-}10}$) particles having greater spatial variability since they tend to aggregate into larger particles or deposit out of the atmosphere while fine particles ($PM_{2.5}$) will remain suspended longer and have less spatial variability. $PM_{2.5}$ sources include gasoline and diesel engines, biomass burning, and secondary formation through gaseous precursors.

Nitrogen dioxide (NO_2), a component of NO_x, is monitored as a gaseous marker for combustion of fossil fuels in stationary sources (e.g., power generation) and in motor vehicles (internal combustion engines). NO_2 is mostly converted from primary nitric oxide (NO) emissions in the atmosphere and is a major source of tropospheric ozone. NO_2 has greater spatial variability than other pollutants because of its chemical reactivity in the atmosphere, and geographical distribution of local sources that in urban areas are major roadways. Ozone (O_3) is a secondary gaseous pollutant generated in the troposphere from reactions of NO_x with VOCs and light. Spatial variability within cities can be high as it is chemically reactive with traffic emissions. Because of reliance on ultraviolet light and temperature, ozone levels generally are lower in the winter. Sulfur dioxide (SO_2) is primarily emitted during combustion of fossil fuel combustion for energy production or industrial processes although it can also be a marker of diesel combustion in vehicles.

A substantial body of evidence links exposure to $PM_{2.5}$ to adverse acute and chronic health outcomes, in particular to the respiratory and cardiovascular systems. $PM_{2.5}$ exposure has been found to be associated with increased hospital admissions (Atkinson et al. 2014; Bell et al. 2013; R. D. Peng et al. 2009; Ostro et al. 2009; A Zanobetti, Schwartz, and Dockery 2000), decreased lung function (Adam et al. 2015; Rice et al. 2015), preterm birth (Fleischer et al. 2014; Stieb et al. 2012), and premature mortality (Atkinson et al. 2011; Evans et al. 2013; Laden et al. 2006; Jerrett, Burnett, et al. 2005; Dockery et al. 1993). These impacts on health have been shown to be consistent across geographic areas in both developing and developed countries with no signs of a safe threshold of $PM_{2.5}$ exposure. NO_2 is frequently used as a marker for the complex mixture of pollutants from combustion in epidemiological studies. Therefore disentangling the effects of NO_2 alone is challenging. NO_2 exposure has been shown to increase the incidence of and exacerbate asthma, decrease lung function, although mixed results were found with total and cardiovascular mortality (Weinmayr et al. 2009; McCreanor et al. 2007; Samoli et al. 2006; McConnell et al. 2003). Exposure to a respiratory tract irritant, SO_2, can increase airway resistance, cough, and decrease lung function (Johns and Linn 2011); the effects of long term ambient exposure are not as clear as the effects of SO_2 are difficult to disentangle from that of PM (World Health Organization 2005). Increases in ambient O_3 have been associated with short term increased hospital admissions, exacerbated asthma symptoms, decreased lung function, and mortality (Jerrett et al. 2009; Weschler 2006; Ito, De Leon, and Lippmann 2005; Hubbell et al. 2005).

Because of the body of evidence linking these pollutants to adverse health effects, the United States Environmental Protection Agency (US EPA), China's Ministry of Environmental Protection (MEP), and the World Health Organization (WHO) have set ambient air quality standards for these pollutant (Table 2-1), in addition to others, to protect public health. The US EPA and the WHO's standards are called the National Ambient Air Quality Standards (NAAQS) and Air Quality Guidelines (AQG), respectively. China's most recent Ambient Air Quality Standards, GB 3095-2012, were updated in February 2012 and included the first $PM_{2.5}$ standards for China.

Table 2-1 Comparison of regulatory standards for ambient NO_2, $PM_{2.5}$, SO_2, and O_3 set by US EPA, China MEP, and the WHO

	Averaging Time	Unit[1]	US EPA[2]	China MEP[3]	WHO
NO_2	Annual	ppb	53	21	21
	1 hour	ppb	100	106	106
$PM_{2.5}$	Annual	µg/m^3	12	35	10
	24 hour	µg/m3	35	75	25
SO_2	24 hour	ppb	--	57	8
	1 hour	ppb	75	23	--
O_3	8 hour	ppb	75	80	50

[1]Mass concentrations (µg/m^3) converted to ppb using following conversion factors for NO_2, SO_2, and O_3: 1.88, 2.62, and 2.00 µg/m^3 per ppb, respectively
[2]Primary standards to protect public health
[3]Grade II standards for Residential, Commercial, Industrial, and Rural Areas

2.2.3 Air quality in Xi'an, China

Xi'an has one of the worst air pollution records in China (HEI 2010). From 2003 to 2013, the annual average $PM_{2.5}$ concentration of 167 µg/m^3 was 4.8 times China's annual standard (35 µg/m3), 14 times U.S. EPA's annual average standard (12 µg/m^3), and 17 times WHO's standard (10 µg/m^3) (J. Cao 2014). From 2004 to 2012, Xi'an remained below China's daily $PM_{2.5}$ standard (75 µg/m^3) only 11.6% of the time. Although annual $PM_{2.5}$ levels have decreased over the last decade from 192.5 to 158.1 µg/m^3, Xi'an air pollution problems are exacerbated by terrain and meteorology, reliance on coal burning, urban growth, and increased motorization. Xi'an's location in the Yellow River Basin, low wind speeds (45% of the time in the winter with no wind), and little precipitation in the winter exacerbates air quality issues by limiting natural dispersion of pollutants (J. Cao 2014).

Xi'an has 13 government monitoring stations within the six urban districts that are home to over 8 million residents. In addition to a limited number of continuous monitoring sites covering a total area of over 800 km^2, obtaining data from government operated monitoring sites is bureaucratically challenging. Daily air quality indices (AQI) are available online but to convert AQI values to mass concentrations, additional data are required. Because of data access and spatial resolution issues, fast and affordable methods of exposure assessment are desirable to help collect these data and understand spatial variability of air pollutants in Xi'an.

2.2.4 Land-use regression (LUR)

Air pollution epidemiology studies have relied on various methods to assess a person's or a group's exposure to air pollution (Jerrett, Arain, et al. 2005). While these range in complexity in data requirements and analysis, land-use regression (LUR) was chosen for this study based on the types of data and resources available. Land-use regression incorporates actual air pollution measurement data but estimates concentrations at unsampled locations (Y) using surrounding site information including population density, traffic volumes, roads, and land use type (X) within zones of influence (buffers of varying distances) around the location of interest (Briggs et al. 1997). An assumption of these models is these land use factors are surrogates for air pollution sources of concern, and hence, to some degree can explain nearby air pollutant concentrations. These multivariate regression models can then be applied to the area of interest to predict concentration surfaces.

LUR has been used to model pollutants including VOCS, NO_2, PM, SO_2, and O_3 over cities, states, or countries. Data from existing monitoring networks can be used to create the models or short-term sampling conducting at 20 to 100 sites can be used in areas with low spatial resolution or poor monitoring. LUR models have a wide range of abilities to predict pollutant concentrations with coefficient of determination (R^2) ranging from approximately 0.50 to 0.90, depending on pollutant type, size of study area, and density of empirical data sites (Beelen et al. 2013; Hoek et al. 2008).

While the reliance on empirical data is a major strength, these models are limited by their ability to extrapolate pollutant concentrations in areas with vastly different land use, population, and sources, as compared to the one upon which the original model was built. Generally, models created for one site cannot be directly applied to another location that has different air pollution sources and land use patterns. In addition, because of the reliance on short term sampling or monitoring data, LUR models only provide limited information about temporal variations in pollutants. Sampling usually occurs during time periods determined to best estimate the annual average concentrations (e.g., during heating and non-heating periods) but information about diurnal trends or more temporally resolved trends are not available. Finally, LUR models are unable to provide definitive information linking specific sources to predicted pollutant levels at a site of interest. Despite these limitations, LUR modeling can still be a useful approach to rapidly assess environmental exposures over large areas when data are too limited for more complex atmospheric transport and dispersion modeling and the existing monitoring network is sparse.

2.3 MATERIALS AND METHODS

2.3.1 Sampling Location Determination

The study area covers the central parts of the densely populated areas of Xi'an (833 km^2), mostly within the 3rd Ring Road surrounding the city (Figure 2-1). At the start of this study, the Xi'an municipal government operated 13 monitoring sites that provide publicly available daily Air Quality Indices (AQI) for NO_2, SO_2, and PM_{10} within the 6 districts (Xi'an Environmental Protection Bureau 2015). However due to the limited number of sites and difficult in obtaining data or access to these monitoring stations, a short-term sampling network was deployed in Xi'an to capture higher resolution air pollution data for gaseous pollutants (NO_2, O_3, and SO_2) and $PM_{2.5}$.

The sampling periods for summer and winter seasons were determined by the availability of equipment borrowed from IEECAS collaborators in Xi'an. We also tried to identify days of low precipitation and avoided holidays where ambient pollution patterns would not be representative of typical situations. Because detailed historical air quality data for Xi'an were unavailable and we did not want to bias sampling based on any a priori models of spatial variations in air pollutant concentrations, using existing quantitative methods to determine sampler allocation spatially to capture maximum variability in concentrations were infeasible (J G Su, Jerrett, and Beckerman 2009; Jason G Su et al. 2009; Kanaroglou et al. 2005). Instead, the study sites were chosen in an attempt to capture variability based on knowledge of Xi'an's sources, population of interest, and pollutant behaviors.

Six categories of sites were identified: background, near road, industrial, commercial, residential, and academic/government. With the assistance of local collaborators at Chinese Academy of Science's Institute for Earth Environment (IEECAS), potential sites were identified within each category across Xi'an. The sites were chosen where equipment could be placed unobstructed with minimal theft and vandalism risks and access by researchers was permitted. While collocation with the existing government network would have been ideal, obtaining the necessary approvals was difficult. Therefore, data from the thirteen government operated monitoring sites were not included in the analysis.

2.3.2 Measurement and Analysis Methods

NO_2, O_3, and SO_2 Sampling

Time-integrated concentrations of NO_2, O_3, and SO_2 were measured using passive samplers (Ogawa & Co., USA) for two campaigns from June 7 to June 23, 2013 and from December 2 to December 16, 2013 to capture heating and non-heating seasons. In the summer, Ogawa samples collected one week (7 day) samples for each pollutant, resulting in two samples per gas species per site during the two week campaign. In the winter, because concentrations were expected to be higher and saturation of the sampling pads was a concern, sampling durations were shorter for each sample. Three samples per pollutant per site were collected during the two week winter campaign. Sampling durations were four (December 2 to 6, 2013), five (December 6 to 11, 2013), and five (December 11 to 16, 2013) days at each site.

A total of 34 sites were sampled but in the winter campaign, two sites were lost due to problems accessing the sites by the researchers. Number of sampling sites, durations, and timing of sampling campaigns are comparable to that of other LUR studies (Hoek et al. 2008). Seven duplicates and six blanks were also collected every week with each batch of samples. Blanks filters were prepared with the samples and remained inside their traveling containers and bags provided by Ogawa & Co. during the sampling periods. Site locations were confirmed with a global positioning system (GPS) device (Garmin GPSMAP 62SC). Each sampling site contained an Ogawa pad for each pollutant. Loaded samplers were protected with covers from weather while allowing for sufficient airflow. Samplers were placed 2 to 4 floors above street level to minimize vandalism. Meteorological data were collected from IEECAS. Ogawa samples were analyzed according to standard protocols using colorimetry and ion chromatography (Ogawa & Co., USA, Inc. 2006; Ogawa & Co., USA, Inc. 2001).

The mean of the blank Ogawa filters was subtracted from the samples. Each batch of samples analyzed contained at least 3 blank samples. The time-integrated Ogawa samples for each season were averaged to represent the seasonal average for summer and winter. The seasonal averages were averaged to calculate the annual concentration for each pollutant.

$PM_{2.5}$ Sampling

Daily (24 hour) filter samples of $PM_{2.5}$ were collected using mini-volume (MiniVol) samplers (Airmetrics, Oregon, USA) at 19 sites that also contained Ogawa samplers. Summer sampling ran from June 7, 2013 to June 23, 2013. Winter sampling ran from December 2, 2013 to December 16, 2013. Because of large distances between sampling sites, a local person for 17 of the 19 the MiniVol sites was trained to change the filter each morning between 8am and 10am. MiniVol samplers operated with flow rates of 5 L/min. MiniVols had been calibrated prior to deployment.

$PM_{2.5}$ filters from the MiniVols were analyzed by IEECAS staff. $PM_{2.5}$ filters (47 mm Whatman quartz microfiber) were pre-heated at 900°C for three hours before sampling to remove carbon contamination. Exposed filters were stored in a 4°C refrigerator before analysis to minimize evaporation of volatile components. All pre- and post-sampling filters were weighed using a Sartorius MC5 electronic microbalance with ±1ug sensitivity. Filters were reweighed until the differences between replicate weights were less than 20ug and less than 10ug for samples and for blanks, respectively. Replicate weights were then averaged to represent the pre- and post-sampling mass of the filters. Mass concentrations were calculated from dividing the net change in mass by the total volumetric flow during the sampling time of each filter.

2.3.3 Predictive Model Selection

Spatial Covariates

Independent covariates used for prediction models included land use, population density, and road length within circular buffers of varying distances from each sampling point (Table 2-2). Population data were obtained from the 2010 Census. Because NO_2 is a key component in O_3 formation, NO_2 concentrations were included as a covariate in the annual and seasonal O_3 models. Road types were obtained from a commercially purchased road network map of Xi'an (2011). Roads were categorized into the following: highways, axis, major, and city. Highways included provincial highways and the 3rd Ring Road. Axis roads included the first and second Ring Roads and the major north-south and east-west corridors. Major roads were roads that comprised the majority of the urban grid-like network. City roads were smaller roads that connected sections of major roads or were dead end roads.

Because land use data for Xi'an was not available, greenness, wetness, and brightness measures were used (Jason G Su et al. 2009). Landsat Enhanced Thematic Mapper Plus (ETM+) imagery (spatial resolution 30m) from USGS (June 2010) was downloaded which provided six bands (1, 2, 3, 4, 5, and 7). Using a linear transformation, these six bands were summed after multiplying with the appropriate coefficients to calculate greenness, brightness, and wetness (Table 2-3). Brightness is associated with bare soil and man-made and natural features like concrete, gravel, and asphalt. Greenness is associated with green vegetation and wetness is associated with water bodies, soil moisture, and other moist features. The arithmetic mean of the layer's values within each buffer around the sampling point resulting layer was used as covariates.[2]

Population density data were obtained from the 2010 Census. Because population density data were only available down to the district level, population density within each buffer was estimating based on relative area of "urban areas" within each buffer. To calculate the percentage of each buffer that is urban versus non-urban, "Image Classification" in Spatial Analyst was used to classify base map imagery according to urban versus non-urban land use based on a training dataset. For instance, if only 50% of the area of a buffer was considered urban, the population density of that district that the buffer falls within would be halved. Creation of data layers for the covariates was completed in ArcGIS 10.2 and QGIS 4.2.0.

Predictive Model Selection and Cross-Validation

A 10-fold deletion/substitution/addition (DSA) algorithm was used for selecting predictive models for $PM_{2.5}$, NO_2, SO_2, and O_3 (S. E. Sinisi and M. J. van der Laan 2014; Haight et al. 2010). The DSA algorithm first divides the full dataset into training and validation datasets. Using the training dataset, DSA builds a model space comprised of subspaces where each one

[2] Because the Zonal Statistics python tool in ArcGIS 10.2 doesn't allow for overlapping polygons, QGIS 2.4.0 software was used for portions of this analysis.

represents different combinations of model size and complexity, based on user-specified constraints. This model space approximates the entire set of potential model forms available to fit the dataset. DSA selects the “best” model form for each type of model complexity by minimizing empirical risk. To prevent overfitting the data (i.e., largest and most complex models would always be selected), cross validation is also used to determine model fit and selection. The models selected using the training data are now applied to the validation data to test robustness. The cross-validation risk (CV risk), average residual between observed and predicted values by the models, is calculated for each model. This process is repeated for each division (v-folds) of the full data set into training and validation. The model complexity that has the lowest average CV risk over the total number of training datasets is chosen as the final model form to apply to the full dataset.

The constraints for the DSA algorithm in this study are the following:

1. Base form only includes an intercept. No covariates will be forced into the final model.
2. Maximum of 10 terms (excluding intercept) allowed in final model.
3. No interactions are allowed.
4. Terms are only allowed raised to the power of 1.

These constraints were chosen to provide the model sufficient room to test different model forms (i.e., allowed up to 10 terms as covariates) and limit bias by forcing covariates into the final model without making the results difficult to interpret. We limited the number of interactions in the model to allow for ease of interpreting results, although future models may include interaction terms and polynomial terms to improve prediction. The DSA algorithm was run at least five times per pollutant with a different random seed number to determine how the dataset will be split into 10 parts. If the same final model form is not selected 3 out of the 5 runs, more runs are completed with different random seeds until the algorithm converges upon a final model form. The coefficient of determination (R^2) was reported as a measure of the model’s goodness of fit. Model selection using the DSA algorithm and cross validation were completed using R 3.1.2 software.

2.3.4 Prediction Map Creation

After the models have been selected by DSA and cross-validated, the resulting model forms are applied to data layers to predict concentrations of each pollutant for a 30 by 30m grid across the 6 urban districts of Xi’an. Creation of air pollution surfaces was completed in ArcGIS 10.2 and QGIS 4.2.0.

Table 2-2 Land-use regression covariates

Variable	Description	Buffer Distance (m)
Land-use Category		
Greenness	Green vegetation	
Wetness	Water, soil moisture	
Brightness	Bare soil, man-made surfaces (asphalt, concrete)	
Road Length (m)		100, 250, 500, 750, 1000, 1500, 2000, 3000
Highway	3rd ring road, roads connecting 3rd ring to 2nd ring road	
Major Roads	Contains majority of vehicular traffic	
Axis	1st and 2nd ring roads, two roads (E-W and N-S) that divide Xi'an into four quadrants	
City	Less-trafficked minor roads (often dead end streets)	
Population Density	Number of people/km^2	

Table 2-3 Coefficients for the linear transformation of Landsat ETM+ bands

	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Greenness	-0.2848	-0.2435	-0.5436	0.7243	0.0840	-0.1800
Brightness	0.3037	0.2793	0.4343	0.5585	0.5082	0.1863
Wetness	0.1509	0.1793	0.3299	0.3406	-0.7112	-0.4572

2.4 RESULTS

2.4.1 Descriptive Analysis: Sites, Meteorology, and Mass Concentrations

Thirty-four sites were selected (Figure 2-1). Site descriptions are available in Appendix A. We had to rely on social connections to find safe and accessible sites. The sites skewed towards residential sites but we tried to capture residential areas with different environments: villages, old neighborhoods, and new high-rises. Academic institutions, commercial areas, and public sites were also selected.

Ambient temperatures were lower in the winter while relative humidity was approximately the same in both seasons. During the summer campaign, average temperatures and relative humidity (RH) were 25°C (range: 18 to 33°C) and 60% (range: 44 to 88%), respectively. During the winter campaign, average temperatures and relative humidity (RH) were 2°C (range: 0 to 6°C) and 58% (range: 41 to 72%), respectively. Pollutant concentrations were higher in the winter than in the summer for all pollutants except for ozone (Figure 2-2). City-wide mean NO_2, SO_2, and $PM_{2.5}$ concentrations were 2.5, 5.8, 2.4 times higher, respectively, in the winter than in the summer. Mean winter O_3 levels were 6.0 times lower than in the summer. Across the 19 $PM_{2.5}$ sites, $PM_{2.5}$ mass concentration ranges were wider in the winter (Figure 2-3).

The concentration differences between duplicate samples of NO_2, SO_2, and O_3 collected at 7 sites averaged 4.7, 22.1, and 16.1%, respectively, for both seasons. Correlations between pollutants were generally small (Figure 2-4). The strongest Pearson's correlation in the summer was between NO_2 and O_3 (r= -0.61), between O_3 and SO_2 (r = -0.50), and between NO_2 and SO_2 (r = 0.45). The strongest winter correlations were between SO_2 and O_3 (r = 0.50) and between NO_2 and SO_2 (r = 0.32). The Pearson correlations for the predictive covariates are shown in Figure 2-5. There are strong negative associations between population density and brightness variables, between wetness and brightness, and between all roads and brightness. Brightness is associated with road layers except for the highway layers. Because of the limited number of sites spread out over the large area, spatial autocorrelation, as measuring using Moran's I, was only seen in the summer SO_2 data (p = 0.006) at the 0.05 significance level.

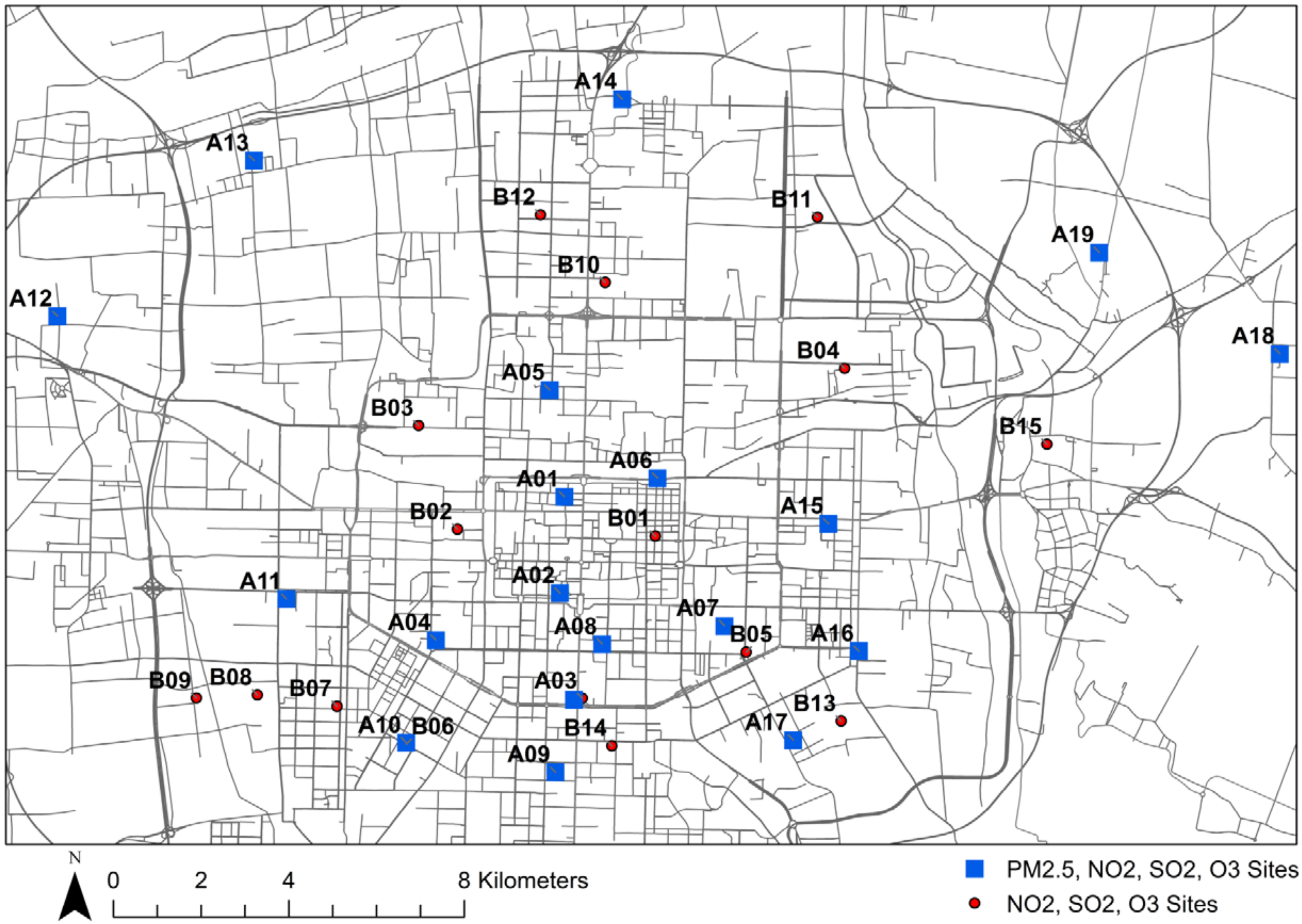

Figure 2-1 Map of air pollution sampling sites in Xi'an, China

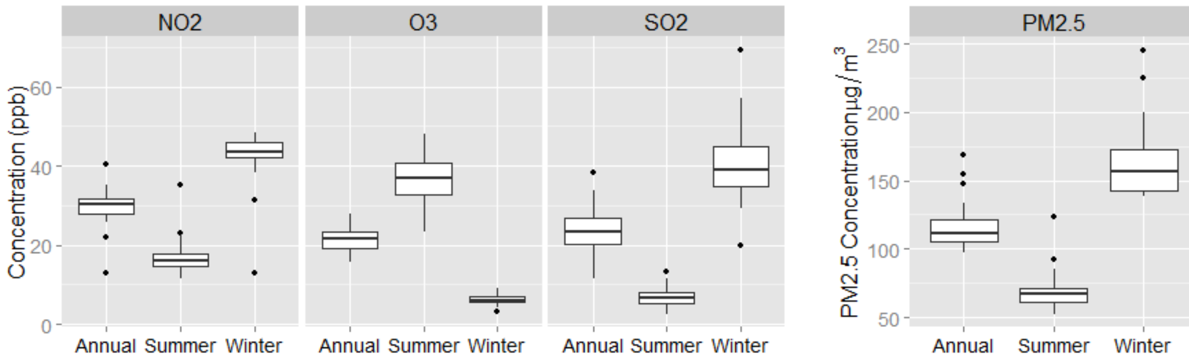

Figure 2-2 Boxplots of seasonal and annual NO_2, O_3, SO_2, and $PM_{2.5}$ concentrations

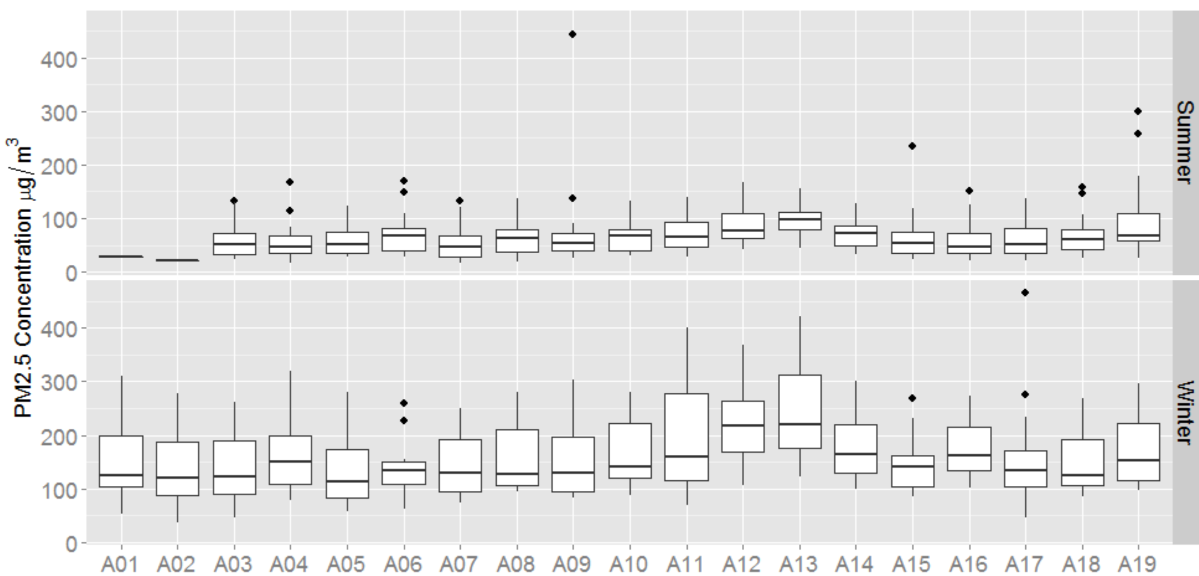

Figure 2-3 Distributions of summer and winter $PM_{2.5}$ concentrations by site

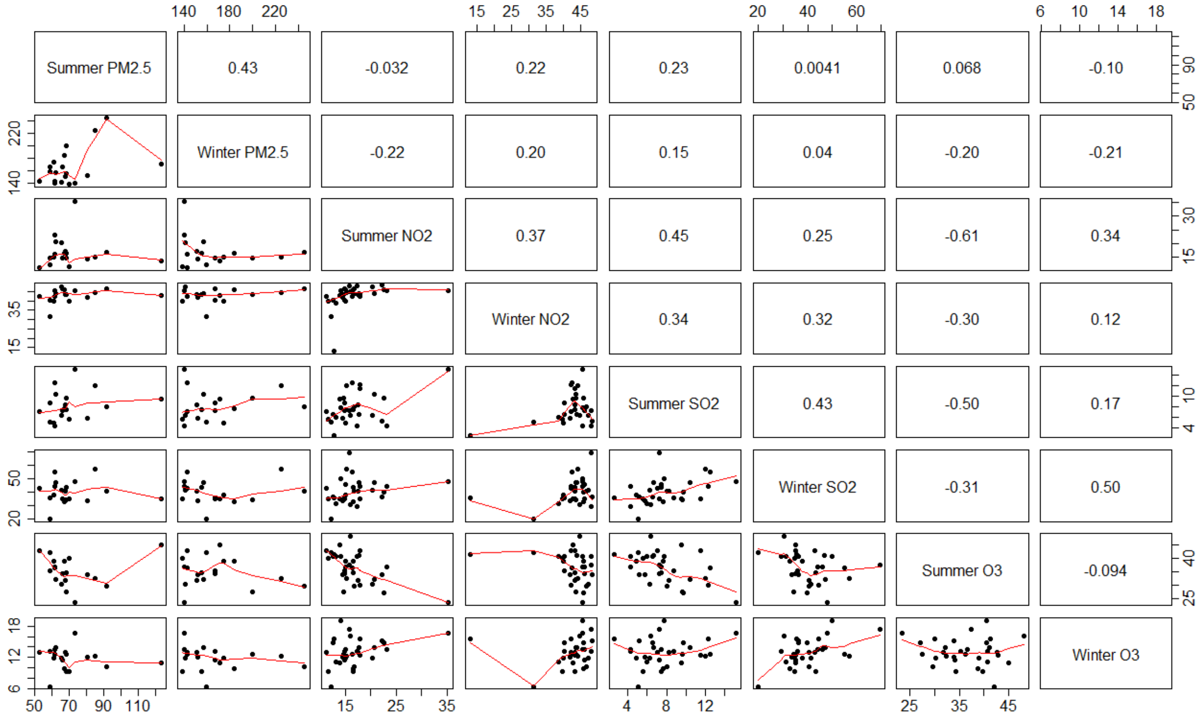

Figure 2-4 Pairwise correlations among summer and winter $PM_{2.5}$ ($\mu g/m^3$), NO_2, SO_2, and O_3 (ppb) concentrations

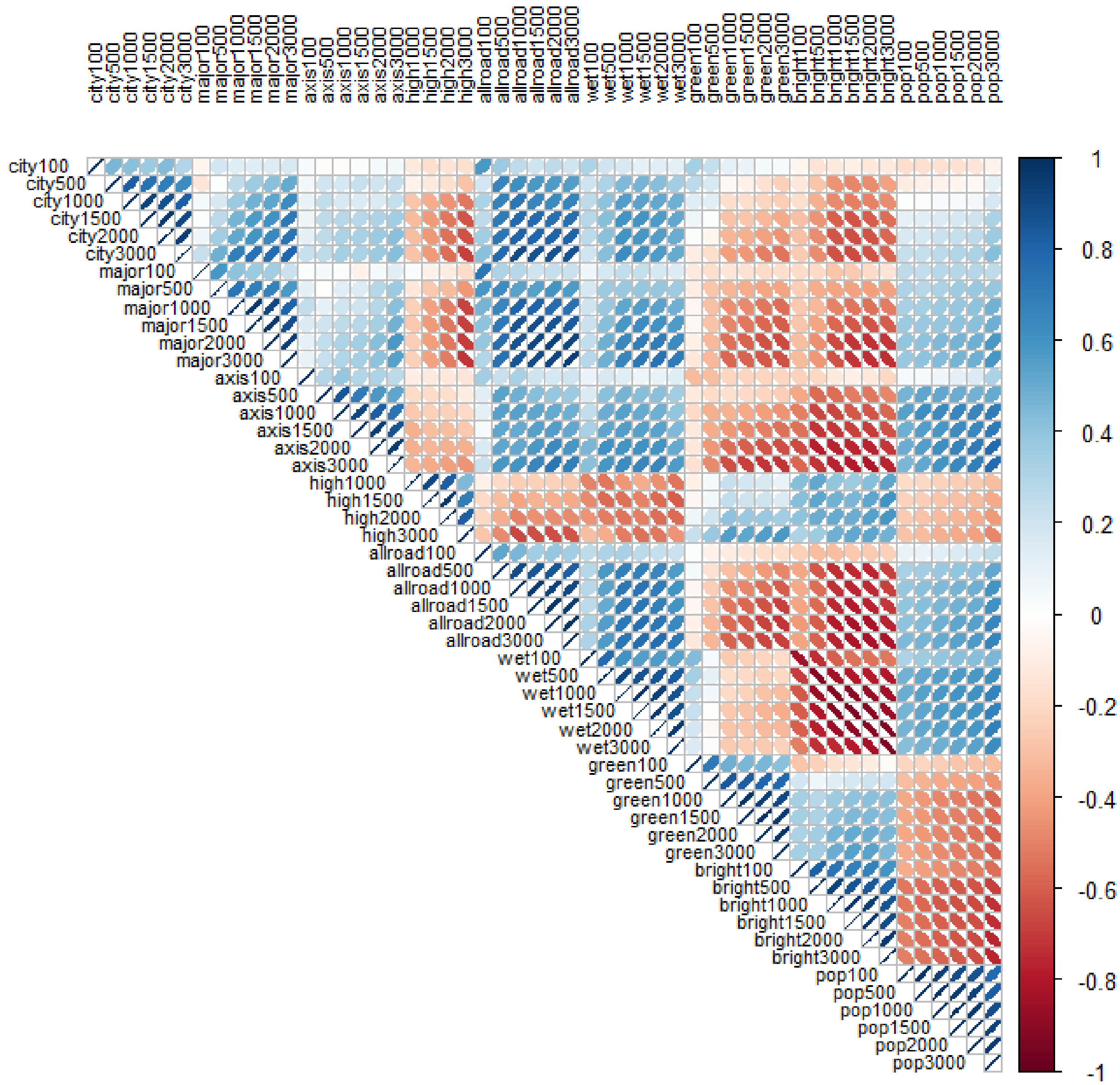

Figure 2-5 Correlation matrix of spatial covariates

The slope (negative or positive) of the major axis of the ellipse provides directionally of correlation between two variables. The size of the secondary axis of the ellipse represents the magnitude of the correlation. If a circle, correlation is close to 0. Symbols closer to a thin line approach correlations of 1.

2.4.2 Model Selection Results

The log base 10-transformed concentrations of each pollutant were used in the models because there was a slight right skew. The transformation also prevents the prediction of negative pollutant concentrations. Final models selected and model fit for each pollutant are summarized in Table 2-4. R^2 values of the models indicated these variables were able to explain 57%, 60%, 26%, and 56% of the variability in the annual NO_2, SO_2, O_3, and $PM_{2.5}$ concentrations, respectively. Because O_3 levels are low in the winter, when the summer O_3 model was run separately, the coefficient of determination increased to 49%. Seasonal models for pollutants not shown were excluded due to poor model convergence.

Table 2-4 Model selection results for NO_2, SO_2, O_3, and $PM_{2.5}$

Pollutant	Variables[a]	Beta	SE	R^2
log(Annual NO_2)	Intercept	2.150000	0.181974	0.57
	Green500	-0.000775	0.000150	
	Bright1000	-0.000180	0.000048	
	Green1000	0.000655	0.000161	
log(Summer NO_2)	Intercepts	1.222995	0.013223	0.63
	Axis100	0.000752	0.000171	
	Green500	-0.000333	0.000087	
log(Annual SO_2)	Intercept	2.041291	0.137369	0.60
	Green100	-0.000249	0.000069	
	Bright100	-0.000254	0.000047	
	Wet500	-0.000385	0.000101	
log(Annual O_3)	Intercept	1.422602	0.012778	0.26
	Axis2000	-0.000003	0.000001	
log(Summer O_3)	Intercept	1.710692	0.036269	0.49
	Summer [NO_2]	-0.007624	0.002362	
	Axis2000	-0.000002	0.000001	
log(Annual $PM_{2.5}$)	Intercept	1.794589	0.015584	0.56
	Highway2000	0.000004	0.000001	
log(Summer $PM_{2.5}$)	Intercept	1.794589	0.015584	0.59
	Highway3000	0.000004	0.000001	
log(Winter $PM_{2.5}$)	Intercept	2.1831610	0.0139310	0.50
	Highway2000	0.0000070	0.0000017	

[a]Note: The number following the variable name refers to the circular buffer distance (m).

2.4.3 Cross-validation Results

The DSA algorithm selected the models with the lowest CV risk. Average CV risk for the model selected for each pollutant is low (Table 2-5) and a CV risk plot (Figure 2-6) shows the expected prediction error as a function of number of covariates included in the model tested. The maximum is 11 because a maximum of 10 terms (excluding intercept) were specified in the DSA algorithm. The CV risks for $PM_{2.5}$ models with 10 and 11 terms were reported as “infinite”; therefore, these were not shown (Figure 2-9).

Table 2-5 Cross-validation parameter results for NO_2, SO_2, O_3, and $PM_{2.5}$

Pollutant	Average CV risk
NO_2 (Annual)	0.0046
NO_2 (Summer)	0.0086
SO_2 (Annual)	0.0060
O_3 (Annual)	0.0021
O_3 (Summer)	0.0031
$PM_{2.5}$ (Annual)	0.0032
$PM_{2.5}$ (Summer)	0.0056
$PM_{2.5}$ (Winter)	0.0036

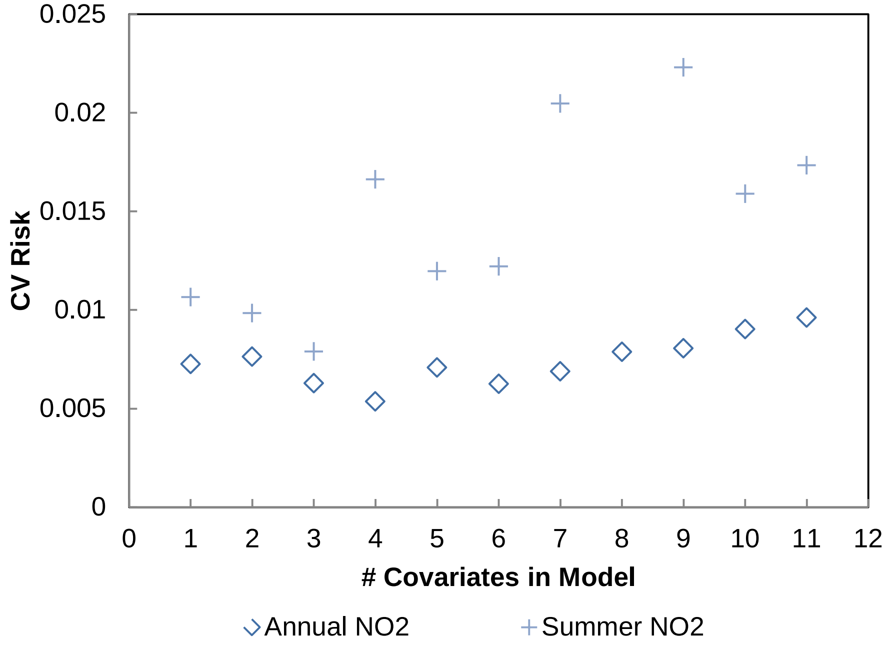

Figure 2-6 CV risk plotted against NO_2 models of given size, selected by DSA algorithm

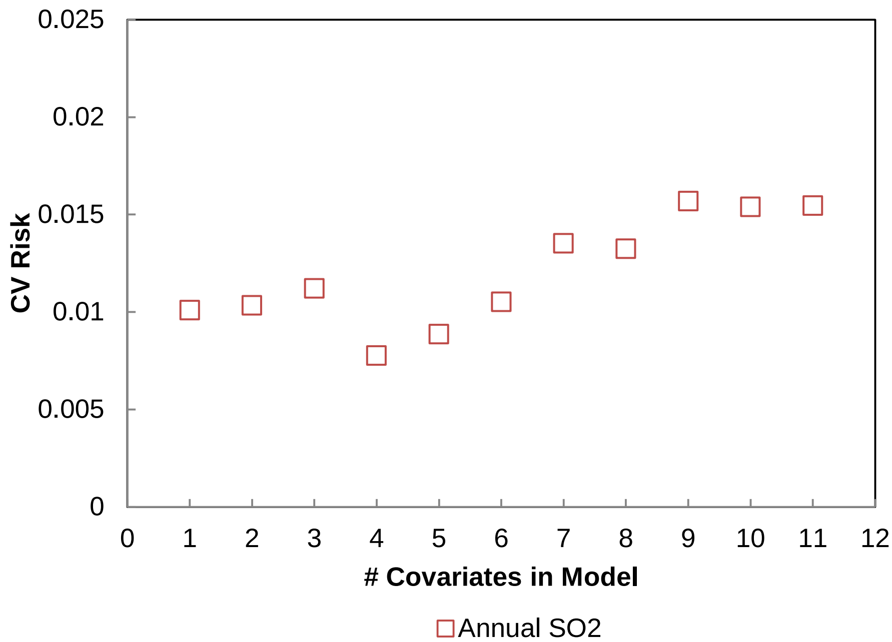

Figure 2-7 CV risk plotted against SO_2 models of given size, selected by DSA algorithm

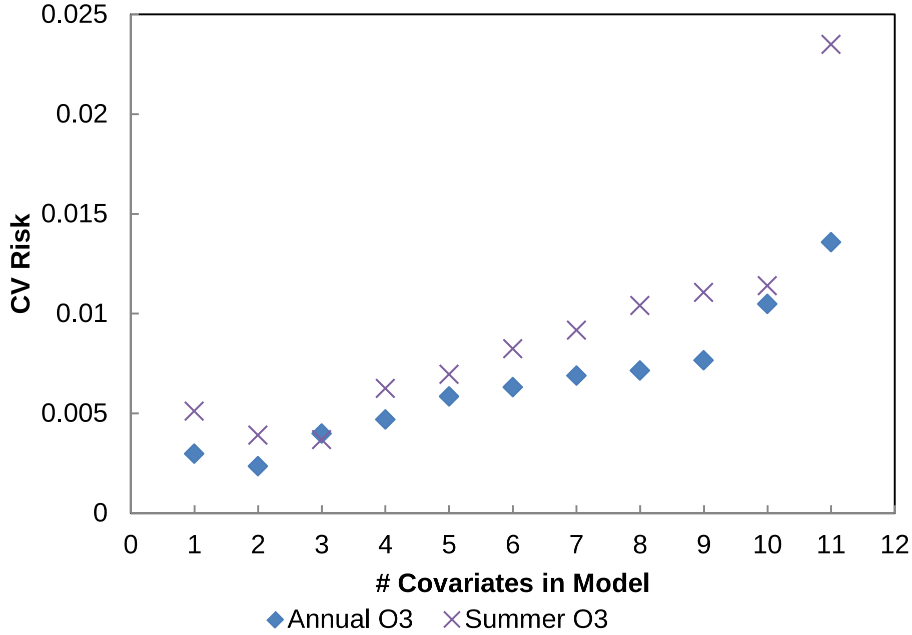

Figure 2-8 CV risk plotted against O_3 models of given size, selected by DSA algorithm

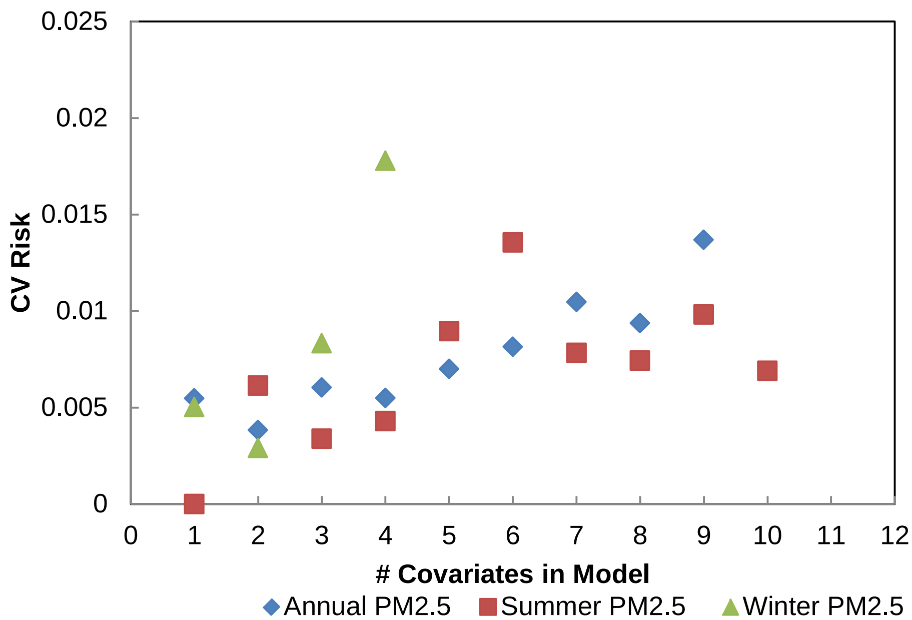

Figure 2-9 CV risk plotted against $PM_{2.5}$ models of given size, selected by DSA algorithm

2.4.4 Predicted Air Pollution Maps

Predicted concentration maps were created for annual $PM_{2.5}$, SO_2, and NO_2. Maps were also created for summer O_3 and NO_2 concentrations. Because summer and winter $PM_{2.5}$ models were similar, only the annual $PM_{2.5}$ surface was created. Descriptive statistics of predicted concentrations compared to sampled results are summarized in Table 2-6.

NO_2 concentrations are higher in the central part of the city where the road network is denser. NO_2 levels are lower in the summer but still the highest in the downtown area (Figure 2-12 and Figure 2-13). SO_2 concentrations were highest in the northern and western parts of the city (Figure 2-10). Ozone concentrations are higher away from large roads (Figure 2-11). $PM_{2.5}$ concentrations were highest around the highway networks (Figure 2-14).

Table 2-6 Measured and predicted concentrations for NO_2, SO_2, O_3 (ppb), and $PM_{2.5}$ ($\mu g/m^3$)

		Measured		Predicted	
Pollutant	Type	Mean (SD)	Range	Mean (SD)	Range
NO_2	Annual	29.65 (4.48)	12.87 – 40.37	25.91 (5.15)	7.69 – 58.60
NO_2	Summer	16.76 (4.34)	11.34 – 35.23	13.25 (3.03)	4.36 – 26.04
SO_2	Annual	23.57 (4.48)	11.50 – 38.30	19.29 (5.63)	5.26 – 67.26
O_3	Summer	36.64 (5.50)	23.39 – 47.97	38.47 (5.21)	15.00 – 47.58
$PM_{2.5}$	Annual	118.18 (19.15)	97.42 – 168.56	71.78 (14.11)	62.31 – 166.50

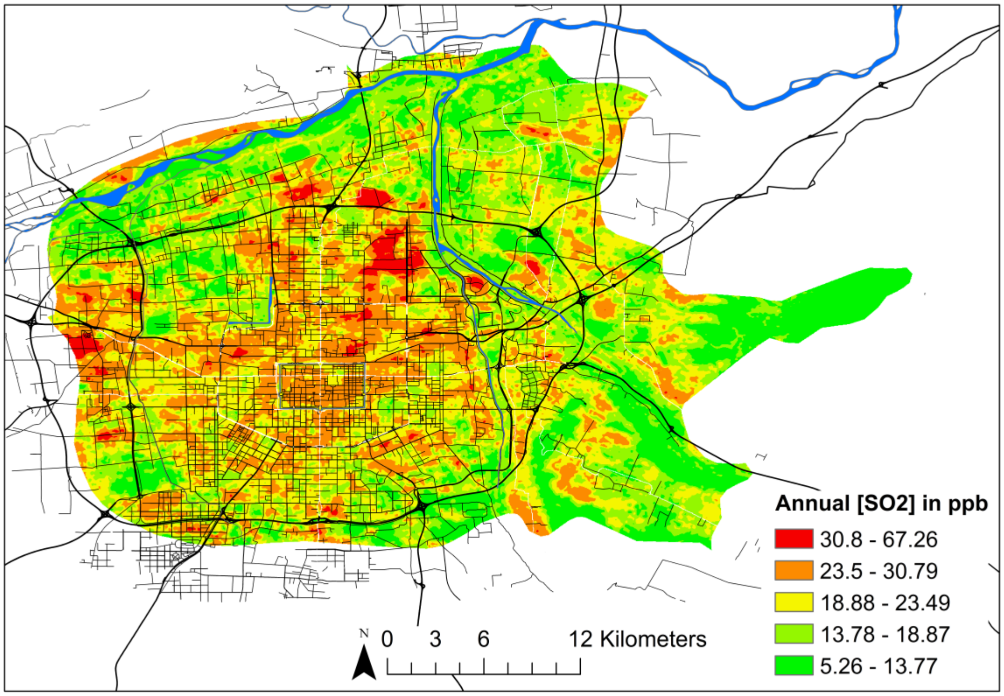

Figure 2-10 Prediction surface for annual SO_2 concentrations (ppb) in Xi'an, China

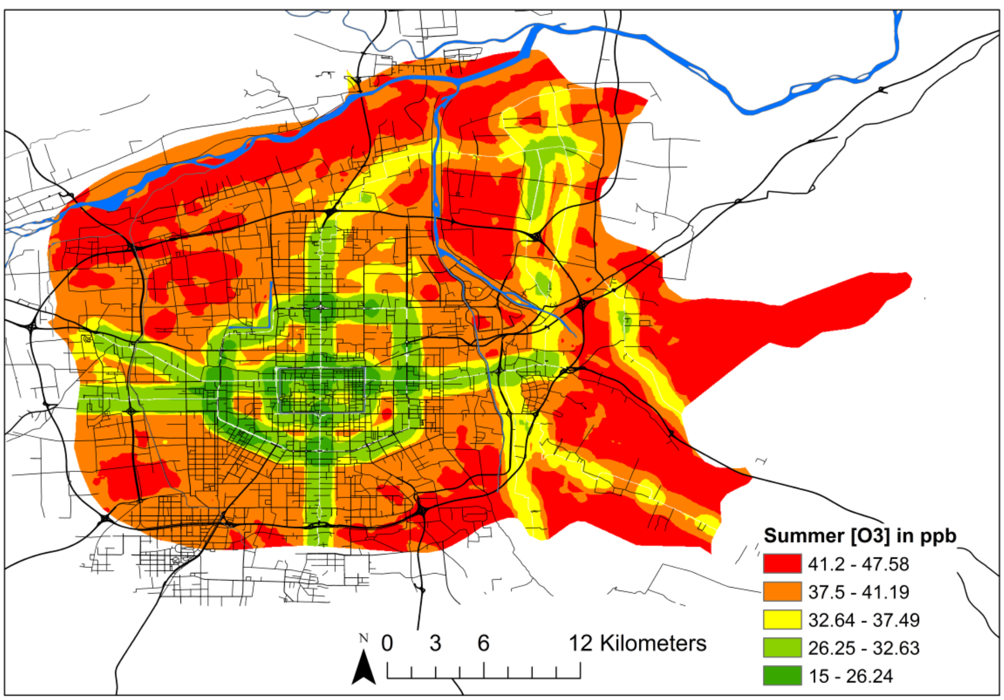

Figure 2-11 Prediction surface for summer O_3 concentration (ppb) in Xi'an, China

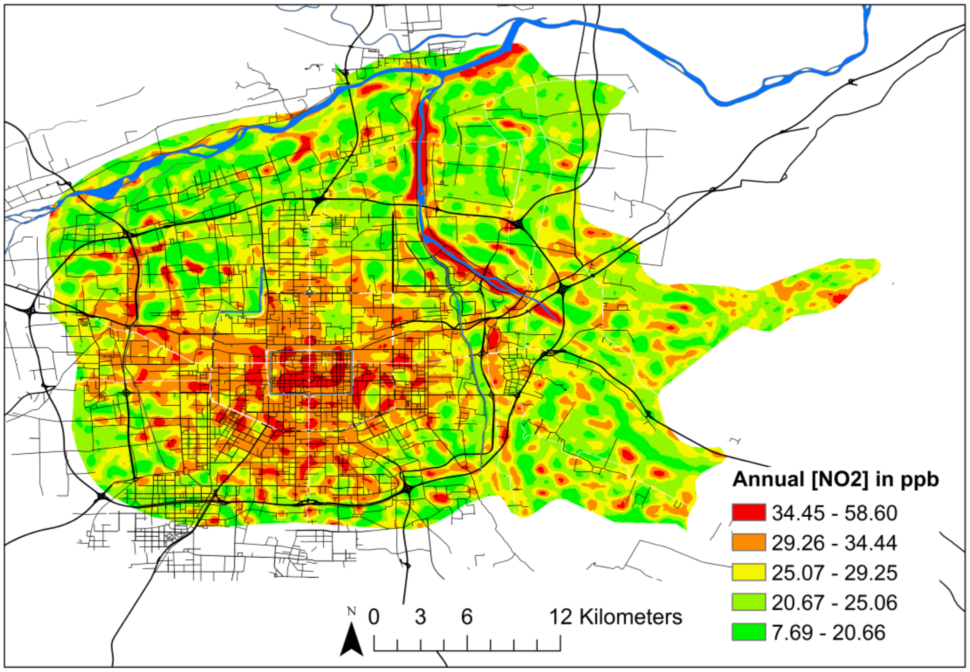

Figure 2-12 Prediction surface for annual NO_2 concentrations (ppb) in Xi’an, China

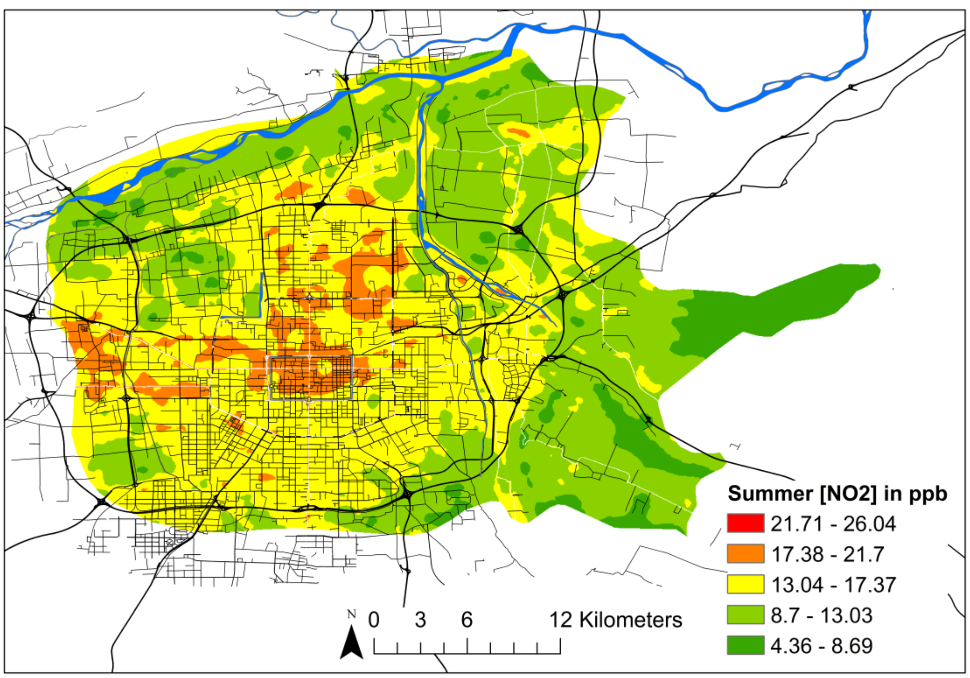

Figure 2-13 Prediction surface for summer NO_2 concentrations (ppb) in Xi'an, China

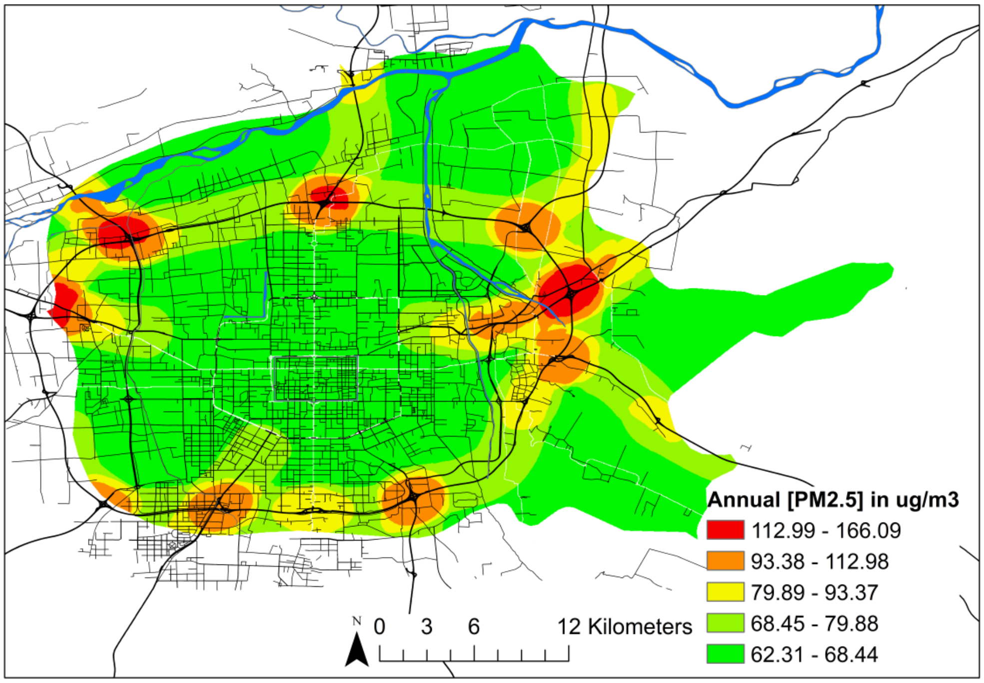

Figure 2-14 Prediction surface for annual $PM_{2.5}$ concentrations ($\mu g/m^3$) in Xi'an, China

2.5 DISCUSSION

2.5.1 Predictive models

The DSA selected models explained a moderate amount of the variability observed in the pollutant levels (R^2 = 0.49 to 0.60) and cross-validation results reported small expected errors in prediction (CV risks), indicating a good model fit and prediction of pollutant concentrations.

The directions of associations between land use or road types and pollutant levels were generally as expected. For SO_2,green space and vegetation (greenness), water and soil moisture (wetness), and soil or man-made surfaces (brightness) had negative associations, indicative of fewer industrial sources in these natural areas as measured by greenness and wetness or dense urban areas (buildings or roads) as measured by brightness. For $PM_{2.5}$, increased length of highways within 2000 m was associated within increased $PM_{2.5}$ concentrations, most likely a result of increased mobile emissions. In the seasonal models, highway length was significant within a smaller radial buffer (2000 m) in the winter than in the summer. This difference could result from lower mixing layers in the winter that prevents the dispersion of mobile emissions over longer distances.

In the summer O_3 model, the inverse relationship of ozone with NO_2 is expected. Near roads where there are higher levels of NO, a primary mobile emission, NO is converted to NO_2 in the atmosphere in the presence of oxygen, resulting in higher levels of NO_2 near mobile sources. Farther away from the mobile sources, NO_2 generally will break down into NO and oxygen radical, with faster degradation rates in the presence of sunlight and warmer temperatures. The oxygen radials then can form O_3 with oxygen, leading to higher ozone in areas where there are depleted NO_2 level. This relationship between ozone and mobile emissions also explains the inverse relationship seen with axis roads.

In the NO_2 models, higher values of greenspace within 500 m is associated with lower NO_2 levels as we would expect lower mobile emissions in these areas. However, the negative association of brightness within 1000 m with annual NO_2 levels was more difficult to interpret. Brightness represents both bare soil and man-made surfaces liker roads and tops of buildings. Increased brightness could be explained by the following scenarios (1) high-density urban areas or (2) more bare soil indicating fewer mobile sources, resulting in lower NO_2 concentrations. Because traffic volumes and congestion are still high in high-density areas, the second scenario seems more plausible for Xi'an.

In addition, more greenspace within 1000 m was associated with higher NO_2 levels. Within the 500 m buffer, we could assume a high greenness value at a site could be result from a park, academic campus, large residential complex, or government compound. As expected, mobile emissions within these areas are low. However, within a 1000 m buffer, we would expect this area to be beyond the confines of a single residential complex or government office building complex. If the greenness within a buffer of 1000 m is high, it is possible that the area covers multiple densely populated residential complexes that often have increased greenspace for residents. Higher population density areas could increase NO emission from more traffic in the area, leading to increased NO_2.

2.5.2 Predicted air pollution concentrations

The spatial predictions of pollutants generally correspond to the spatial distribution of sources in the city. NO_2 and ozone maps are inversely related with higher NO_2 near the center of the city where road networks are denser, while ozone levels are higher farther away from mobile sources where ozone is produced from the oxygen radicals generated by the breakdown of NO_2 in the presence of sunlight. NO_2 levels are higher in areas north and west of downtown. These are also areas of Xi'an with lower population density and emissions of SO_2 from industrial activity could be plausible. In addition, the general wind direction in Xi'an is to the northeast which could transport SO_2 along the north-east axial through downtown into northeastern parts of the city. There are also higher ozone concentrations in the eastern regions of the city which have fewer roads and less development activity. The $PM_{2.5}$ levels throughout the city are generally elevated above 60 µg/m^3 but the predictive model shows there are hotspots around highways especially near the 3rd Ring Road.

The annual $PM_{2.5}$ levels were exceeded in both the measured and predicted concentrations. As reference, the annual $PM_{2.5}$ concentrations standards have been set at 10 and 15 µg/m^3 by the World Health Organization (World Health Organization 2005) and the U.S. EPA (US EPA 2012), respectively. Substantial areas of Xi'an also exceed the WHO standards for NO_2 (21ppb). While an annual standards for SO_2 is not available, the predicted annual SO_2 (19 ppb) exceeds the 24 hour averaged standard set by the WHO (8 ppb), signifying potential adverse health effects.

The city-wide annual mean $PM_{2.5}$ predicted by the model (72 µg/m^3) is lower than the annual average measured by IEECAS' monitoring station using a MiniVol (152 µg/m^3, SD: 103 µg/m^3) and E-BAM (142 µg/m^3 SD: 121 µg/m^3) but this is a result of using data from 19 sampling sites in this study. In a previous paper, IEECAS' monitoring site in the High-technology Zone was identified as having higher ambient $PM_{2.5}$ levels than in other samples locations in Xi'an (Gao, Cao, and Seto 2015).

2.5.3 Limitations

As with many other land-use regression models, these predicted pollutant models are based on short-term (2 week) sampling in two seasons for one year. They do not incorporate other temporal variations that occur within and between seasons. Also, the two weeks of sampling ideally would have been chosen by examining the historical pollutant concentrations to determine which months would represent the best times to sample to represent seasonal or annual averages. However, because this study relied on sampling equipment borrowed from IEECAS, deployment dates and times were constrained.

There are several ways to improve model prediction. Although the measured air pollution dataset has already been collected, the covariates used for model selection could be improved. First, using data layers for 2013 could improve predictions. The road network is from 2011 and the Land Sat ETM+ imagery was from June 2010. Because Xi'an changes so rapidly, using the most recent data layers would improve air pollution predictions. Increasing the number sampling sites and campaigns would also improve prediction but also comes with increased costs.

In addition, the other types of data could be obtained to supplement the existing data including traffic volumes, more detailed road classification, and land use type. While we have assumed road types are a proxy for air pollution sources, traffic volumes and types on different roads could better approximate air pollution levels. Using Landsat classification provides adequate model prediction but the results were sometimes difficult to interpret, as seen in the NO_2 model. Because our road classification was crude and not based on actual traffic volume data, improved categorization of roads using traffic flow could improve prediction models. For example, ozone and $PM_{2.5}$ models were predicted using road network data. As a result, the final predicted surfaces, $PM_{2.5}$ especially, captured less spatial variability than the other surfaces that included land use covariates in their final models.

2.6 CONCLUSIONS

This study demonstrates the feasibility of using land use regression to increase knowledge of spatiotemporal viability in air pollutants in areas where monitoring is difficult. While the covariates used in the prediction models could be improved with a dataset that contained up to date data for 2013, the models selected using the deletion/substitution/addition (DSA) algorithm had small prediction errors and generated reasonable pollutant concentration surfaces.

Chapter 3 Field Validation of Low Cost Particulate Matter Sensor

3.1 OVERVIEW[3]

This chapter supplements the preceding Chapter 2 on a city-wide assessment of air pollutant spatial variability by focusing on evaluating a new low-cost particular matter sensor for use in high pollutant settings and areas where full-scale monitoring networks are unable to keep up with the pace of development.

3.2 BACKGROUND

The past few decades of rapid economic growth in China has led to increased emissions of ambient air pollution from increased motorization, urbanization, and energy consumption (Haidong Kan, Chen, and Tong 2012). Ambient air pollution is a growing health burden for China's population of 1.35 billion as the country's fourth largest health risk and has been estimated to result in 1.2 million premature deaths in 2010 (G. Yang et al. 2013b). The increased focus on the health effects of ambient fine particulate matter ($PM_{2.5}$) has led to new policies aimed at controlling ambient air pollution. Stricter emission standards, cleaner fuels, relocation of polluting industries, and rezoning efforts have led to some improvements in air quality (Haidong Kan, Chen, and Tong 2012). However, China still ranks globally as one of the countries with the worst air pollution.

Effective management of air pollution is limited by sparse monitoring networks, and the high investment costs of running and maintaining monitoring sites hinder the ability to increase coverage and quality of air pollution data (Briggs et al. 1997). Routine monitoring of $PM_{2.5}$ recently began in China in 2012, but current regulatory networks fail to capture spatiotemporal variations in air pollution exposures that can occur due to local emissions sources such as urban transportation and finer scale meteorology, which limits the ability of regulatory agencies to identify at risk or vulnerable populations, control relevant emissions that contribute to exposures, and protect public health.

Effective management is particularly difficult in sprawling Chinese cities. Filter-based integrated instruments mask temporal patterns while continuous monitoring instruments are expensive and limit spatial coverage. In Xi'an, China only ten $PM_{2.5}$ regulatory monitoring stations exist with six urban districts that cover an area of 833 km^2 (Statistical Bureau of Shaanxi Province 2010). Yet, new lower-cost continuous monitoring instruments for $PM_{2.5}$ are available, which can potentially fill in gaps in the regulatory monitoring network to enhance understanding of

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[3] Portions of this chapter are taken from previously published material in Gao, Meiling, Junji Cao, and Edmund Seto. 2015. "A Distributed Network of Low-Cost Continuous Reading Sensors to Measure Spatiotemporal Variations of $PM_{2.5}$ in Xi'an, China." *Environmental Pollution* 199 (April): 56–65. doi:10.1016/j.envpol.2015.01.013.

pollution hotspots. Previously, an affordable portable optical aerosol sensor, the Shinyei PPD42NS was calibrated with reference instruments in an urban area of the United States, and its measurements were found to be highly correlated with monitoring conducted by a regulatory agency and with other optical instruments (Holstius et al. 2014). At lower concentrations present in the U.S., approximately linear relationships were found between the sensor's response and a U.S. EPA Federal Equivalent Method instrument (MetOne Instruments BAM-1020) and other instruments (TSI DustTrak and GRIMM 1.108). However, there is limited understanding of how the same low-cost PM sensor performs in high concentration environments that exist in China. Further, the previous study was primarily concerned with sensor calibration, and only deployed these instruments at a single fixed site.

This chapter focuses on a simultaneously distributed deployment of these monitors in Xi'an, China to (1) evaluate the performance of low-cost sensors in high concentration environments against other reference instruments, (2) demonstrate the benefits of using affordable continuous monitors to identify at risk areas or populations, and (3) test the ability of these instruments to capture spatiotemporal variability across a range of environments to inform more targeted emissions reduction policies.

3.3 MATERIALS AND METHODS

3.3.1 Study Area

As the capital of Shaanxi province and the largest city in northwestern China with almost 8.5 million residents, Xi'an is a major city in the expansion and development of central and western China (Statistical Bureau of Shaanxi Province 2010). Xi'an also has one of the worst air pollution records in China (HEI 2010). In the last ten years (2003 to 2013), the annual average $PM_{2.5}$ concentration of 167 µg/m^3 was 4.8 times China's annual standard (35 µg/m^3), 14 times U.S. EPA's annual average standard (12 µg/m^3), and 17 times WHO's standard (10 µg/m^3) (J. Cao 2014, 5). From 2004 to 2012, Xi'an met China's daily $PM_{2.5}$ standard (75 µg/m^3) only 11.6% of the time. Although annual $PM_{2.5}$ levels have decreased over the last decade from 192.5 to 158.1 µg/m^3, Xi'an air pollution problems are exacerbated by terrain and meteorology, reliance on coal burning, urban growth, and increased motorization. Xi'an's location in the Yellow River Basin, low wind speeds (45% of the time in the winter with no wind), and little precipitation in the winter exacerbates air quality issues by limiting natural dispersion of pollutants (J. Cao 2014, 5).

3.3.2 The PUWP Monitor

We developed the Portable University of Washington Particle (PUWP) monitor, which consists of a low-cost PM sensor (Shinyei PPD42NS, $15 USD) that measures particle counts based on the principle of light scattering, a microprocessor, real-time clock, data logger, and temperature and relative humidity sensor, and a small LED display (Figure 3-1). The specifications of the Shinyei sensor are described in the manufacturers datasheet (Shinyei Corp. 2010), which indicate that it is designed to sense particles primarily 1 µm in diameter. The sensor is sampled by the microprocessor according to the manufacturer's specifications, continuously over a 30-second interval, which produces a raw uncalibrated sensor signal (low pulse occupancy time). The only calibration data provided by the manufacturer's datasheet is for cigarette smoke particle count concentration. Based on these data, there is an approximate error of 25% in particle measurement across most of the sensor's range. At very low concentrations, the error becomes substantial (e.g., over 50% error below 100,000 particles per cubic feet). For outdoor ambient monitoring applications, the sensor's raw signal must to be calibrated with co-located reference instruments to obtain mass concentration measurements. The calibration and performance of the Shinyei PPD42NS has been previously described for lower ambient air concentrations found in the U.S. (Holstius et al. 2014), but is reassessed in this study for the different particle composition and higher concentrations found in Xi'an. Although the PUWP monitor is designed to operate on a rechargeable lithium polymer battery, for this study, all monitors were connected to 240 V wall outlet power because outlet power was readily available and because this was a pilot study, resources were not available to change the batteries for the PUWPs deployed at more remote sampling sites. The battery allows it to continue to operate during short-term power outages. Larger batteries can be used to provide greater protection from outages as necessary.

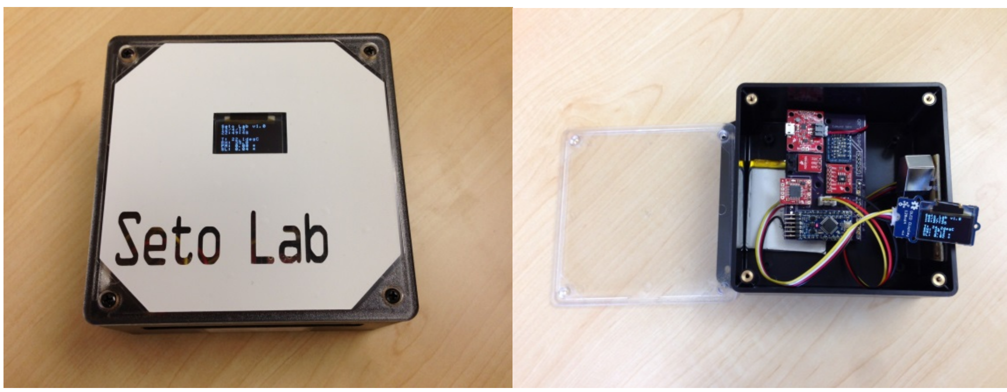

Figure 3-1 The Portable UW Particle (PUWP) monitor (left), and internal components (right)

3.3.3 Field deployment

Calibration of Sensors

To calibrate the raw sensor readings from the PUWP monitors, and to assess between-monitor variations, seven PUWPs were co-located alongside an optical instrument (TSI DustTrak II Model 8532) equipped with a $PM_{2.5}$ impactor, 24 hour gravimetric filter measurements (Airmetrics MiniVol Tactical Air Sampler) of $PM_{2.5}$, and an hourly beta-attenuation monitor (MetOne Instruments E-BAM). During the calibration phase, the PUWP monitors, DustTrak, E-BAM, and MiniVol were co-located on the roof of the Institute of Earth Environment Chinese Academy of Sciences (IEECAS) in Xi'an, China from December 16 to 20, 2013.

MiniVol filters were changed daily between 8 to 10 am. $PM_{2.5}$ filters (47 mm Whatman quartz microfiber) for the MiniVols were pre-heated at 900 °C for three hours before sampling to remove carbon contamination. Exposed filters were stored in a 4 °C refrigerator before analysis to minimize evaporation of volatile components. All pre- and post-sampling filters were weighed using a Sartorius MC5 electronic microbalance with ±1 µg sensitivity. Filters were reweighed until the differences between replicate weights were less than 20 µg and less than 10 µg for samples and for blanks, respectively. Replicate weights were then averaged to represent the pre- and post-sampling mass of the filters. Mass concentrations were calculated from dividing the net change in mass by the total volumetric flow during the sampling time of each filter.

The DustTrak data from the calibration phase were adjusted using the gravimetric MiniVol results to account for humidity effects and local PM composition. The DustTrak was co-located with a MiniVol measuring 24 hour samples of $PM_{2.5}$ during the four day calibration phase. DustTrak $PM_{2.5}$ measurements were time-matched with the start and end sampling times of the co-located MiniVol for each of the four 24 hour samples. The resulting ratio of the MiniVol-DustTrak 24 hour $PM_{2.5}$ mass concentration from the DustTrak was used to adjust the 1 minute DustTrak $PM_{2.5}$ data.

Because the DustTrak was able to give higher time-resolution $PM_{2.5}$ mass concentrations, we decided to use the MiniVol-corrected DustTrak as the reference instrument in this study. After correcting DustTrak data using co-located MiniVol mass concentrations, we established a calibration relationship between each PUWP's raw sensor readings and the $PM_{2.5}$ mass concentration from the DustTrak.

Pairwise plots between the instruments' were compared after smoothing data using 1 minute and hourly averages. Coefficients of determination (R^2) were used to assess the strength of linear correlations. Based on evidence of a non-linear sensor response at middle to high concentrations, polynomial regression was used to model the relationship between each PUWP's raw sensor values and mass concentration measurements obtained from the co-located DustTrak. We also examined the effects of including temperature and relative humidity in the models. The number of terms in the polynomial models was assessed using the Bayesian information criterion (BIC) and standard error of the regression (S) to select the best fit model for each PUWP. A predictive model was selected for each PUWP monitor.

Distributed Sensor Network

To assess concentrations at different sites in Xi'an, we established a network of eight locations across Xi'an, which were monitored from December 9 to 16, 2013. The eights sites were located in residential, commercial, governmental, and academic areas and were varying distances from major roads with different types of traffic intensities during the day (Table 3-1). The sampling heights (3 to 13m) also varied to find a safe, accessible location for the devices. At each site, one PUWP monitor was co-located with a MiniVol that collected 24 hour filter measurements of $PM_{2.5}$. MiniVol filters were changed daily between 8-10 am. Sites were selected to capture environments with varying sources and conditions typical of a Chinese city. Sites included (A-B) residential neighborhoods, (C-D) university campuses, (E-F) villages, (G) a building in Xi'an High-technology Zone (location of IEECAS, where the calibration described in 2.3.1 was conducted), and (H) public library near a busy intersection (Figure 3-2).[4]

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[4] Sites A, B, C, D, E, F, G, and H correspond to sites A02, A16, A09, A07, A19, A13, B07, and A03, respectively, as listed in Chapter 2.

Raw sensor data from each of site's PUWP was converted to a time series of 1 minute mass concentrations using the PUWP's corresponding best-fit calibration model derived during the calibration phase. This time series was further aggregated into 24 hour averages, which were then compared to the 24 hour integrated mass concentration measurements from each site's MiniVol using coefficients of determination (R^2). Aside from 1 minute and 24 hour averaging, which provides some low-pass filtering and smoothing of outliers, no other signal processing was applied to the data.

To test if integrated PM measurements could be misclassifying or masking differential exposures, we compared the mean concentrations from the PUWP monitors to each site's MiniVol measurements, to determine if the sites rank ordered in the same manner regardless of instrument, and quantified the presence of extreme values, defined as more than 1 standard deviation from the city-wide mean of the MiniVol mass concentrations across all the sites for that day. A standard deviation above the city-wide average concentration was chosen as the threshold for comparison because 24 hour $PM_{2.5}$ conditions in Xi'an exceeded existing health standards. For reference, 24 hour $PM_{2.5}$ concentrations standards have been set at 25 and 35 µg/m^3 by the World Health Organization (World Health Organization 2005) and the U.S. EPA (US EPA 2012), respectively.

Table 3-1 Descriptions of sampling sites in the distributed sensor network

Site	Type	Environment	Sampling Height (m)	Distance to Major Road[a] (m)	Type of Traffic
A	Residential	Medium-rise housing within old city walls, one-lane tree-lined roads	10	255	Medium
B	Residential	Medium-rise housing	3	105	Heavily congested due to subway construction
C	Academic	Campus	3	242	
D	Academic	Near 2^{nd} ring road	3	476	Congested
E	Village	Near new high-rise developments	13	1,150	Light
F	Village	Near 3^{rd} ring road	3	828	Light
G	High-technology Zone Office	Mix of office buildings and residential high rises	10	66	Congested
H	Public Library	Near intersection of 2^{nd} ring road and major corridor	10	72	Heavily congested

[a] Major roads include highways, ring roads, major arterials in the east-west and north-south direction.

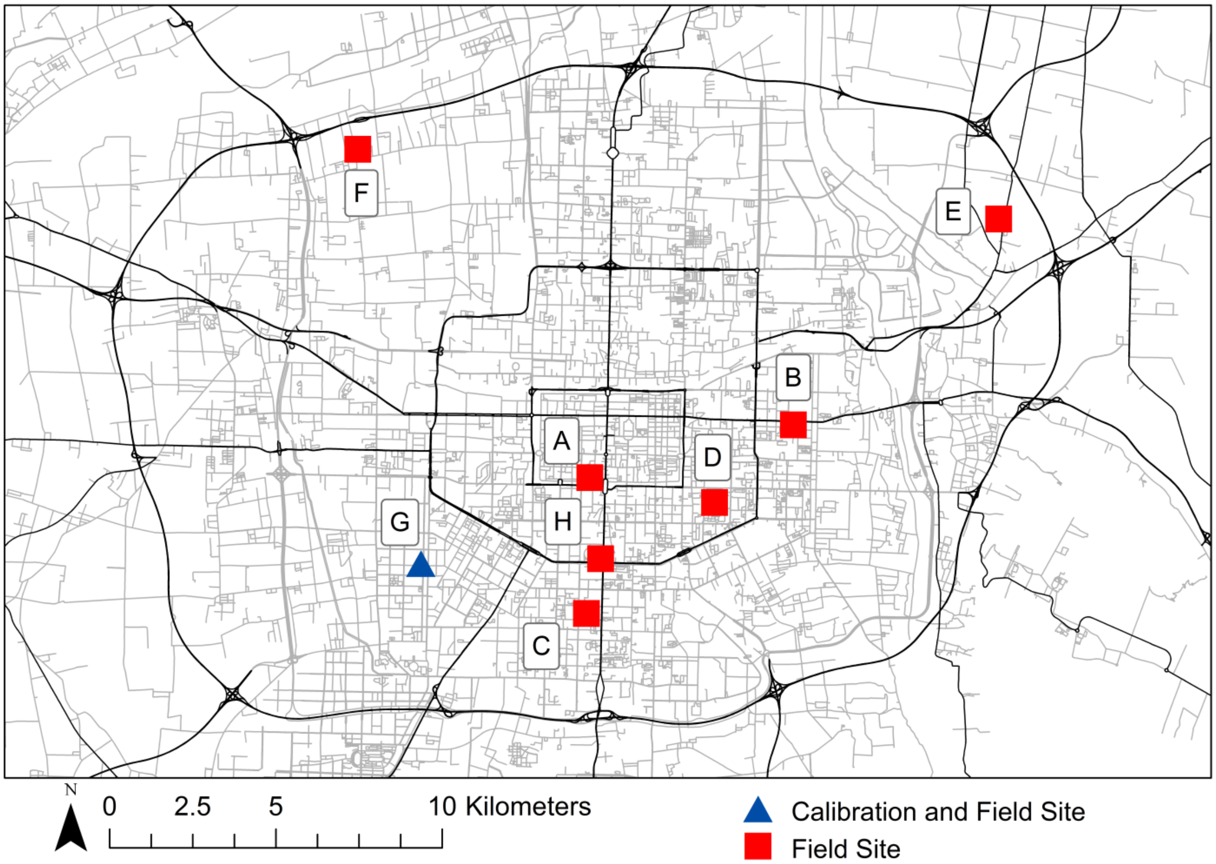


Figure 3-2 Map of calibration and field sampling sites in Xi'an, China

3.4 RESULTS

3.4.1 Calibration Phase PM Concentration, Relative Humidity, and Temperature

The 1 minute DustTrak $PM_{2.5}$ measurements averaged 328.3 (range: 66.6 to 563.7 µg/m^3), hourly E-BAM $PM_{2.5}$ concentrations averaged 485.0 µg/m^3 (range: 77.0 to 889.0 µg/m^3), and 24 hour integrated $PM_{2.5}$ concentrations from the MiniVol ranged from 330.47 to 413.45 µg/m^3. Relative humidity averaged 6.1% (range: 3.2 to 16.9%) and temperatures averaged 11.4°C (range: -3.5 to 19.2°C).

3.4.2 Calibration Phase PUWP Raw Correlations with DustTrak and E-BAM

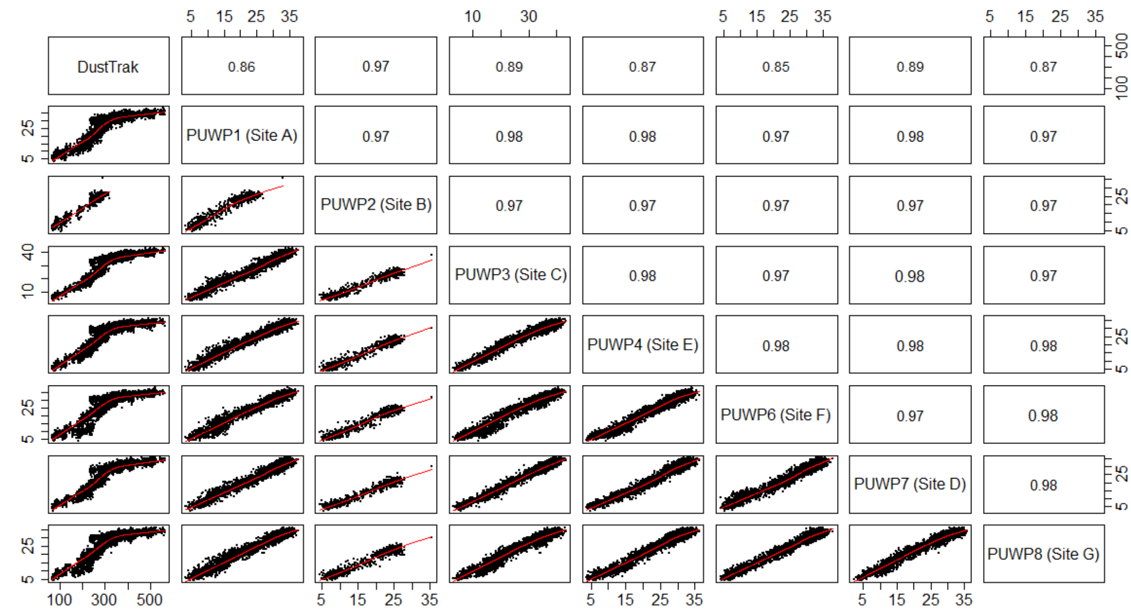
Under the high ambient $PM_{2.5}$ concentrations observed in Xi'an, China, the PUWPs performed well against the commercially available reference monitors, the DustTrak and the E-BAM, in both the 1 minute and hourly comparisons (Figure 3-3). Raw sensor (low pulse occupancy) units are shown for the PUWPs. Loess smoothers are superimposed on pairwise plots. PUWP5 (Site H) was excluded because the sensor was lost.

Pairwise correlations among the 1 minute averaged individual PUWPs raw data (R^2 = 0.97-0.98) and between the PUWPs raw data and the DustTrak (R^2 = 0.86-0.89) were high. The 1 hour averaged correlations among the individual PUWPs, between the PUWPs and the DustTrak, between the PUWPs and the E-BAM, and between the DustTrak and the E-BAM were also high (R^2 = 0.97-1.00, 0.86-0.89, 0.85-0.90, 0.91, respectively). PUWP2 logged than two days of data and fewer data points resulted in a higher correlation (R^2 = 0.97) for PUWP2 with the DustTrak as compared with the other PUWPs.

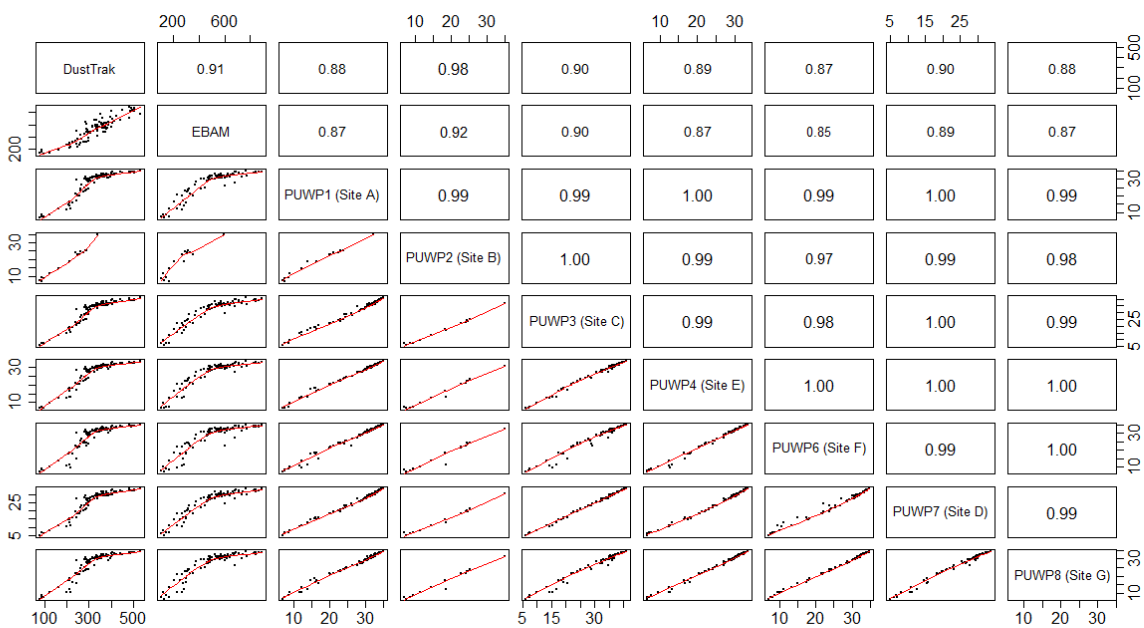
3.4.3 Predictive Models

Using the Bayesian information criterion (BIC) and standard error of regression (S) (Table 3-2 and Table 3-3, respectively) as indicators of model fit, a separate model was selected for each sensor using 1 minute averaged DustTrak data. A lower BIC when comparing two models for the same data indicates a better fitting model while accounting for complexity of the model. A smaller S indicates better model fit with lower values indicating smaller average distances between data points to the model's regression line. Fifth order polynomial models that included relative humidity (RH %) and temperature (°C) was found to best convert PUWP signals into $PM_{2.5}$ mass concentrations. Because the correlations between the PUWPs and the DustTrak followed a sinusoidal form (Figure 3-3), second order models were not considered. The correlations between predicted $PM_{2.5}$ concentrations from each PUWP after applying the model and the MiniVol-corrected DustTrak readings had R^2 ranging from 0.91-0.94.

When comparing models with and without relative humidity and temperature variables, models including these two variables had improved fit to the data. All models had significant ($P < 0.001$) relative humidity (RH) and temperature (T) terms. Although the lowest BIC and S values were associated with sixth order polynomials, we found very small improved model fit to the data when comparing the fifth and sixth order models as measured by the decreases in BIC and S. Therefore, fifth order polynomial models were selected.



(a)



(b)

Figure 3-3 Pairwise correlations between (a) 1 minute averaged PUWPs and DustTrak data and (b) 1 hour averaged PUWPs, DustTrak (μg/m^3), and E-BAM (μg/m^3).

Table 3-2 Predictive models comparison using Bayesian information criterion (BIC)

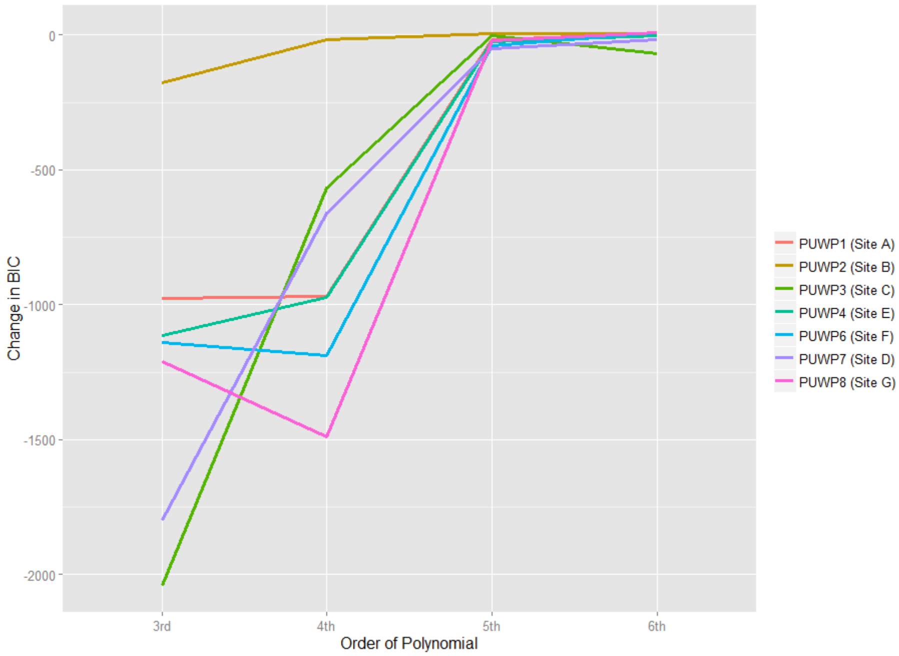
	Bayesian Information Criterion (BIC)[b]						
Model[a]	PUWP1 (Site A)	PUWP2 (Site B)	PUWP3 (Site C)	PUWP4 (Site E)	PUWP6 (Site F)	PUWP7 (Site D)	PUWP8 (Site G)
Linear	58888	7094	57649	58368	59103	57945	58673
Linear with RH and T	58522	7082	57435	58271	58789	57650	58484
3rd Order Polynomial	57530	7039	55641	57146	57681	55962	57292
3rd with RH and T	57546	6906	55397	57159	57649	55852	57274
4th Order Polynomial	57021	7022	54889	56697	57366	55374	56831
4th Order with RH and T	56578	6887*	54829	56188	56460	55193	55785
5th Order Polynomial	57028	6969	54897	56704	57368	55369	56837
5th Order with RH and T	56559*	6893	54827	56164	56422*	55141	55764*
6th Order Polynomial	57017	6969	54897	56687	57375	55342	56845
6th Order with RH and T	56564	6899	54759*	56160*	56430	55124*	55772

[a]All models were specified to have an intercept of zero.
[b]Models with lowest BIC are marked with an asterisk (*) for each PUWP.

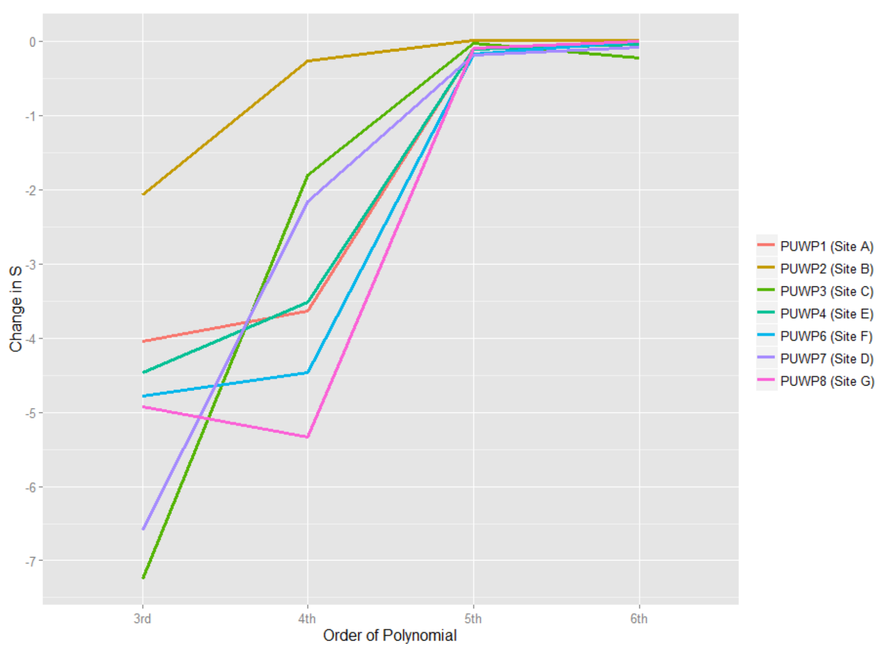
Table 3-3 Predictive models comparison using standard error of regression (S) of models

Model[a]	Standard Error of Regression[b] (S) in µg/m^3 PUWP1 (Site A)	PUWP2 (Site B)	PUWP3 (Site C)	PUWP4 (Site E)	PUWP6 (Site F)	PUWP7 (Site D)	PUWP8 (Site G)
Linear	48.89	19.25	43.72	46.65	49.85	44.90	47.95
Linear with RH and T	47.24	18.98	42.83	46.18	48.39	43.67	47.08
3rd Order Polynomial	43.20	17.72	34.86	40.50	42.97	36.01	40.95
3rd with RH and T	43.20	16.91	35.59	41.72	43.61	37.08	42.16
4th Order Polynomial	41.23	17.48	33.99	40.05	42.52	35.54	40.53
4th Order with RH and T	39.56	16.64*	33.79	38.20	39.15	34.92	36.83
5th Order Polynomial	41.23	17.48	33.87	39.98	42.52	35.54	40.51
5th Order with RH and T	39.47	16.65	33.76	38.09	38.98*	34.73	36.74*
6th Order Polynomial	41.16	17.51	34.02	39.95	42.51	35.39	40.52
6th Order with RH and T	39.46*	16.66	33.53*	38.05*	38.98*	34.65*	36.74*

[a]All models were specified to have an intercept of zero.
[b]Models with lowest S are marked with an asterisk (*) for each PUWP.



(a)



(b)

Figure 3-4 Diminishing returns in improved model fit as measured by changes in (a) BIC and (b) S with increasing model complexity when comparing models (linear, third, fourth, fifth, and sixth order polynomials) that include relative humidity (RH) and temperature.

3.4.4 Distributed Field Deployment

Pairwise comparison between the 24 hour integrated PUWP and the MiniVol data across all sites was moderate ($R^2 = 0.53$). PUWP monitors reported 24 hour averaged $PM_{2.5}$ mass concentrations that on average were 39.39 µg/m^3 lower that reported from their co-located MiniVol monitors (Figure 3-5). Temperature (°C) and relative humidity (%) across the sites averaged -2.7°C and 9.4%, respectively (Table 3-4). The average temperatures during the deployment phase were markedly lower than those during the calibration phase. During the field deployment, one sensor was lost (site H) and two (sites E and F) had incomplete data due to power or data logging issues. Sites with substantial missing data (Sites E and F) were not included in this analysis.

When rank ordering the sites according to mean concentrations (Table 3-4), the PUWPs and the MiniVols were generally both able to identify the areas with higher level of pollution, specifically identifying the High-Technology Zone (Site G) as the site with the highest average $PM_{2.5}$ concentrations in this study. Sites varied in the number of hours per day (range: 0 to 13.3 hours) a high concentration threshold was exceeded, which was defined as greater than or equal to one standard deviation above the daily city-wide mean calculated from the MiniVol samples across all sites (Figure 3-6). The PUWPs were also able to identify Site G also as the site with the most hours of concentrations considered high as compared to the rest of the city (mean: 3.97 hours, range: 0.16 to 13.6 hours) (Figure 3-6). Temporally, the sites generally had similar trends with most of the extreme $PM_{2.5}$ concentrations occurring in the early morning before 9am. However, for Site G, these extreme concentrations had a peak in the early morning and also another peak mid-day (Figure 3-7).

Table 3-4 Distributed deployment 24 hour averaged site summary statistics

	PUWP ($\mu g/m^3$)		MiniVol ($\mu g/m^3$)		Relative Humidity (%)		Temperature (°C)	
Site	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A	106.90	25.72	133.67	40.21	10.56	1.88	-3.88	2.97
B	85.91	27.91	154.63	47.64	9.00	3.49	-2.86	4.03
C	108.47	22.66	140.16	42.08	9.47	3.67	-3.44	3.99
D	84.06	27.93	133.67	42.34	9.29	2.65	-2.20	3.51
E	Incomplete Data		148.83	51.92	Incomplete Data			
F	Incomplete Data		253.04	88.70	Incomplete Data			
G	153.23	32.99	175.60	56.91	9.68	5.07	-1.38	5.76
H	Sensor lost		134.51	37.39	Sensor lost			

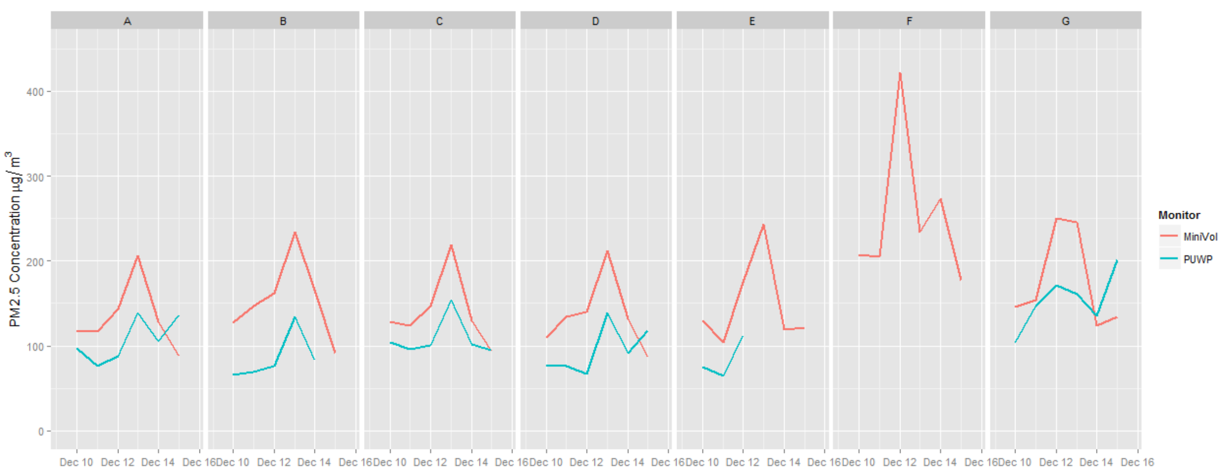


Figure 3-5 PUWP monitor compared to co-located MiniVol 24 hour $PM_{2.5}$ concentrations across distributed deployment sites.

Sites B, E, and F had missing data that prevented calculation of complete 24 hour $PM_{2.5}$ data.

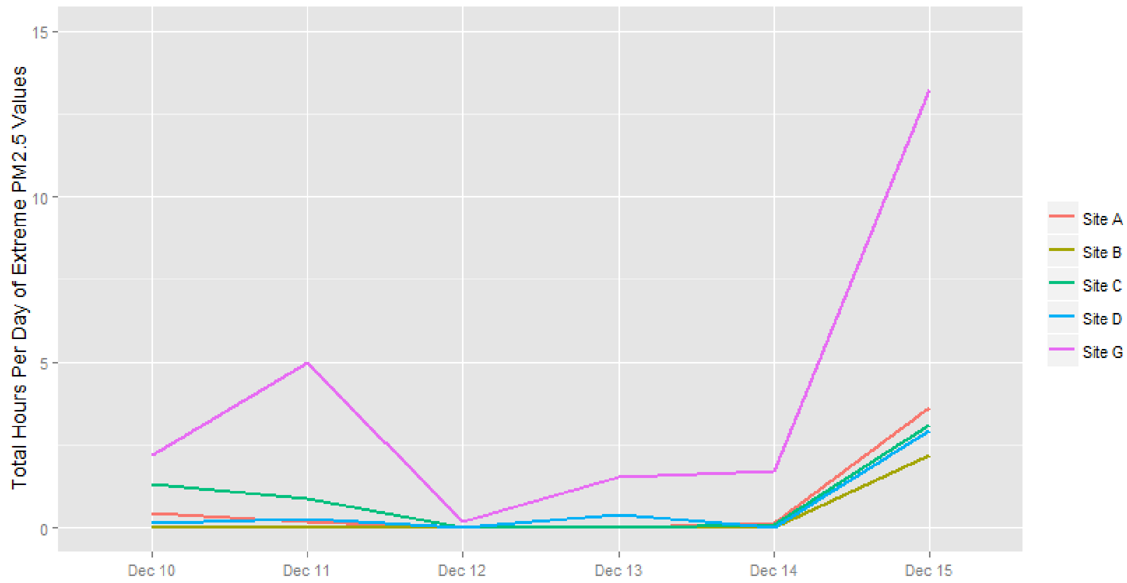


Figure 3-6 Total hours per day where mass concentrations of PUWPs exceeded one standard deviation above the daily city-wide average (as calculated from the mean of the MiniVol samples from all sites).

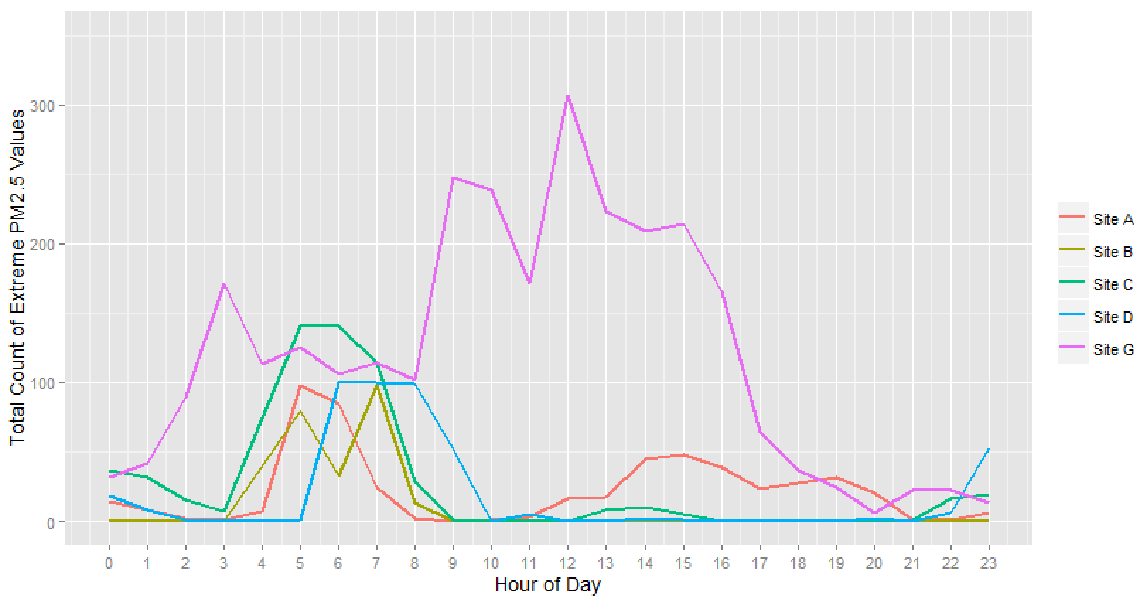


Figure 3-7 Daily temporal variation of high $PM_{2.5}$ mass concentrations from PUWP monitors across the sites over the days sampled showing the count of 1 minute averaged samples where mass concentrations exceeded one standard deviation above the daily city-wide average.

3.5 DISCUSSION

3.5.1 Main Findings

Our main objective was to determine how the low-cost PUWP sensor would perform in areas with high $PM_{2.5}$ levels. The 24 hour averages of $PM_{2.5}$ concentrations from the PUWPs had a moderate correlation ($R^2 = 0.53$) with their co-located MiniVol monitors. While this correlation may not seem high, when identifying potential air pollution hotspots among the sites, both the PUWPs and the MiniVols identified Site G as having the highest $PM_{2.5}$ level. Given the cost difference between the two monitors, the PUWPs performed well and has potential to be used to rapidly screen large areas to help identify where more targeted monitoring is necessary.

Identifying the High-Technology Zone site (Site G) as a hotspot was unexpected because the area is considered to be cleaner and better planned area with more green space, lower population densities, higher property values, and higher socioeconomic status of residents. However, the high ambient $PM_{2.5}$ levels may result from our site being close to a major road (66m, Table 3-1) and the High-Technology Zone bordering western areas of Xi'an that are undergoing development and renovation. The high $PM_{2.5}$ concentrations could be a result of the increased emissions from high polluting vehicles such as construction trucks and biomass burning that are then dispersed to the east, as the dominant wind direction in Xi'an is to the northeast.

Site G also had a different temporal pattern for its extreme values as compared to other sites. The increase in counts of extreme values in the early morning (before 9am) is most likely due to the lower mixing layer in the winter evenings and mornings. Site G's first peak in the early morning is following by another larger peak mid-day that is sustained until 4pm while other sites only had a peak in the early morning hours. While more information about sources is necessary to parse out the reasons for this trend, we can speculate that this increase is not a result of increased vehicle traffic because it does not seem correspond with traffic trends which are higher in in the morning and evenings. Increased construction activity during the day from the western neighborhoods could be a potential reason.

While we have identified a potential PM hotspot in this study relative to the other sites, the 24 hour health guidelines have far been exceeded across all the sites every day. Using the PUWP monitors provided insights into the temporal patterns of when extreme concentrations occur. However, the health effects of exposure to $PM_{2.5}$ at the highly variable 1 minute and 1 hourly time scale is not yet well understood. Further, health standards are not yet available for the general population at these finer time scales.

In calibrating the PUWP monitors, this study found that at high concentrations of $PM_{2.5}$, a fifth order polynomial model fit the data best. A previous study in the US found that the relationship was linear (Holstius et al. 2014). The difference in calibration models is most likely due to gradual saturation in the ability of the Shinyei optical sensor in the PUWPs to detect ambient concentrations above 300 $\mu g/m^3$, as observed from the sinusoidal relationships. This saturation at higher concentrations is consistent with chamber studies conducted using monodispersed particles (paper forthcoming). We also observed higher pairwise correlations (R^2= 0.87-0.89) of the PUWP monitors with the DustTrak and E-BAM than Holstius et al. did (R^2 = 0.64-0.70). We believe this is due to the larger errors in detection at the low concentrations, as shown in the Shinyei's manufacturing specification sheet (Shinyei Corp. 2010). Because the concentrations at the US site are lower than the ones in this paper, we would expect lower R^2 values at lower ambient concentrations.

In addition, the standard error of regression (S) averaged 34 µg/m^3 across the PUWPs between the predicted $PM_{2.5}$ values estimated by the 5th order polynomial models and the corresponding 1 minute DustTrak concentrations (average of 328.3 µg/m^3). This 10% measurement error can be expected because we created the models using nosier 1 minute DustTrak data. We would expect this error to be lower had we used 1 hour averaged data. As expected, in Holstius et al., the measurement error was found to be 1 to 10 µg/m^3 based on hourly $PM_{2.5}$ data. The magnitude of measurement error depends on the time resolution selected of the reference instruments and suggests tradeoffs between precision and temporal resolution should be considered based on the purpose of the study.

Finally, this study found significant effects from relative humidity and temperature in the predictive models while these variables were not found to be statistically significant previously. This difference in findings could result from differences in meteorological conditions between the spring and summer seasons. This study's December mean temperatures and relative humidity were lower than those in the US study which was conducted in April and had slightly larger diurnal temperature changes and less variability in relative humidity (approximately range of 3 to 17% versus range of 10 to 60%). The significance of relative humidity and temperature in this study is most likely due to the diurnal trends of these two variables correlating with time of day, which plays a larger role in determining PM concentration in this study. The inversion layer during the winter is more pronounced and has a diurnal pattern, resulting in concentrating PM by preventing particle dispersion at night and in the early mornings. Therefore, relative humidity and temperature were found to be significantly associated with $PM_{2.5}$ concentrations in this winter study.

3.5.2 Limitations

The findings that indicate the usefulness of low-cost PM monitoring at higher ambient concentrations in Xi'an were comparable to the ones found in a collocation study conducted in the United States (Holstius et al., 2014). However, the detection of a saturation point in the field, as also observed in chamber studies (paper forthcoming), requires more work to understand the technological limitations of the device and environmental parameters under which these PUWPs can be used. In addition, studies thus far have not examined the effects of different optical and chemical $PM_{2.5}$ compositions, seasonal variation, and meteorological conditions (e.g., temperature, precipitation, and relative humidity) on PUWP detection and calibration. More tests are needed to understand how variability in PM composition can change the PUWP monitor's performance. While fifth order polynomials were determined to be the best fitting for this Xi'an study, this same model may not necessarily hold in another location. Presently, new calibrations must be conducted prior to any field deployment in new study sites and more studies should be conducted under different seasonal and environmental conditions to test how well this calibration model holds.

In addition, we selected Site G as our calibration site but the aerosol composition, optical properties, and size distribution at one site could differ from that of other sampled sites around the city. While resource limitations prevented us from creating calibration curves specific to each sampling site in this pilot study, we believe using one local site for calibration is an improvement over using pre-existing calibration data. In some research applications, the use of less accurate lower cost sensors to estimate exposure for a population over a large area may outweigh the benefits of using a few more accurate but expensive instruments.

In the current study, because we were primarily interested in calibrating the PUWPs at all deployment sites, they were co-located with reference instruments. In future studies, once co-location of the PUWPs at a single regionally representative site, and the relationships between the PUWPs sensors and a reference instrument like the E-BAM or DustTrak is observed, a large number of PUWPs can be distributed across a city. Given the low cost of the sensor ($15 USD) and of each PUWP monitor (<$500 USD), which is several orders of magnitude lower than that of the E-BAM or DustTrak, such large deployments considerably more cost-effective than deploying traditional gravimetric samplers like the MiniVols. Moreover, because the instruments are optical and continuous logging, they require less field staff involvement compared to filter pre and post-weighing, and exchange of filters every 24 hours as necessitated by gravimetric methods. These future deployments could be focused in city regions where we have initially identified relatively high concentrations (e.g., the High-technology Zone region G in Xi'an) to better understand PM sources, secondary aerosol formation, dispersion, and population exposures. This hierarchical approach of city-wide screening, followed by more spatially dense deployments in hotspots is made easier by the fact that the instruments are low-cost and highly portable, and can lead to increasingly focused monitoring important emission and population exposure areas of the urban environment.

Additionally, more affordable direct-reading monitors like the PUWPs can be used to enhance air pollutant exposure assessments through land-use regression (LUR) (Briggs et al. 1997), where sampling is often conducted in short campaigns in select seasons of the year to represent seasonal or annual averages, but limited to no temporally-resolved data are available to inform how concentrations vary on finer spatial and temporal scales. This lack of data limits the LUR models' ability to identify hotspots for use in regulatory applications where emissions and resulting population exposures vary temporally (e.g., on the order of minutes to hours). The combination of spatially and temporally resolved data available from PUWPs could potentially solve these problems for future health effects and air quality management studies.

3.6 CONCLUSIONS

This study demonstrated that the PUWP monitors could be used to enhance existing $PM_{2.5}$ sampling networks and for use in health-related studies as an affordable technology to increase spatiotemporal resolution of $PM_{2.5}$ datasets, both in ambient monitoring networks and even in higher $PM_{2.5}$ conditions for rapid screening. Although additional calibration studies under varying meteorological conditions in different regions would be useful, the PUWPs show promise as a viable lower cost aerosol sensor that can be used in developing or industrializing area applications where obtaining expensive instrumentation to monitor air quality can be costly but where the need for monitoring is especially urgent to protect public health.

Chapter 4 Associations of the Built Environment and Quality of Life

4.1 OVERVIEW

This chapter evaluates the relationships between seven perceived dimensions of one's residential neighborhood's built environment and self-reported health-related quality of life (HRQOL) from a cross-sectional study of 1608 adults in Xi'an, China. By examining these relationships, we determined aspects of both physical and mental health that should be considered as Chinese cities modernize and evolve. Because neighborhoods are changing so quickly, Chinese cities provide interesting opportunities to study relationships between urban design and quality of life.

4.2 BACKGROUND

4.2.1 Built Environment and Health

The World Health Organization (WHO) defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (World Health Organization 2006). The built environment – the surroundings built or made by people - has particular influence on risk factors for disease. The built environment is modifiable and can be designed to promote health, improve quality of life, and reduce health inequalities. Because the built and natural environments are modifiable and have been estimated to contribute up to 20% to total health (McGovern, Miller, and Hughes-Cromwick 2014), urban design is increasingly recognized has having widespread implications for population health. In fact, the health in all policies (HiAP) approach to designing public policy is increasingly popular in cities around the world to create more "livable" neighborhoods that are dense, walkable, accessible, and mixed-use (Wernham and Teutsch 2015).

There is a rich body of literature describing the associations between the built environment and physical activity. Neighborhood walkability, a measure of availability of pedestrian infrastructure and connectivity of the streets, is positively associated with increased walking for both leisure and transportation (Lovasi, Grady, and Rundle 2012; Saelens and Handy 2008; Frank et al. 2005; Saelens, Sallis, and Frank 2003), physical activity (Van Holle et al. 2012; Durand et al. 2011), and lower body mass index (BMI) (Leal and Chaix 2011; Feng et al. 2009). Walking is an important part of physical activity (Haskell et al. 2007; Eyler et al. 2003) and can provide health benefits (Sattelmair et al. 2011; Eyre, Kahn, and Robertson 2004). Studies have also found neighborhood esthetics are positively associated with active travel choices like walking (Nasar, Holloman, and Abdulkarim 2015; Michael, Green, and Farquhar 2006) and physical activity (Van Dyck et al. 2011; Boone-Heinonen et al. 2010). The associations between the built environment and physical activity may be mediated by the reliance on non-active forms of transportation like cars in low-density areas, and through limited availability of parks and recreational facilities (Sallis et al. 2006).

Neighborhood design can influence human behaviors. Those living in denser, mixed-use neighborhoods tend to walk more and drive less (Duncan et al. 2010; Frank et al. 2006), which can affect vehicle emissions. Greater exposure to vehicle emissions are associated with higher BMI in children (Jerrett et al. 2014) and increased risks of adverse pregnancy outcomes including low birth weight and preterm birth (Padula et al. 2014; Ghosh et al. 2012). Exposure to emissions can trigger cardiac events and can contribute to the development of cardiovascular disease (Franklin, Brook, and Pope 2015). The built environment has also been linked to risk factors for poor health and chronic disease. Poor neighborhood design has been found to be associated with obesity with unhealthy dietary intake through limited access to healthy or diverse food options (Story et al. 2008). Poor neighborhood infrastructure perceptions have also been found to be associated with increased smoking and binge drinking (Jitnarin et al. 2015).

Much less well understood is the impact of the built environment upon social health. It is hypothesized that neighborhood design may influence how people interact with each other within their communities. For instance, mixed-land use, pedestrian-oriented designs, green spaces, and esthetics may play a role in promoting social interactions and relationships – more generally labeled as social capital – which have been shown to be associated with higher self-rated health and improved mental well-being (Kim, Subramanian, and Kawachi 2008).

Attributes of neighborhoods have been measured (1) objectively using geographic information systems (GIS), environmental audits, or databases of existing resources or (2) subjectively using self-report (Casey et al. 2014). Each measurement approach depends on data availability and resource restraints for primary data collection (H. Lin, Sun, and Li 2015). Studies have found there are frequent mismatches between objective measures and self-reported subjective perceptions with perceptions potentially being more proximally associated with behaviors (Gebel et al. 2011; Gebel, Bauman, and Owen 2009; Ball et al. 2008).

While many studies have found significant but frequently small associations between various neighborhood designs and positive health behaviors, these studies are usually limited in their abilities to test causality. In particular, neighborhood self-selection is a limitation for cross-sectional studies where individuals living in certain neighborhoods chose to live there because they already are inclined toward healthier behaviors. Results from relocation studies, randomized trials (Ludwig et al. 2012; Ludwig et al. 2011; Votruba and Kling 2009), natural experiments (Garvin, Cannuscio, and Branas 2013), and longitudinal studies (Hirsch et al. 2014; Knuiman et al. 2014) that circumvent the self-selection issue are more mixed and inconclusive than the cross-sectional studies regarding magnitude and significance of independent associations between neighborhood attributes and behaviors or health outcomes (Oakes 2004). The effort to isolate independent effects of neighborhood on health has been deemed both difficult and futile, as the measured “neighborhood effect” is a result of complex relationships between both context (the place) and composition (the people). Rather than trying to isolate the independent effects of the built environment, framing the role of built environment in determining one’s health within the larger relationships of behaviors, perceptions, and socioeconomic factors is a start to understanding these complex relationships.

4.2.2 Built Environment in China

Cities undergoing rapid urbanization provide unique opportunities to see how changing built environments are affecting the population that resides there (H. Lin, Sun, and Li 2015). The rapid growth rate in Chinese cities allows for a unique comparison of old neighborhoods co-existing alongside newer modern ones. In a single city, a larger variability in built environment attributes and neighborhood types can be observed.

Health-conscious urban design and policies are becoming increasingly important in Chinese cities where economic growth and population migration have led to dramatic changes in the physical and social environments. Urban areas have experienced dramatic growth both in population size and land area since the 1980s. Urbanization (proportion of population living in urban areas) is already over 50% and is expected to reach 60 to 65% by 2020 (Bai 2008).

Urban forms changed when the central government starting viewing cities as potential global commercial hubs during the transition to the market economy rather than as centers of industrial production as they were during the socialist planned economy period (S. Li, Zhu, and Li 2012; P. Zhao, Lu, and de Roo 2011). During the planned economy period from 1949 to the late 1970s, clustered development around the work units (*danwei)* was prominent. These were separated from the city centers and were areas where workers of large state-owned enterprises (SEO) worked and lived together (J. Yang et al. 2012). The state controlled all aspects of daily life including work, marriage, family planning, meal provisioning, and access to social services.

After the economic reforms in 1978 that led to the new market economy, the gradual dissolution of the work units began. The development strategy for cities focused on building a city center surrounded by satellite communities, which would be anchored by the infrastructure of the remaining work units, universities, or other enterprises, and would be connected to each other and the city center through ring and radial roads (Figure 4-1). The satellite communities would also be separated from each other and the city center through green space.

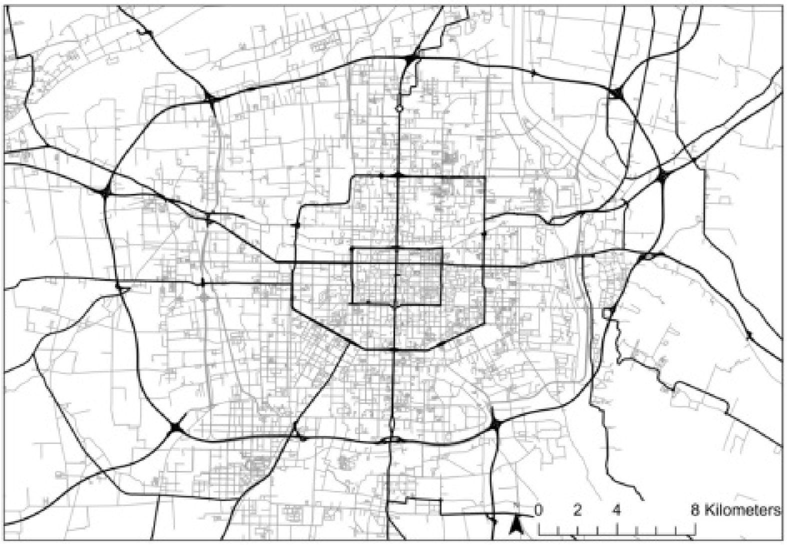


Figure 4-1 Typical ring and radial road structure of Chinese cities (Xi'an, China)

However in reality, the city center engulfed the nearby satellite communities as it grew in size and became a high-density monocentric city rather than one with multiple clusters of development. The municipal governments prioritized infrastructure and social service (e.g., healthcare, education) development in the city center and as a result, living near the city center was still coveted. Although manufacturing and construction became increasingly decentralized, moving to the outskirts of the city, employment in the service industries still remained in the city center (P. Zhao 2010), resulting in the overgrowth of city centers.

The green spaces also disappeared as the land was used for highly coveted and profitable commercial and residential development. To attract both domestic and foreign investments, local governments created development zones and industrial parks that consumed large tracts of land. In 2003, over 3,800 industrial parks were created and this number increased to 6,015 in 2006 (Y. Li 2010). The creation of industrial and technology parks that decentralized residential areas while raising real estate prices in the city centers often pushed low- and middle-income households to the periphery near the rural-urban fringe (Pucher et al. 2007). Because local governments control the urban land, additional revenue from land leases to real estate developers became a significant part of a local government's income, with much of the land coming from converting existing farmland to new plots of urban land for development (S. Cao et al. 2014). In extreme cases, governments are leveling mountains to make more land available for cities and industries (Clark 2014).

Government support for increasing private vehicle ownership also influenced the form of the new cities. In 2009, China passed the United States in becoming the world's largest car market. Although car ownership rates are still lower than in the US (69 versus 786 cars for every 1,000 persons in 2011), planning policies became car-centric to accommodate this boom in private vehicle ownership (The World Bank 2011). China more than doubled its length of roads (Z.-R. Peng, Zhu, and Song 2006), while bicycle lanes were narrowed or eliminated in the repaving of roads to decrease congestion (Schipper 2006). This motorization trend means the Chinese population participates less in active modes of transportation such as walking, biking, and public transportation which contributes to overall sedentary behavior (W.-S. Ng, Schipper, and Chen 2010). Between 1991 and 2006, average weekly physical activity dropped by 32% in adults (R. Zhou et al. 2013) . With about 200 million people estimated to be overweight or obese in 2002, overweight and obesity prevalence reached 22.8% and 7.1%, respectively (The World Bank Human Development Unit 2011).

Previous research has examined the relationships among built environment, behaviors, and health in the US, Europe, and Japan but research on the urban environments in China has been limited mostly within the transportation literature. Much of the research has focused on the association between objective measures of built environment (distance to city, density, distance to transit, etc.) and travel behaviors where higher density neighborhoods with more connected streets and transit options were found to be associated with more walking and less driving (Y. Zhang et al. 2014; D. Wang, Chai, and Li 2011; J.-J. Lin and Yu 2011; Jiawen Yang 2010; D. Wang and Chai 2009). A study in Hangzhou also found that higher self-reported neighborhood esthetics and lower residential densities were associated with increased leisure-time physical activity in adults (M. Su et al. 2014) while in another study in Shanghai, residential density, street connectivity, and traffic safety were positively associated with physical activity (R. Zhou et al. 2013). To our knowledge, the associations between built environment and mental health-related quality of life have yet to be explored.

4.2.3 Types of Chinese neighborhoods

Because this was a cross-sectional study, we relied on being able to capture a diverse range of types of neighborhoods that represent different stages of China's economic development, as proxy for change over time. Therefore, the type of residential neighborhood is important in grouping our sample population. The transition away from a centrally planned economy in the 1980s created several distinct types of neighborhoods that co-exist today: (1) lane/courtyard urban neighborhoods, (2) work units, and (3) commodity housing. These neighborhoods have distinct socio-demographic characteristics, built environment features, and social network structures (S. Li, Zhu, and Li 2012).

Lane and courtyard urban neighborhoods include both neighborhoods built pre-1949 prior to the reorganization of housing into work-unit communities, and neighborhoods that formed following the dissolution of the work units after the reforms. Both were designed before the advent of motor vehicles with mixed land use, and are organized and overseen by residential committees comprised of local citizens. These are usually the first areas to be developed for public squares, new housing, and commercial complexes because they often make up the oldest and most central parts of the city.

While some work-unit communities were gradually dissolved, some still remain today. The work-unit compounds were built in the pre-reform period from the early 1950s to the late 1970s. These neighborhoods were organized by state owned enterprises (SOE) to house workers and their families. Usually gated, these neighborhoods are dense, mixed-use with diverse resources as these SOEs often had their own cafeterias, schools, health clinics, and post offices, markets, etc. and were where most of these workers lived and socialized, leading to strong social connections and neighborhood identities (S. Li, Zhu, and Li 2012). These neighborhoods were also built when residences were close to places of employment before motor vehicles were common (D. Wang and Chai 2009) so neighborhood design prioritized pedestrians with wide, tree-lined sidewalks and one-lane roads.

After the economic reforms, employers were no longer required to provide housing for their workers; therefore, the commodity housing market grew as people had to rent or purchase housing (J. Yang et al. 2012). The commodity developments became heavily guarded gated housing ('urban enclaves') for the growing middle class (S. Li, Zhu, and Li 2012). Because of the growing car ownership rates in China, these newer neighborhoods are built during a period when increased traffic flows necessitate the need for wider roads. While the older housing buildings in urban neighborhoods and work units are usually 8 stories or lower (before the use of elevators), commodity housing types are usually high-rises. In this study, these commodity-housing neighborhoods are divided further into two groups – high-density and low-density commodity housing. High-density developments are often built on demolished old city plots previously inhabited by residents of the old lane/courtyard neighborhoods. The areas around these developments are frequently still dense, mixed-use and are transitioning away from the old neighborhoods. Low-density commodity housing neighborhoods, developed from previously industrial or agricultural land, have lower population density and fewer amenities as surrounding areas have not fully urbanized.

Photos for each neighborhood type are available in Appendix C.

4.2.4 Social Concerns in Chinese Cities

As the "urban enclave" nature of the new urban gated neighborhoods grows and Chinese become more mobile, urban Chinese are increasingly distrustful of their neighbors (Wissink et al. 2012; S. Li, Zhu, and Li 2012; Hazelzet and Wissink 2012). In 2012, trust among people was a record low with only 30% saying strangers can be trusted (J. Wang and Yang 2013). Because studies have shown social capital and trust are associated with health and well-being in Chinese populations (Norstrand and Xu 2012; Yip et al. 2007), erosion of trust and social cohesion can weaken population health, undermine social stability, and subsequently limit economic growth.

In addition, the continued existence of China's household registration system (*hukou)* further divides city residents into two classes – rural or urban – which contributes to distrust as rural to urban migration continues. Originally created to restrict movement between the urban and rural areas starting in the 1950s, the *hukou* system determined where and what type of social services one was able to receive – grain rations, housing, education, healthcare, social welfare, etc. (Chan and Zhang 1999). As labor demands increased in the cities from industrialization and urban development, restrictions placed on rural residents were loosened to allow rural to urban migration. From 1978 to 2004, an estimated 300 million rural residents migrated to cities (S. Li, Zhu, and Li 2012). Migrant workers are relatively young, predominantly male, and poorly educated (L. Shi 2008b). Because of their low educational attainment, migrant workers often accept undesirable manual jobs permanent urban residents avoid. Migrant workers also face social stigmas, exploitation, and discrimination due to their *hukou* status (Human Rights Watch 2008). A migrant worker's wages can be a quarter of that of local urban workers; they often work seven days a week and work more hours per day than urban residents (L. Shi 2008b). Long hours, stressful work conditions, and low pay increase the vulnerability of this group to experiencing higher health risks. In addition, surveys have shown migrants are less aware of and have less access to social and health services in the cities (L. Shi 2008b). The migration of those with rural *hukou* into cities for employment in recent decades has led to marginalization, stigmatization, and exploitation of this group of urban residents (Human Rights Watch 2008).

Within this context of rapid urban development and shift away from state control of private life for citizens, this study explores the general well-being of residents in Xi'an, China.

4.3 MATERIALS AND METHODS

4.3.1 Study Site

As the capital of Shaanxi province with over 8 million residents, Xi'an is a sub-provincial city in central China and a major city in the expansion and development of central and western China (Statistical Bureau of Shaanxi Province 2010). With an average gross domestic product (GDP) growth above 10% every year since 2000, Xi'an is experiencing a surge in economic development as the central government focuses on developing central and western China (Statistical Bureau of Shaanxi Province 2010; C. C. Fan 2010). Nearly half of the population in 2010 is considered "agricultural residents" or those with a rural *hukou* (Statistical Bureau of Shaanxi Province 2013). Since 2000, the investment in real estate development has grown at an average annual rate of 30.4% and in 2013, $25 billion was invested in real estate with an additional $20 billion invested in residential real estate (Statistical Bureau of Shaanxi Province 2013). The area of paved roads per capita has nearly doubled since 2006; the number of passengers taking public transit has quadrupled since 2000 while the number of public buses has only doubled, contributing to additional stress on a municipal transportation system trying to keep pace with motorization, population growth, and spatial expansion.

4.3.2 Sampling Design

Data for this study comes from a 2013 cross-sectional health and behaviors survey of adults (18 years old and above) in Xi'an, China that collected socio-demographic information, perceived neighborhood characteristics, social capital, physical activity, diet, travel behaviors, health outcomes, and quality of life data (Appendix B). The study sample was drawn from the six urban districts which include 6.5 million people and cover an area of 833 km^2. I used a multi-stage cluster sampling method to probabilistically select neighborhoods, defined as areas overseen by neighborhood committees. After stratifying on the six districts, I selected 20 neighborhoods using population proportional to size (PPS) where neighborhoods with large populations are more likely to be selected than those with smaller populations. An additional 10% of neighborhoods in each district were selected as backup per district if neighborhood committees declined to participate for a total of 38 neighborhoods.

Within each of the 20 neighborhoods (Figure 4-2), 80 adults were selected using quota sampling matched to the 2010 Census data for Xi'an according to sex and age.[5] Neighborhoods were visited in the morning and afternoons until the quotas for each age and sex category were met. Subjects were approached by an interviewer in the public areas of the neighborhood including parks, courtyards, and around residential buildings. Verbal consent and eligibility for the study (subject could communicate in Mandarin and was an adult resident of the neighborhood) was confirmed prior to starting the pen and paper survey. Surveys were completed within approximately 45 minutes and following the interview, subjects were compensated with a tray of

[5] Before quota sampling in selecting individuals within neighborhoods, we attempted to use probabilistic methods (systematic sampling) but were unsuccessful in recruiting individuals even after repeated visits over several days. More than 80% of the households approached declined to be surveyed. Due to time and resource constraints, quota sampling matched on age and sex from the 2010 Census was eventually used.

eggs. All surveys were completed from July 2013 to August 2013. [6] Human subject research approval was obtained from the University of California, Berkeley.

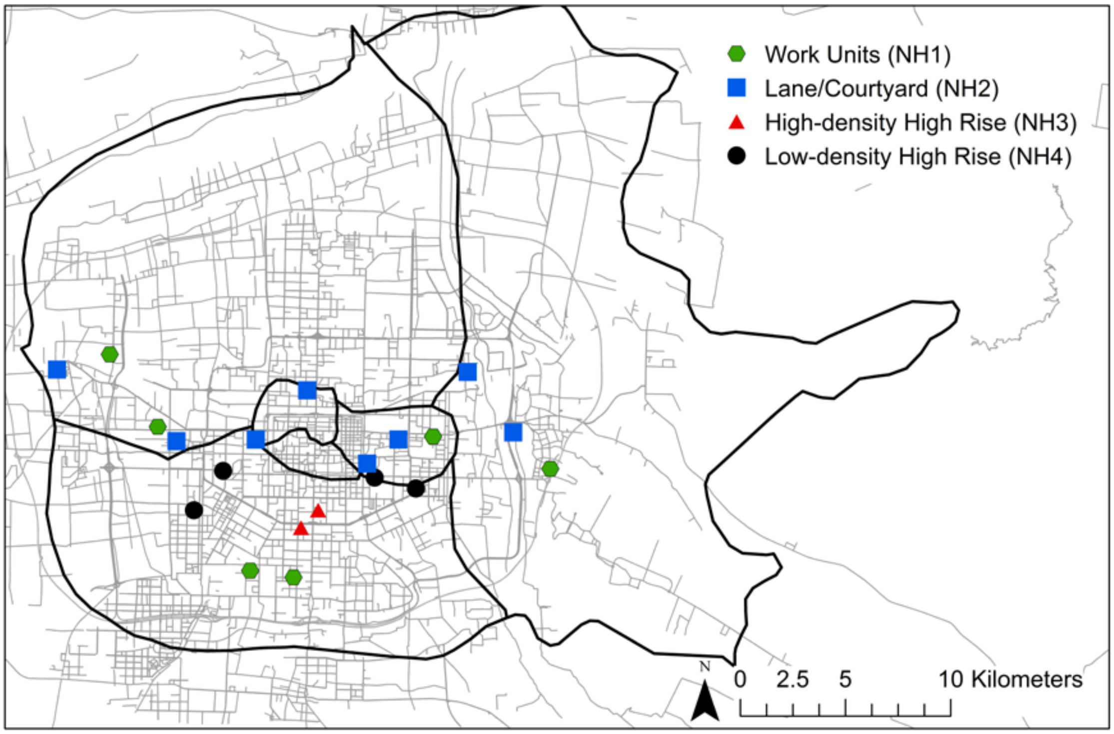


Figure 4-2 Surveyed neighborhoods by type within six urban districts of Xi'an, China

[6] A team of 15 medical students from the Medical University of Xi'an Jiaotong University was recruited to help with the surveys. Because many spoke the local dialect, they could communicate with local residents more easily. Students attended two training sessions to review the surveys, consent forms, and the data collection procedures and practice with each other prior to starting the surveys in the field. Each student was compensated for each survey completed with a limit on the total number per day to guarantee quality. At the end of each survey day, all completed surveys were reviewed and any feedback was provided the following day to each student. Any unclear responses were also clarified. Students worked in teams of two for safety.

4.3.3 Self-reported Measures of Neighborhood Characteristics (NEWS-A)

Studies have found that awareness of one's neighborhood's attributes plays a more relevant role influencing behaviors like physical activity than objective measures of neighborhood (Gebel et al. 2011; Gebel, Bauman, and Owen 2009). The abbreviated Chinese version of the Neighborhood Environmental Walkability Survey (NEWS-A) was used to assess an individual's perceptions of his/her neighborhood that was determined to be valid and reliable in a Chinese population (Cerin et al. 2007; Cerin et al. 2006). Before use in this study, the survey was converted from traditional Chinese to simplified Chinese text as the original survey was developed and translated from English for a Cantonese-speaking population in Hong Kong.

The 54-question survey assessed seven subscales of neighborhood characteristics: (1) diversity of resources, (2) pedestrian infrastructure, (3) safety, (4) neighborhood esthetics, (5) ease of access to/from neighborhood, (6) street connectivity, and (7) and residential density. Diversity of resources refers to the availability of commercial stores and public spaces including markets, parks, schools, libraries, etc. that are within walking distance to the home. Pedestrian infrastructure refers to availability of walking and biking paths and separation from motor vehicle traffic. Safety includes questions about crime, lighting at night, feeling safe while crossing roads, and traffic speeds. Neighborhood esthetics includes questions about the presence of trees, views, and attractive buildings. Access refers to the ability to move within the neighborhood easily and options for transit to leave the neighborhood. Street connectivity assesses the distances between intersections and presence of dead end streets.

Except for diversity of resources and residential density, responses to statements are rated using a 4-point Likert scale: *There are crosswalks and pedestrian signals to help walkers cross busy streets in my neighborhood. (1) Strongly Disagree (2) Somewhat Disagree (3) Somewhat Agree (4) Strong Agree.* Subscale scores are calculated as the mean of the group of questions in each category. Diversity of resources is assessed by the walking time to a list of various stores and facilities ranging from under 5 minutes to over 30 minutes. Residential density questions were scored on a 5-point Likert Scale. The score in this category is determined from a weighted average of the various contributions of housing types to the neighborhood's population density (Saelens et al. 2003). Some reverse coding was necessary to ensure that higher scores in each category indicate a higher rating of the neighborhood on that scale.

4.3.4 Self-reported Quality of Life (SF-12)

Health-related quality of life (HRQOL) is a multi-dimensional concept that captures perceived physical, mental, psychological, and social functioning beyond clinical measures of disease outcomes and is considered a valid indicator of health status of the general population beyond objective, clinical morbidity and mortality metrics (Hennessy et al. 1994; DeSalvo et al. 2006). Previous studies have found that economic development has had detriment effects, widening the quality of life disparities in Chinese populations (H. Wang, Kindig, and Mullahy 2005).

The simplified Mandarin version of Medical Outcomes Study Short Form 12 (SF-12 v2) Health Survey was used to capture mental and physical quality of life in twelve questions. This survey has been previously validated in Chinese populations and has been widely used to assess general population health (Lam et al. 2013). The SF-12 was scored using software, QualityMetric Health Outcomes ™ Scoring Software 4.5, provided by QualityMetric Inc. to give each individual an overall mental component score (MCS) and physical component score (PCS). The software also estimated missing data for individuals using Full Missing Score Estimation (MSE) which estimates the component scores (MCS and PCS) based on regression of available responses to questions (Maruish and DeRosa 2009). The two component scores are scaled to center around 50 (SD = 10). Higher scores indicate better mental and physical health with scores ranging from 0 to 100.

4.3.5 Statistical Analysis

Missing data for the NEWS-A and SF-12 were assessed.[7] Imputation of the SF-12 was included as part of the scoring algorithm software. Because missing data from the NEWS-A survey were minimal, imputation methods were not applied. We examined bivariate associations between the outcomes of interest (MCS and PCS) and the seven neighborhood subscales and socio-demographic variables to observe the unadjusted relationships. Because of the clustered nature of the data, we used general estimating equations (GEE) with survey weights for both the bivariate and multivariate analysis.

Intraclass correlations (ICC) were 0.04 and 0.02 for mental and physical health outcomes (MCS and PCS), respectively, and ranged from 0.04 to 0.27 for the seven neighborhood perceptions, indicating samples were correlated within neighborhoods. When stratified by the four types of neighborhoods, the ICC was found to be very close to 0 for the two types of high-rise commodity housing neighborhoods (NH3 and NH4), indicating that the individuals of these neighborhoods types were less correlated in both perceptions variables and HRQOL outcomes. The ICC for MCS, PCS, and the seven neighborhood perceptions ranged from 0.01 to 0.37 for the work-unit and lane/courtyard neighborhoods.

Population-averaged models using survey weights were used for both mental and physical health to examine the associations between the seven neighborhood perceptions and mental and physical aspects of quality of life. A separate model was built for each of the neighborhood characteristics to avoid issues of collinearity between the seven variables. A population-averaged model was selected due to the cross-sectional nature of the study (Hubbard et al. 2010). Age, sex, occupation, household income, education level, and *hukou* (rural or urban) status were included in the models as confounders. Household income was categorized into quartiles. Types of neighborhood were also included as confounders because they are theorized to be associated with individual perceptions and are associated with quality of life.

Multivariate analyses were first examined for the entire population. Then, because the associations between neighborhood perceptions and quality of life could vary across the types of neighborhoods, we examined each type of neighborhood separately – work units (NH1), lane/courtyard (NH2), high-density high-rise commodity (NH3), low-density high-rise commodity (NH4) housing neighborhoods – to investigate how the relationship between neighborhood perceptions and health related quality of life varied across types of neighborhoods. All analyses were conducted in STATA 12.1.

[7] Data from the paper surveys were digitized using EpiData 3.1. All data were double-entered by two separate individuals and mismatched entries were reviewed and corrected.

4.4 RESULTS

4.4.1 Descriptive Analysis

A total of 1,608 adults in 20 neighborhoods were surveyed.[8] The age and sex distribution within each neighborhood was matched to the 2010 Census (Table 4-1). Approximately half of the sample population was female (50.3%), aged 30-55 (47.8%), and 13.7% had rural *hukou* status. The percentage of residents interviewed with college level education or higher was highest (58.3%) in the low-density high-rise neighborhoods and lowest (26.6%) in the lane/courtyard neighborhoods.

The household income variable had the most missingness (27.7%) in the sample and missingness ranged from 22.5% to 34.0% across the four types of neighborhoods, with higher missingness in the high-rise commodity neighborhoods. Missing income was included in multivariate models as a separate income category. On the NEWS-A survey, 957 (59.5%) had no missing responses and on average, 1.6 questions (SD: 4.7) were missing from each survey. Of the 1,608 surveys, 44 surveys (2.7%) had any missing responses on the SF-12. After using the data recovery algorithm provided by the survey developer, 12 surveys (0.007%) still had missing physical and mental health scores. Because of the missing data from the outcomes of interest (physical and mental health scores) 1,596 and 1,597 adults were used in the physical and mental health models, respectively.

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[8] Four neighborhoods selected either declined to be surveyed or we replaced them with a backup neighborhood if the selected neighborhood was a work unit for top-secret state owned enterprises. Because China's space program and many high-tech industries are based in Xi'an, we avoided approaching these residential complexes although they can often house over 10,000 individuals and were selected based on our methods. Because our consent forms included UC Berkeley's logo, we were concerned about approaching these complexes as foreigners.

Table 4-1 Descriptive statistics of sampled adults

Variable	Full Dataset	By Type of Neighborhood: Work-Unit (NH1)	Lane/Courtyard (NH2)	High-density High-rise (NH3)	Low-density High-rise (NH4)
# of Neighborhoods	20	6	8	2	4
# of Subjects (% of total sample population)	1608	481 (29.9)	643 (40.0)	160 (10.0)	324 (20.1)
# Female (%)	809 (50.3)	250 (52.0)	322 (50.1)	80 (50.0)	157 (48.5)
Age: # Under 30 (%)	447 (27.8)	130 (27.0)	180 (28.0)	47 (29.4)	90 (27.8)
# 30-55 (%)	769 (47.8)	230 (47.8)	312 (48.5)	74 (46.3)	153 (47.2)
# 55+ (%)	392 (24.4)	121 (25.2)	151 (23.5)	39 (24.4)	81 (25.0)
Marital Status: # Single (%)	260 (16.2)	82 (17.1)	106 (16.5)	19 (11.9)	53 (16.4)
# Married (%)	1,270 (79.0)	371 (77.1)	507 (78.9)	135 (84.4)	257 (79.3)
# Divorced or widowed (%)	73 (4.5)	26 (5.4)	29 (4.5)	6 (3.8)	12 (3.7)
# Rural *Hukou* (%)	219 (13.7)	45 (9.4)	119 (18.6)	27 (16.9)	28 (8.8)
Median Household Income (¥/month)	4,000	4,000	3,400	5,000	6,000
% with College-level Education or Higher	588 (36.7)	169 (35.6)	171 (26.6)	61 (38.1)	187 (58.3)
Self-reported Neighborhood Attributes (NEWS-A): mean (standard deviation)					
Land-use Diversity	2.66 (0.67)	2.67 (0.75)	2.48 (0.57)	3.15 (0.62)	2.74 (0.62)
Ease of Access	2.86 (0.34)	2.84 (0.34)	2.86 (0.36)	2.97 (0.27)	2.83 (0.31)
Street Connectivity	3.09 (0.61)	2.99 (0.59)	3.07 (0.65)	3.29 (0.51)	3.17 (0.56)
Residential Density	657.14 (197.78)	627.59 (207.22)	615.99 (202.57)	734.56 (148.61)	741.72 (154.57)
Esthetics	2.59 (0.60)	2.64 (0.58)	2.44 (0.59)	2.70 (0.64)	2.76 (0.59)
Safety	2.74 (0.33)	2.71 (0.35)	2.67 (0.31)	2.90 (0.27)	2.83 (0.31)
Pedestrian infrastructure	3.00 (0.59)	2.92 (0.57)	2.93 (0.62)	3.27 (0.51)	3.13 (0.51)
Health-related Quality of Life (SF-12): mean (standard deviation)					
Mental Health (MCS)	52.74 (7.16)	51.85 (7.81)	53.53 (7.00)	52.32 (6.85)	52.72 (6.42)
Physical Health (PCS)	51.16 (7.34)	50.37 (7.45)	51.27 (7.31)	52.34 (6.89)	51.52 (7.36)

Comparing built environment attributes and quality of life outcomes (MCS and PCS) across neighborhood types (Figure 4-3 and Figure 4-4)

When comparing across the four types of neighborhoods, the low-density high-rise (NH4) neighborhoods had the highest perceived residential density and perceived esthetics ratings ($p=0.004$), lane/courtyard housing (NH2) had the worst rated esthetics ($p=0.018$). The high-rise commodity neighborhoods (NH3 and NH4) also had statistically significantly better ratings in terms of diversity, access, street connectivity, safety, and walkability, as compared to the work units and lane/courtyards ($p<0.05$). Quality of life outcomes were comparable although higher MCS scores in lane/courtyard neighborhoods were observed, compared to work units; and higher PCS scores were observed in in high-density high-rise neighborhoods than in work units ($p=0.047$).

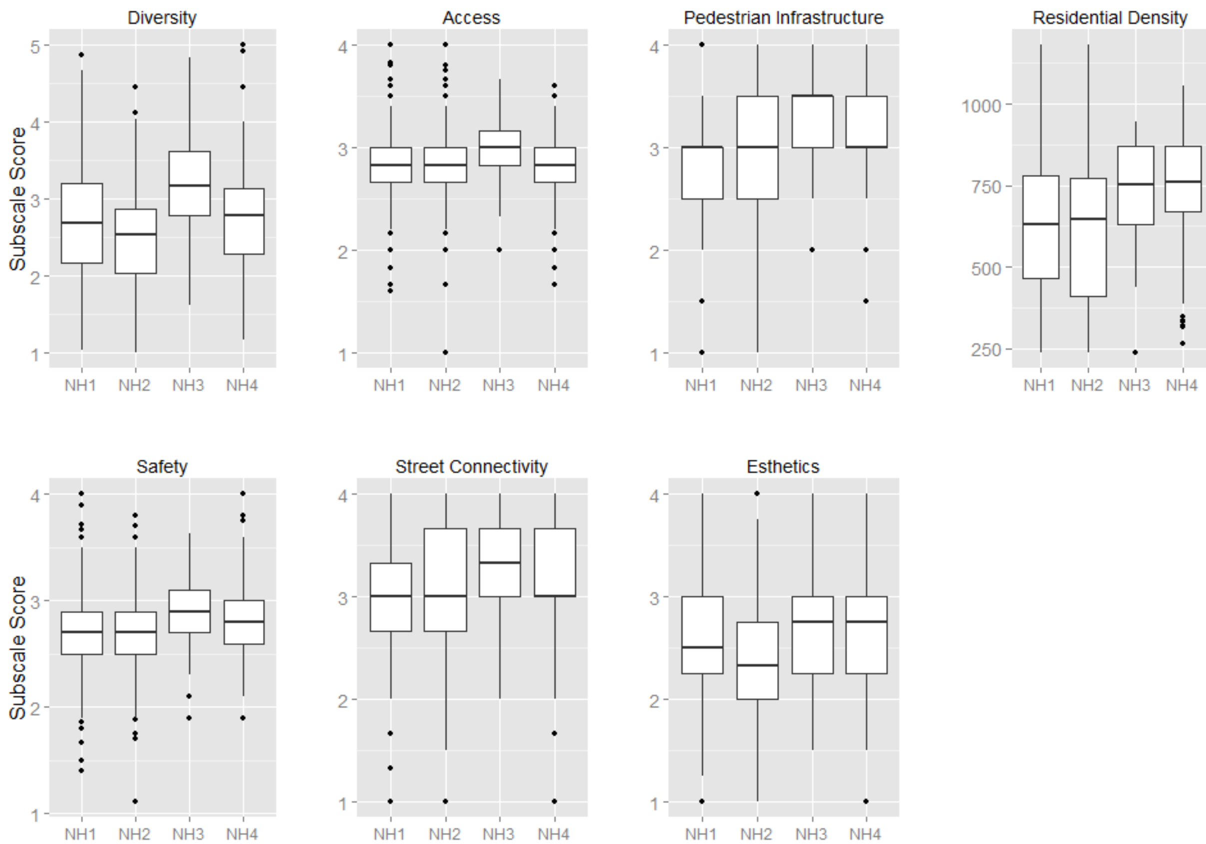

Figure 4-3 Distributions of perceived neighborhood attributes variables by type of neighborhood

Key: Work-unit (NH1), Lane/courtyard (NH2), High-density high-rise (NH3), Low-density high-rise (NH4) neighborhoods

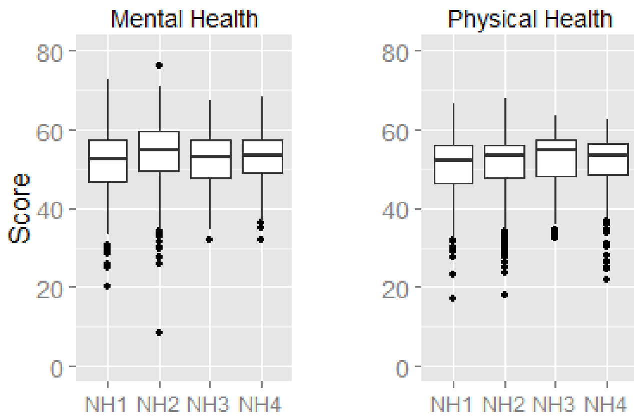

Figure 4-4 Distributions of quality of life outcome variables (MCS and PCS) by type of neighborhood

Key: Work-unit (NH1), Lane/courtyard (NH2), High-density high-rise (NH3), Low-density high-rise (NH4) neighborhoods

Comparing social capital across neighborhood types (Figure 4-5)

Residents of lane/courtyard neighborhoods (NH2) have significantly lower (1.2 to 1.7 points, p<0.01) total social capital than the residents of the other three neighborhood types. These residents (NH2) also have the lowest bonding social capital. Work-unit residents (NH1) have significantly more bridging social capital (p<0.05) but lower bonding social capital (p<0.01) than those living in the new commodity housing neighborhoods (NH3 and NH4).

In the social capital survey, responses to the following three questions were examined for differences across type of neighborhood:

1. With how many of your neighbors do you keep a routine contact?
2. Among your neighbors, how many can you trust?
3. Among your neighbors, how many will definitely help you upon your request?

When comparing responses in two groups (Most/All versus Some/A few/None), residents of work-unit (NH1) and lane/courtyard (NH2) neighborhoods had significantly higher odds of reporting they keep in routine contact with Most/All of their neighbors, than those in low-density high-rise neighborhoods (NH4). Work-unit residents also had higher odds of responding that they trusted most/all of their neighbors, as compared to the residents of the other three types of neighborhoods. No statistically significant differences in responses were found among the four neighborhoods types for getting help from their neighbors.

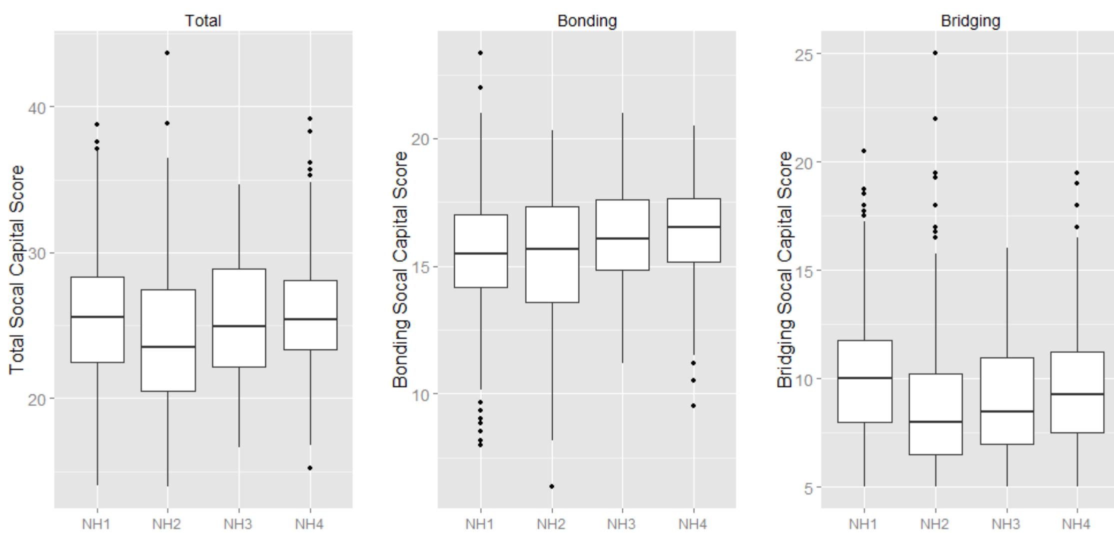

Figure 4-5 Distributions of quality of life outcome variables (MCS and PCS) by type of neighborhood

Key: Work-unit (NH1), Lane/courtyard (NH2), High-density high-rise (NH3), Low-density high-rise (NH4) neighborhoods

Bivariate Analysis
Bivariate analyses suggest significant positive associations ($p \leq 0.05$) of increased perceived land-use diversity, ease of access, and esthetics, safety, and availability of pedestrian infrastructure with higher mental and physical health (Table 4-2). A college education or higher was found to be associated with lower mental health but improved physical health. Urban *hukou* holders were found to have lower physical health than their rural counterparts. Physical health also declined with increasing age.

Table 4-2 Bivariate associations of socio-demographic and neighborhood variables with mental and physical health

	Mental Health (MCS)		Physical Health (PCS)	
Variable	Beta (SE)	p	Beta (SE)	p
Female[a]	0.08 (0.28)	0.781	-0.62 (0.71)	0.383
Age[b]	0.01 (0.01)	0.261	-0.22 (0.01)	<0.001
Urban *Hukou*[c]	0.08 (0.51)	0.879	-1.55 (0.54)	0.004
College[d]	-0.53 (0.57)	0.354	3.62 (0.48)	<0.001
Household Income (¥/month)[e]				
2000-3999	1.23 (0.62)	0.048	0.77 (0.64)	0.229
4000-5999	0.75 (0.610	0.218	0.91 (0.63)	0.147
6000+	0.96 (0.58)	0.097	3.27 (0.59)	<0.001
Missing	3.08 (0.55)	<0.001	1.61 (0.57)	0.005
Neighborhood Type				
Lane/Courtyard (NH2)	1.73 (0.92)	0.059	1.11 (1.16)	0.335
High-density high rise (NH3)	-0.04 (0.66)	0.950	0.98 (0.52)	0.059
Low-density high rise (NH4)	-0.06 (0.68)	0.930	0.35 (0.61)	0.565
Neighborhood Characteristics				
Land-use Diversity	1.03 (0.55)	0.060	2.26 (0.44)	<0.001
Ease of Access	3.14 (0.96)	0.001	0.93 (0.51)	0.068
Street Connectivity	0.76 (0.34)	0.025	-0.10 (0.36)	0.772
Residential Density	0.0003 (0.0016)	0.851	-0.0003 (0.0099)	0.728
Esthetics	1.15 (0.58)	0.047	1.00 (0.35)	0.005
Safety	1.69 (0.80)	0.035	0.64 (0.69)	0.351
Pedestrian infrastructure	1.19 (0.46)	0.009	-0.11 (0.34)	0.739

[a]Referent is male.
[b]Continuous age variable.
[c]Referent is an individual with rural *hukou* status (household registration).
[d]College education or higher.
[e]Referent is less than 2000 yuan per month group.

4.4.2 Multivariate Model Results

Overall Model

A population-averaged model without interactions was run for each of the seven neighborhood characteristic for mental (MCS) and physical (PCS) health, while controlling for confounders (age, sex, occupation, household income, education level, and *hukou*). Higher reported scores of pedestrian infrastructure, diversity of resources, ease of access, safety, esthetics, and street connectivity were found to be associated increased self-rated mental health (MCS) (Table 4-3). Higher reported scores of diversity of resources, ease of access, and esthetics were found to be associated with improved self-rated physical health (PCS) (Table 4-4).

Neighborhood-specific Models

While the full model found significant positive associations between perceived neighborhood characteristics and MCS and PCS, we observed through the neighborhood-specific models that these associations differed across the four types of neighborhoods. For example, a one point increase in perceived pedestrian infrastructure was significantly ($p \leq 0.001$) associated with a 2.01 and 3.89 point increase in MCS in the lane/courtyard (NH2) and high-density high-rise (NH3) neighborhoods, while these associations were not statistically significant in other neighborhood types. The positive associations of pedestrian infrastructure, access, and safety with MCS were the highest in the high-density high-rise neighborhoods (NH3). Associations of neighborhood characteristics with PCS were smaller in magnitude and less significant than in the MCS models. The largest associations in the PCS models were seen in the newer high-rise (NH3 and NH4) neighborhoods.

Regression model results for all covariates are available in Appendix D.

Table 4-3 Associations between perceived neighborhood characteristics and mental health-related quality of life (MCS)

	No Interactions[a]		NH1		NH2		NH3		NH4	
	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Walking	1.10*	0.49	0.21	0.60	2.01***	0.23	3.89***	0.88	1.30	0.92
Diversity	1.22*	0.49	0.99	0.68	1.59*	0.71	2.36**	0.93	1.35	0.72
Access	3.13***	0.98	4.11**	1.46	0.97	0.83	7.00***	0.80	2.87***	0.53
Safety	2.03**	0.69	2.78**	0.88	0.37	1.05	4.78**	1.58	0.64	0.85
Esthetics	1.02*	0.49	0.26	0.80	2.29***	0.44	-0.04	0.28	1.37*	0.64
Streets	0.72*	0.36	1.03	0.59	0.29	0.50	0.32	0.59	0.76	0.68
Density	<0.001	0.003	-0.002	0.002	0.002	0.002	0.005*	0.002	<0.001	0.004

*P≤0.05 ** P≤0.01 *** P≤0.001

[a]Uses data from all neighborhoods without considering interactions of neighborhood characteristics with type of neighborhood.

[b]All associations are adjusted for confounders

Table 4-4 Associations between perceived neighborhood characteristics and physical health-related quality of life (PCS)

	Full Model		NH1		NH2		NH3		NH4	
	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Walking	0.21	0.33	0.32	0.54	-0.13	0.26	1.80***	0.45	<0.01	0.26
Diversity	0.73*	0.30	0.46	0.50	1.08*	0.43	0.56*	0.23	1.62***	0.31
Access	2.06***	0.63	3.24***	0.39	-0.68	0.58	1.98***	0.59	3.25***	0.70
Safety	0.61	0.43	0.37	0.19	1.18	1.08	3.80***	0.92	-0.05	2.10
Esthetics	1.02***	0.27	1.12***	0.31	0.69	0.57	1.46***	0.19	1.18***	0.12
Streets	0.30	0.43	0.34	0.73	0.19	0.54	1.67***	0.45	0.02	0.11
Density	-0.001	0.001	-0.002	0.002	<0.001	0.002	0.003***	0.001	<-.001	0.002

*P≤0.05 ** P≤0.01 *** P≤0.001
[a]Uses data from all neighborhoods without considering interactions of neighborhood characteristics with type of neighborhood.
[b]All associations are adjusted for confounders.

4.5 DISCUSSION

4.5.1 Main Findings

This cross-sectional study of Chinese adults in Xi'an, China found significant associations between an individual's perceived neighborhood's attributes and his/her mental- and physical-health related quality of life. In particular, the positive associations of perceived neighborhood characteristics were the strongest in the new commodity housing neighborhoods.

New Commodity Neighborhoods

The overall model found that higher rated perceptions of a neighborhood's pedestrian infrastructure, diversity of resources, ease of access, safety, esthetics, and street connectivity were significantly associated ($p<0.05$) with better mental health. However, these associations varied by type of neighborhood. The most surprising findings were the significance and the magnitude of associations in the high-density commodity neighborhoods (NH3) between neighborhood perceptions and mental-health related quality of life (MCS). For instance, on average an increase in a point in perceptions of access was found to be significantly associated ($p<0.001$) with 7.00 point increase in MCS. The magnitude of associations with perceptions of pedestrian infrastructure (3.89 points) and safety (4.78 points) in the high-density commodity neighborhoods (NH3) were also larger than significant associations seen in the other three types of neighborhoods.

The stronger associations between each neighborhood perception variable and mental health could result from pride in home ownership, living in a newer neighborhood, and feelings of "gatedness" and exclusivity which has been documented in previous literature (S. Li, Zhu, and Li 2012). The lack of local social networks but a sense of pride in home ownership and in the neighborhood (S. Li, Zhu, and Li 2012) could boost quality of life, outweighing the lack of closer neighborly contacts found in the older neighborhoods. In contrast, lack of significant associations or smaller associations found in the older neighborhoods (NH1 and NH2) could result from other variables that more strongly influence mental health related quality of life, making neighborhood design less important. For instance, interactions and trust of neighbors were higher in the work-unit neighborhoods, indicating stronger local social networks in the older neighborhoods. Because of weaker social ties and trust with neighbors, these results indicate that built environmental perceptions could play a more significant role in determining mental health-related quality of life in these newer but still high-density neighborhoods.

Work-unit Neighborhoods

In the work units (NH1), increased access to and from the neighborhood was found to be significantly associated with both mental and physical health. As seen in Figure 4-2, many of the work-unit neighborhoods were built farther away from the city center within the old city walls because they required larger plots of land for the state-owned enterprise, housing, and other services. Because of the distance of these neighborhoods from the major commercial, entertainment, and cultural centers of the city, how accessible one's neighborhood is to other parts of the city is associated with both mental and physical health. In the past, these neighborhoods were physically isolated but with growth in public bus systems, car ownership, and construction of the new Xi'an subway system, increased mobility around and connectedness with the city could be viewed as desirable while limited accessibility could play a role in diminished mental health. Further, increased access could also be positively associated with better physical health if more trips are being taken using active transport such as walking to/from public transit or biking.

Lane and Courtyard Neighborhoods

Pedestrian infrastructure, diversity of neighborhood resources, and esthetics were found to be positively associated with mental health in lane/courtyard (NH2) neighborhoods. Because these neighborhoods are generally not as well-planned as the work units or the commodity housing, perceiving a more pleasant physical environment despite living in a dense and poorly planned neighborhood could indicate these individuals have a more positive affect which could influence them to respond more positively about their neighborhood, and therefore also have higher quality of life indicators. Because there is a wide geographical distribution of these neighborhoods across the city, we did not find significant associations of access to/from these neighborhoods with quality life, as we did in the work units which are further away from the city center.

Comparison with other studies

The few studies examining the relationships between built environment and HRQOL among the general population in residential settings have found mixed results. A study in Colombia found that land-use heterogeneity and increased park access were associated with improved HRQOL (Sarmiento et al. 2010). However, (Sallis et al. 2009) found that adults in higher-income neighborhoods in the United States had higher physical HRQOL but not mental HRQOL. They found no other significant associations with HRQOL by living in more walkable neighborhoods, although they did find walkability was associated with physical activity levels and lower BMI. Our study found that in the high-rise neighborhoods (NH3) that had higher median household incomes, walkability was associated with both higher mental and physical HRQOL, indicating a potentially stronger role of neighborhood in residents of the commodity housing neighborhoods.

The differences in these results could be explained in part by the different population and social contexts studied, and the tools used to measure neighborhood attributes. In particular, the strength and magnitudes of associations of neighborhood attributes with HRQOL in the high-income neighborhoods (NH3 and NH4) could indicate the stronger role of residential neighborhood on quality of life, while in the older neighborhoods (NH1 and NH2), other factors could be more important to quality of life than attributes of the built environment. It maybe that pride in home ownership and living in a desirable, higher status neighborhood contributes more to neighborhood satisfaction and general happiness in the newer commodity housing neighborhoods (S. Li, Zhu, and Li 2012).

4.5.2 Limitations

While significant associations between several neighborhood attributes and quality of life were found, this study was unable to explore the potential causal relationships between a neighborhood's built environment and its residents' quality of life. It is unclear if the neighborhood attributes have causal relationships with the residents' quality of life or if healthier residents are self-selecting into neighborhoods with certain desirable characteristics. The median length of residence time within the sample population was 10 years with a mean of 14.8 years

(SD = 13.7 years). While the Chinese sample population may not as mobile as those studied in other countries, the issues of residential self-selection and whether or not the current neighborhood is causing the measured quality of life are still present in this study. Future studies could address this issue by using a longitudinal design. Although this study is cross-sectional, the ability to capture a range of types of neighborhoods (work units, lane/courtyard housing, commodity housing) provides a unique opportunity to observe urban development trends in a Chinese city across several decades of dramatic change.

This study also relied on quota sampling to recruit subjects at the final stage of sampling due to logistical issues of access in the neighborhoods. While probability-based sampling methods such as systematic sampling would have been ideal, we matched on age and sex according to the 2010 Census in an attempt to capture a population-representative sample for this study.

In addition, this study relied on perceived rather than objective measures of built environment. Because a person with negative affect will tend to view their neighborhood and self-reported health more poorly, results from this study do not indicate potential impacts from changing built environments of these neighborhoods. While this study does not explore the reasons for why some individuals had negative perceptions and while some had more positive perceptions, it does point to the potential importance of improving negative perceptions of the environment for quality of life.

Further, the pathways through which built environment could affect a person's quality of life are numerous. This study does not investigate the indirect versus direct effects of the residential neighborhood's design. Future analyses could include examining the role of social capital or how behaviors like physical activity or travel choices mediate the relationship between physical design and downstream quality of life.

Finally, because this study relied on perceived neighborhood characteristics, despite the positive associations with perceived neighborhood characteristics and mental and physical–related quality of life, it is unclear how interventions to improve pedestrian infrastructure, for example, would increase one's perception of walkability. We would need to better understand reasons why individuals rate the same neighborhood differently and if there are barriers to use. These differences could be a result of how different groups live in and use their neighborhoods.

4.6 CONCLUSIONS

In general, higher walkability, easy access to/from a neighborhood, neighborhood esthetics, and diversity of resources within walking distance, as self-reported by residents, are associated with increased mental and physical-related quality of life in Xi'an, China. Around newer commodity housing complexes, creating walkable, esthetically pleasing neighborhoods with diverse resources has potential to improve mental and physical health. In work-unit complexes, ensuring these residents are connected to the other parts of the city through various transit options can be important for quality of life. Despite the limitations of a cross-sectional design, this study contributes to a body of literature with evidence that where we live plays a role in determining how well we live and provides urban planners with potential priorities for different types of neighborhoods in Chinese cities.

This study improves upon the existing body of literature by assessing perceived characteristics of the built environment neighborhood, and by measuring both physical health as well as much less researched mental quality of life measures. Although it relies on a cross-sectional design to studying associations between the built environment and health and is subject to self-selection issues, this study has employed systematic sampling of a representative urban population across varied types of neighborhoods that represent different stages of urban development. Moreover, this study extends the built environment literature for China, which although has been experiencing rapid development, has been understudied.

Chapter 5 Multi-pollutant Exposures in Urban Neighborhoods and Associations with Physical Activity and Health

5.1 OVERVIEW

This chapter uses the predicted air pollution concentrations in Chapter 2 and applies them to epidemiological models examining the associations between physical activity and health outcomes across different multi-pollutant ambient air pollution environments.

5.2 BACKGROUND

5.2.1 Leisure-time physical activity (LTPA) and health

Physical activity is associated with reduced risks of obesity, cardiovascular disease, hypertension, diabetes, and other chronic diseases (Fernhall, Borghi-Silva, and Babu 2015; US DHHS 2008). Physical activity has also been found to reduce stress, anxiety, and depression (Herring et al. 2012; Penedo and Dahn 2005; US DHHS 2008). An individual's total amount of physical activity is comprised of from his/her occupation related activities, active travel behaviors including walking or biking, and leisure-time activities. In particular, leisure-time physical activity (LTPA) is becoming more important in urbanized areas where physical activity contributions from occupations and active travel are decreasing as there is a shift away from labor-intensive occupations and reliance on motorized transportation increases (S. W. Ng et al. 2014; Shu Wen Ng, Norton, and Popkin 2009).

Despite the health benefits of physical activity, total physical activity levels are declining globally (S. W. Ng and Popkin 2012) and a third of adults do not attain recommended levels of physical activity for health benefits (Hallal et al. 2012). Between 1991 and 2006, total weekly physical activity levels in Chinese adults fell by 32%, with greatest reductions in work-related physical activities although the amount of LTPA has increased (Shu Wen Ng, Norton, and Popkin 2009). In a 2010 survey, nearly 84% of the surveyed population did not participate in any physical activities (Juan Zhang and Chaaban 2013). From 2012 to 2015 in an effort to prevent non-communicable diseases, the Chinese Center for Disease Control and Prevention aimed to increase the percent of population participating in regular exercise to 32%, although details of how to achieve this goal and what constitutes "regular" exercise were unclear (Lachat et al. 2013). Physical inactivity has been estimated to contribute up to 19% of the risks associated with stoke, hypertension, cancer, type 2 diabetes, and coronary heart disease in China and be responsible for $6.2 billion in associated medical costs (Juan Zhang and Chaaban 2013).

With the decline in occupational physical activity and growing sedentary behaviors in the Chinese population, promoting LTPA, along with other dietary recommendations and active travel, is a key component of China's public health program to improve health by preventing chronic diseases and their risk factors.

5.2.2 Multipollutant air pollution exposures as a potential effect modifier

The trade-offs of promoting physical activity and potential risks from environmental exposures have yet to be explored in Chinese populations. In urban environments where air pollution levels are high, these health benefits could be significantly reduced and the efficacy of programs promoting LTPA would be overstated without simultaneously considering environmental exposures.

As described in Chapter 2, poor air quality in China is a direct result of increased energy consumption from the industrial, real estate, and residential sectors. Participating in physical activities in these high pollution environments are concerning because physical activity increases minute ventilation (volumetric rate of air inhaled or exhaled) and uptake of pollutants into the lungs. Studies of subjects participating in physical activities and living near high pollution areas such as roadways have found that short-term exposures to these pollutants are associated with decreased lung function and heart rate variability (Weichenthal et al. 2011; Adar et al. 2007; H. Kan et al. 2007). Although a recent study from elderly residents in Denmark found long term traffic-related air pollution exposure does not moderate the effects of physical activity on mortality (Andersen et al. 2015), in China where the ambient urban air pollution levels are orders of magnitude higher than in European cities, exposure to ambient air quality could negate the benefits of physical activity or even lead to greater health risks, and thus should be explored.

Further, because people are exposed to complex air pollution mixtures that vary by sources and atmospheric conditions, there has been a growing interest in assessing ambient air pollution as a more realistic mixture rather than single pollutants in air pollution management, regulation, and epidemiological studies. Several methods have been used in epidemiology studies to incorporate multi-pollutant exposures including interaction terms for pairs of pollutants in the same regression model or clustering pollutants based on biological mechanisms or sources (Billionnet, Sherrill, and Annesi-Maesano 2012; Dominici et al. 2010). However, these methods require large amounts of data and can be difficult to estimate when correlations between pollutants are high. Such studies have found associations of $PM_{2.5}$ with total mortality were higher on days with increased contribution from traffic sources (Antonella Zanobetti et al. 2014) and associations of $PM_{2.5}$ and cardiovascular hospital admission were significantly different when $PM_{2.5}$ composition varied (Antonella Zanobetti et al. 2009).

This study considers the role of multi-pollutant ($PM_{2.5}$, NO_2, SO_2, and O_3) exposures at the neighborhood level. Because only cross-sectional data are available and $PM_{2.5}$ composition data not yet available, we categorized neighborhoods according to types of air pollution mixtures based on these four criteria pollutants and then assessed the associations of LTPA with health outcomes. Results from this study could help direct how initiatives to promote active transit and LTPA can consider the modifying effects of ambient air pollution.

5.3 METHODS AND MATERIALS

5.3.1 Physical Activity and Health Data

Data collection methods from the 2013 survey of adults (n=1,608) in 20 neighborhoods of Xi'an, China have been described previously in Chapter 2. Briefly, data for this study came from a multi-stage cluster sample of adults (18 years old and older) in Xi'an, China that collected socio-demographic information, perceived neighborhood characteristics, social capital, physical activity, diet, travel behaviors, health outcomes, and quality of life data. The study sample was drawn from the six urban districts, which include 6.5 million people and cover an area of 833 km^2. Human subject research approval was obtained from the University of California, Berkeley.

Because of the decline in occupation-related physical activity in Chinese populations, this study focuses on leisure time physical activity (LTPA) as the exposure of interest. LTPA was determined from questions that asked about frequency and time spent by type of activity that were grouped as low, moderate, or vigorous, based on expected energy exertion. Low LTPA included walking and using exercise equipment in parks. Moderate LTPA included lifting weights, *taichi*, *wushu*, and ping-pong. High LTPA included soccer, running, tennis, basketball, volleyball, and badminton.

The total time spent per activity type per week was calculated and used to rank activity levels for each subject in four categories (Table 5-1) (US DHHS 2008). Individuals with 150 or more minutes of moderate to vigorous physical activities (MVPA) per week were classified as having high LTPA. Individuals with less than 150 minutes of MVPA per week were classified as having a medium LTPA. And finally, individuals that had no MVPA but participated in other low exertion LTPA were classified as low LTPA. Individuals reporting no LTPA were classified as inactive.

We examined the relationship between the LTPA levels and three outcomes of interest. The first outcome was based on the response to a survey question that asked the subject how frequently in the last 12 months, their lives had been impacted for a week or more due to health reasons. Responses were the following: 1) Frequently 2) Sometimes 3) Infrequently 4) Never 5) Don't know. This variable (adverse health impact) was dichotomized by grouping "Frequently" and "Sometimes" respondents while grouping the others into a second group. We also examined two other outcomes of interests: the mental health and physical health-related quality of life scores (MCS and PCS) from the SF-12 survey, as previously described in Chapter 4.

Table 5-1 Leisure-time physical activity (LTPA) levels criteria

LTPA Level	Criteria (per week) [a]
Inactive	MVPA and LTPA = 0 minutes
Low	No MVPA but some LTPA > 0 minutes
Medium	MVPA < 150 minutes
High	150 ≤ MVPA

[a]MVPA: moderate to vigorous physical activity

5.3.2 Neighborhood Air Pollution

Short-term air pollution sampling across the six urban districts and land-use regression (LUR) modeling methods have been described previously (Chapter 2). Using the predicted air pollutant surfaces, the annual pollutant concentrations for NO_2, SO_2, O_3, and $PM_{2.5}$ were calculated at each of the 20 neighborhoods surveyed. Each neighborhood site was assigned an air pollutant concentration based on an average of the 30 m x 30 m resolution predictions from the LUR model that are within a 500 m buffer around each neighborhood.

In addition to assigning to each neighborhood NO_2, SO_2, O_3, and $PM_{2.5}$ concentrations, we also considered the mixture of air pollutants for each neighborhood. We grouped neighborhoods based on similar exposures to levels of the four pollutants. First, using quartiles of the pollutant distributions across the 20 neighborhoods as cutoffs, pollutant concentrations for NO_2, SO_2, and O_3 at each neighborhood were labeled as low (<25th percentile), medium low (25 to 50th percentile), medium high (50 to 75th percentile), or high (>75th percentile). Because of $PM_{2.5}$ concentrations were not as spatially variable, a 75th percentile cutoff was considered a "high" concentration.

5.3.3 Statistical Analysis

Population-averaged models using survey weights were used for all health outcomes to examine the associations between physical activity levels and each of the three outcomes of interest. A population-averaged model was selected due to the cross-sectional nature of the study (Hubbard et al. 2010). Confounders included age, sex, *hukou*, education, household income, current smoking status, occupations requiring physical labor, seasonal allergies, and type of neighborhood (work units, lane/courtyard, high-density high rise, or low-density high rise).

We considered the associations between physical activity and the three health outcomes across different neighborhood-level air pollution. Neighborhood-level air pollution was assessed in the models in two ways: 1) single pollutant categories and 2) multi-pollutant mixtures. In the single pollutant categories, we ran the models stratifying by air pollutant category according to Table 5-5. The medium low and medium high categories were combined into a single "medium" category for NO_2, SO_2, and O_3. In the multi-pollutant mixture models, the neighborhood was assigned a mixture category based on the combination of concentrations for the four pollutants. Neighborhoods were grouped into three categories of air pollution mixtures: 1) medium levels for all four pollutants, 2) High NO_2 and SO_2, Low O_3, and 3) High $PM_{2.5}$ and O_3.

All analyses were conducted in STATA 12.1.

5.4 RESULTS

5.4.1 Descriptive statistics

Survey Sample

Most of the subjects (47.6%) had low LTPA levels with 14.9% (n=240) not reporting any LTPA (inactive). The high LTPA group comprised younger, more educated subjects, more men, and lower proportion of individuals who responded “Frequently” or “Sometimes” to having their lives affected by health problems lasting a week or longer (Table 5-2).

Neighborhood Air Quality

$PM_{2.5}$, NO_2, SO_2, and O_3 concentrations in the neighborhoods averaged 67.98 µg/m^3 (SD: 10.44), 30.65 ppb (SD: 2.99 ppb), 22.24 (SD: 2.43 ppb), and 32.21 ppb (SD: 5.18 ppb), respectively (Table 5-4). Pairwise correlations between the pollutants were moderately high with correlations coefficients (r) ranging from -0.65 to 0.58 (Figure 5-3).

The cutoff points of categorizations for the mixtures analysis were the 25th, 50th, and 75th percentiles for NO_2, SO_2, and O_3 (Table 5-5). Given the extreme right skewed nature of the distribution (Figure 5-2), $PM_{2.5}$ was dichotomized into “high” (above 75th percentile) and “low” (below 75th percentile). Using this classification, three categories of air pollutant mixtures were created. Category A includes 9 neighborhoods and has pollutant levels that all fall within the medium low and medium high ranges. Category B includes 5 neighborhoods that were grouped together because of high NO_2, low O_3, and high SO_2 concentrations. Category C includes 6 neighborhoods that have high $PM_{2.5}$ and/or O_3 concentrations (Figure 5-4). Spatially, Category C neighborhoods were the farthest from the city center while Category A neighborhoods were the most clustered around the city center (Figure 5-1).

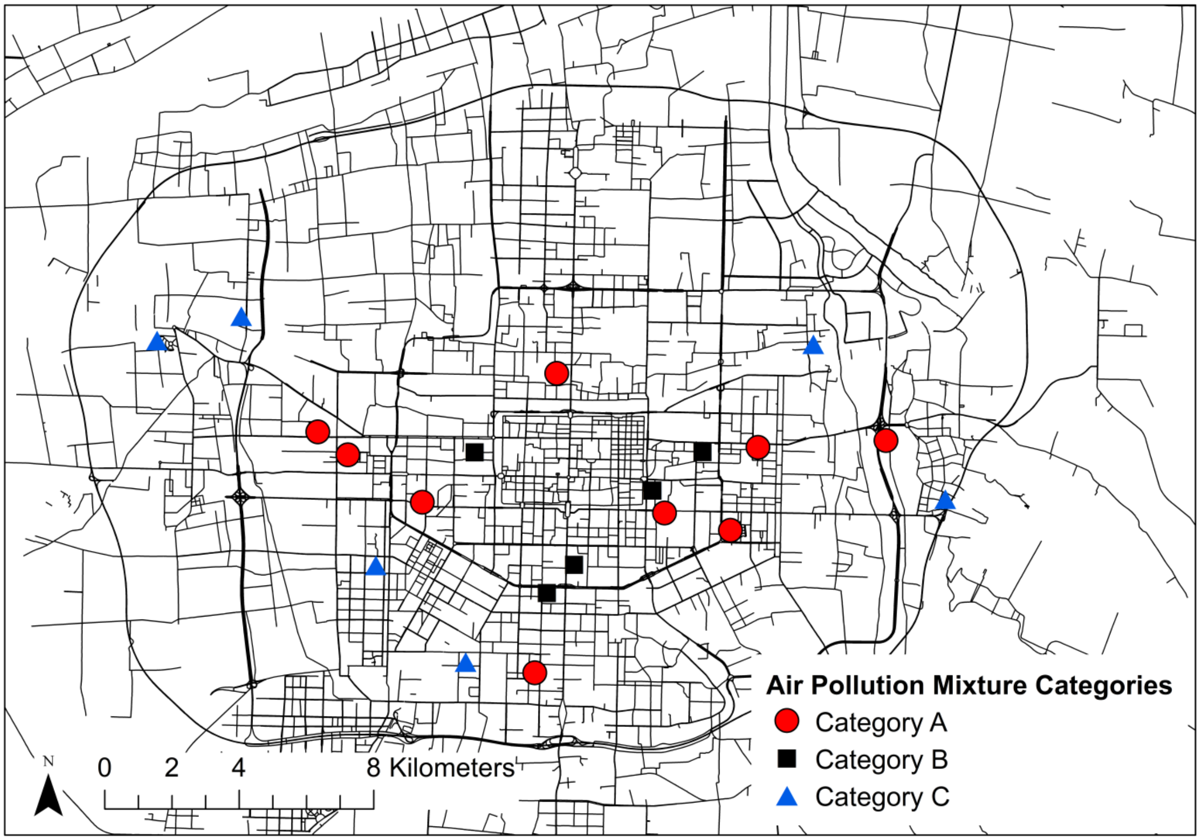

Figure 5-1 Map of Xi'an neighborhoods by air pollution mixture category

Table 5-2 Descriptive statistics of sample by leisure-time physical activity level

		By Leisure-time Physical Activity Level			
	Full Dataset	Inactive	Low LTPA	Medium LTPA	High LTPA
# of Subjects (%)	1608	240 (14.9)	766 (47.6)	221 (13.7)	381 (23.7)
# Female (%)	809 (50.3)	105 (43.8)	448 (59.5)	111 (50.2)	145 (38.1)
Age					
# Under 30 (%)	447 (27.8)	83 (34.6)	142 (18.5)	79 (35.8)	143 (37.5)
# 30-55 (%)	769 (47.8)	120 (50.0)	357 (46.6)	123 (55.7)	169 (44.4)
# 55+ (%)	392 (24.4)	37 (15.4)	267 (34.9)	19 (8.6)	69 (18.1)
# Rural *hukou* (%)	219 (13.7)	47 (19.7)	86 (11.3)	29 (13.1)	57 (15.1)
Median Household Income (¥/month)	4,000	3,250	4,000	5,000	4,000
College-level Education or Higher	588 (36.7)	79 (33.1)	224 (29.3)	123 (55.7)	162 (42.6)
Outcomes of Interests					
Mean MCS (SD)	52.74 (7.16)	51.22 (8.18)	53.39 (6.82)	51.73 (6.89)	52.95 (7.15)
Mean PCS (SD)	51.16 (7.34)	51.01 (8.26)	49.89 (7.70)	52.43 (5.97)	53.07 (6.09)
Adverse health impacts (# reporting "Frequently" or "Sometimes" they have impact of week or more due to health reasons in last 12 months (%)	159 (9.9)	24 (10.0)	95 (12.4)	17 (7.7)	23 (6.0)

Table 5-3 Descriptive statistics of sample by air pollution mixture category

	Full Dataset	Category A: Medium Levels for All Pollutants	Category B: High NO_2 SO_2, Low O_3	Category C: High $PM_{2.5}$ and O_3
# of Subjects (%)	1608	724 (45.0)	400 (24.9)	484 (30.1)
# Female (%)	809 (50.3)	468 (50.8)	201 (50.3)	240 (49.6)
Age				
# Under 30 (%)	447 (27.8)	194 (26.8)	115 (28.8)	138 (28.5)
# 30-55 (%)	769 (47.8)	247 (27.9)	190 (47.5)	232 (47.9)
# 55+ (%)	392 (24.4)	183 (25.3)	95 (23.8)	114 (23.6)
# Rural *hukou* (%)	219 (13.7)	67 (9.3)	63 (15.8)	89 (18.5)
Median Household Income (¥/month)	4,000	2,000	3,500	4,000
College-level Education or Higher	588 (36.7)	284 (39.4)	131 (32.8)	173 (35.8)
Leisure-time Physical Activity				
Inactive	240 (14.9)	95 (13.1)	51 (12.8)	94 (19.4)
Low LTPA	766 (47.6)	342 (47.2)	214 (53.5)	210 (43.4)
Medium LTPA	221 (13.7)	107 (14.8)	53 (13.3)	61 (12.6)
High LTPA	381 (23.7)	180 (24.9)	82 (20.5)	119 (24.6)
Outcomes of Interests				
Mean MCS (SD)	52.74 (7.16)	52.66 (7.24)	52.57 (7.29)	53.00 (6.94)
Mean PCS (SD)	51.16 (7.34)	50.48 (7.52)	51.24 (7.15)	52.10 (7.12)
Adverse health impacts (# reporting "Frequently" or "Sometimes" they have impact of week or more due to health reasons in last 12 months (%)	159 (9.9)	76 (10.5)	48 (12.0)	35 (7.23)

Table 5-4 Descriptive summary of predicted $PM_{2.5}$, NO_2, SO_2, and O_3 concentrations in 20 neighborhoods in Xi'an

	$PM_{2.5}$ (μg/m^3)	NO_2 (ppb)	SO_2 (ppb)	O_3 (ppb)
Mean (SD)	67.98 (10.44)	30.65 (2.99)	22.24 (2.43)	32.21(5.18)
Median	62.32	31.13	22.32	30.95
Minimum	62.32	25.11	18.82	24.64
Maximum	99.59	36.10	28.97	39.67

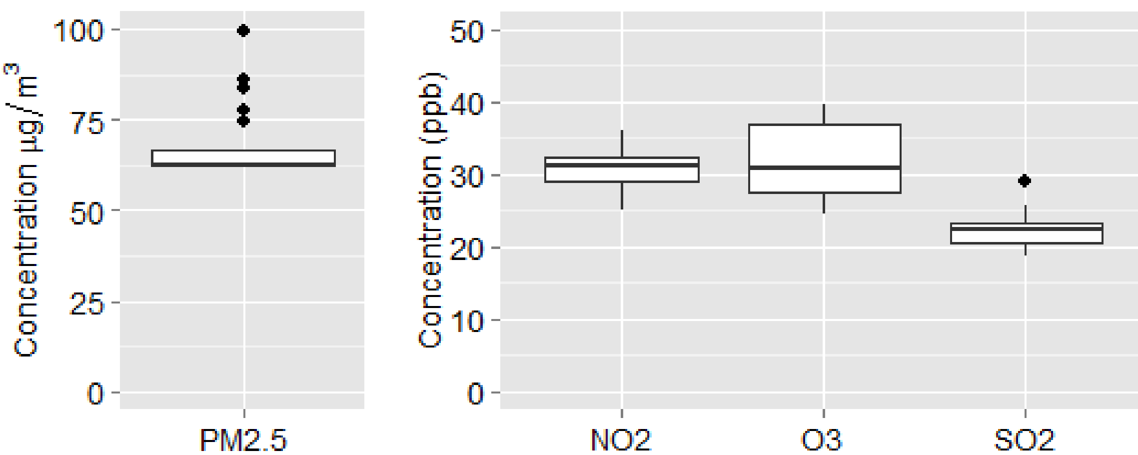

Figure 5-2 Boxplots of predicted $PM_{2.5}$, NO_2, SO_2, and O_3 concentrations in 20 neighborhoods in Xi'an

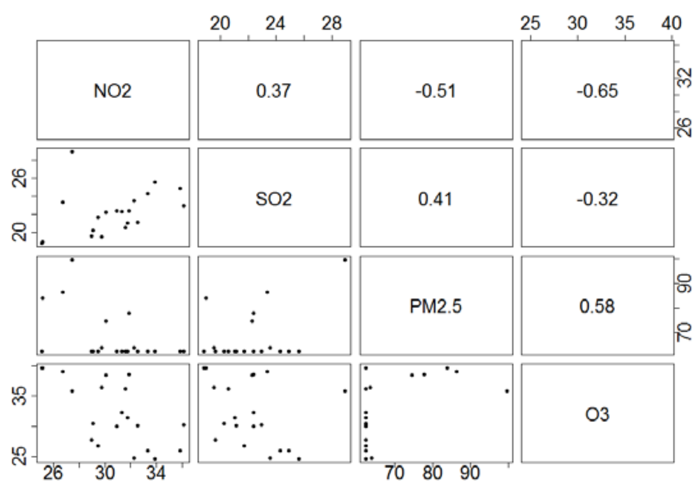

Figure 5-3 Pairwise correlations between $PM_{2.5}$ (μg/m^3), NO_2, SO_2, and O_3 (ppb) concentrations in the 20 neighborhoods

Table 5-5 Pollutant concentration category cutoff points

Concentration Category	$PM_{2.5}$ [a] ($\mu g/m^3$)	NO_2 (ppb)	SO_2 (ppb)	O_3 (ppb)
Low	N/A	≤ 29.03	≤ 20.52	≤ 27.57
Medium Low	N/A	29.02 – 31.13	20.52 – 22.32	27.57 – 30.95
Medium High	N/A	31.13 – 32.32	22.32 – 23.40	30.95 – 36.94
High	≥66.52	≥32.32	≥23.40	≥36.94

[a]Because of the extreme right skewed distribution $PM_{2.5}$ was dichotomized into high and low using the 75th percentile as the cutoff.

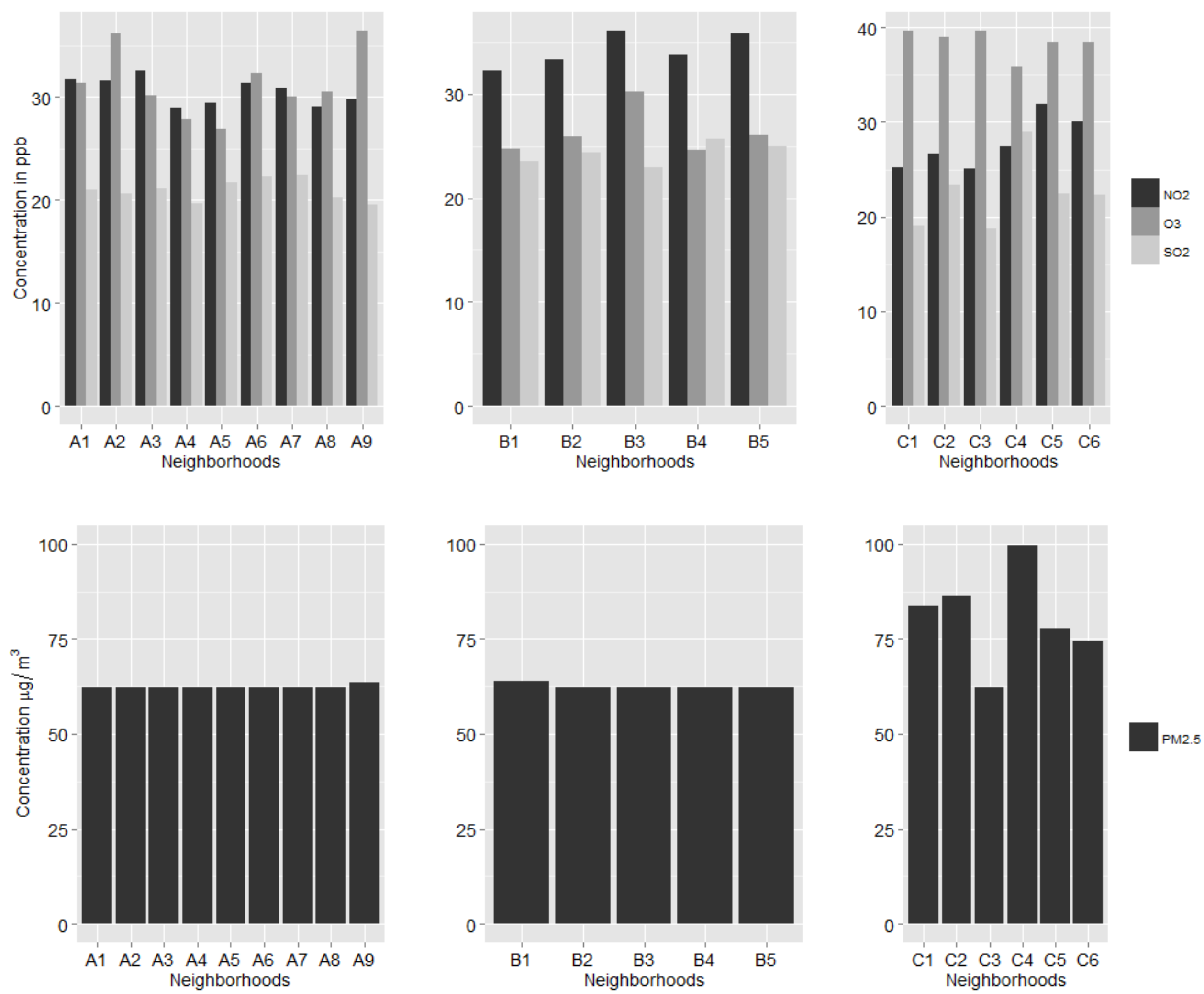

Figure 5-4 Pollutant concentrations by neighborhood for each of the mixture categories

Table 5-6 Types of neighborhoods by air pollution mixture categories

Neighborhood Type	All	Air Pollution Mixture Category: Category A: Medium Levels for All Pollutants	Category B: High NO_2 and SO_2, Low O_3	Category C: High $PM_{2.5}$ and O_3
Work Unit (NH1)	6	3	0	3
Lane/courtyard (NH2)	8	3	3	2
High-density High Rise (NH3)	2	0	2	0
Low-density High Rise (NH4)	4	3	0	1
Total	20	9	5	6

Table 5-7 Types of neighborhoods by single pollutant categories

Pollutant Category	Work Unit (NH1)	Lane/courtyard (NH2)	High-density High Rise (NH3)	Low-density High Rise (NH4)	Total
$PM_{2.5}$					
Low	3	6	2	4	15
High	3	2	0	0	5
NO_2					
Low	5	2	1	2	10
Medium	1	3	0	1	5
High	0	3	1	1	5
SO_2					
Low	4	4	0	2	10
Medium	2	1	0	2	5
High	0	3	2	0	5
O_3					
Low	3	4	0	3	10
Medium	0	3	2	0	5
High	3	1	0	1	5

5.4.2 Associations of LTPA with week-long adverse health impacts, MCS, and PCS

Adverse Health Impacts

In the first analysis, we examined the association between different levels of leisure-time physical activity and the odds of the subject responding "frequently or sometimes" having adverse health impacts lasting a week or more in the last 12 months. Through stratification, the analysis allowed these associations to vary across types of neighborhoods and neighborhood pollution levels.

For single pollutant models, we observed in the "low" $PM_{2.5}$ category that increasing LTPA lowered the odds of reporting an adverse health impact. However, in the "high" $PM_{2.5}$ category the odds were significantly increased with increasing LTPA (Table 5-8). In single pollutant models for NO_2, SO_2, and O_3, the reduced odds of adverse health impact were the most significant in the commodity housing neighborhoods (NH3 and NH4), even in the medium and high pollutant categories.

When stratifying by air pollution exposures across three categories (A, B, and C), we observed statistically significant ($p<0.05$) results in all four types of neighborhoods, which were not observed in the single-pollutant models (Table 5-12). In Category A (medium levels for $PM_{2.5}$, NO_2, SO_2, and O_3) areas, medium LTPA and high LTPA groups on average had lower odds of adverse impacts as compared to the odds of the inactive group, though no significant results were observed in the lane/courtyard neighborhoods (NH2). Medium LTPA groups had greater odds reductions than even the high LTPA group in the work-unit neighborhoods. The lowered odds observed in the single-pollutant models in the low LTPA groups were not observed in Category A areas. Low-density high-rise neighborhoods in Category A (medium levels for $PM_{2.5}$, NO_2, SO_2, and O_3) had comparable reduction in odds of adverse health impacts on average as compared to the work units. In Category B (High NO_2 and SO_2, Low O_3), low LTPA groups in the lane/courtyard neighborhoods had lowered odds than the inactive group. The greatest health benefits of physical activity were observed in the high-density high-rise neighborhoods (NH3) in Category B. In Category C (High $PM_{2.5}$ and O_3), while many of the results were not significant at the 0.05 level, we did observe the medium LTPA group in work-unit neighborhoods had 4.28 times the odds of reporting adverse health impacts as compared to the inactive group.

Health-related Quality of Life (MCS and PCS)

In the $PM_{2.5}$ only models, we observed statistically significant increases in MCS and PCS within increasing LTPA levels in the low $PM_{2.5}$ category (Table 5-13 and Table 5-18). In the high $PM_{2.5}$ category, there was a statistically significant decrease (-1.03 points, $p<0.05$) in MCS in the high LTPA group as compared to the inactive group. We also observed decreases in PCS within increasing LTPA in the lane/courtyard neighborhoods in the high $PM_{2.5}$ category. The increases in MCS were largest in magnitude in the commodity housing neighborhoods (NH3 and NH4) while the increases in PCS were greatest in the work-unit neighborhoods (NH1).

In the NO_2 only models, the increases in MCS and PCS with increasing LTPA were also statistically significant, in the low and high NO_2 areas (Table 5-14 and Table 5-19). However in the medium NO_2 area, there were statistically significant decreases in MCS and PCS with increasing LTPA in the work-unit (NH1) and the lane/courtyard (NH2) neighborhoods.

In the SO_2 only models, increasing LTPA was significantly associated with increased MCS and PCS in the low and medium SO_2 categories, but not in the high SO_2 category (Table 5-15 and Table 5-20). In the O_3 only models, there were significant increases in MCS and PCS even in the high O_3 areas, where the greatest increases were in the low-density high-rise (NH4) neighborhoods (Table 5-16 and Table 5-21).

In the categorical-mixture models, we observed statistically ($p<0.05$) significant increases in MCS with increased physical activity levels in Category A and B areas (Table 5-17). In Category C, increases in MCS were diminished or not statistically significant with increasing LTPA, except in the low-density high-rise (NH4) neighborhoods. We also observed that with increase LTPA, PCS increased in Category A areas while results were not statistically significant in Category B, except for increased PMCS for the high LTPA group in high-density high-rise neighborhoods (NH3) (Table 5-22). In Category C areas, the increases in PCS associated with LTPA in the low-density high-rise neighborhoods were still significant though smaller in magnitude, as compared to those in Category A. In the lane/courtyard neighborhoods, there was also a significant decrease in PCS in the low LTPA as compared to the inactive group.

Categorical air pollution mixture regression model results for all covariates are in Appendix E.

Table 5-8 Associations of leisure-time physical activity (LTPA) and adverse health impact across categories of $PM_{2.5}$ concentration

			By Type of Neighborhood							
	Pooled		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	OR[b]	SE	OR	SE	OR	SE	OR	SE	OR	SE
Low $PM_{2.5}$										
Low LTPA	0.69	0.21	0.70	0.20	0.76	0.25	0.48*	0.17	0.52	0.22
Medium LTPA	0.58	0.16	0.70	0.25	0.76	0.38	0.48	0.20	0.52*	0.17
High LTPA	0.32**	0.12	0.45*	0.16	0.49	0.25	0.31***	0.11	0.34*	0.16
High $PM_{2.5}$										
Low LTPA	1.37	1.14	1.43	1.35	1.21	0.84	--	--	--	--
Medium LTPA	4.75***	1.59	4.21***	1.85	3.55	2.82	--	--	--	--
High LTPA	4.80**	2.62	3.61	3.09	3.04	3.74	--	--	--	--

*P≤0.05 ** P≤0.01 ***P≤0.001
[a]Reference is inactive group.
[b]All associations have been adjusted for confounders.

Table 5-9 Associations of leisure-time physical activity (LTPA) and adverse health impact across categories of NO_2 concentration

	Pooled		By Type of Neighborhood: Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	OR[b]	SE	OR	SE	OR	SE	OR	SE	OR	SE
Low NO_2										
Low LTPA	0.80	0.22	0.88	0.21	0.64	0.28	0.33*	0.17	0.66	0.33
Medium LTPA	0.80	0.42	0.72	0.33	0.52	0.26	0.27*	0.14	0.54	0.30
High LTPA	1.24	0.74	0.90	0.19	0.65*	0.12	0.33***	0.08	0.67	0.19
Medium NO_2										
Low LTPA	2.63	3.66	7.69	11.30	3.11	3.58	--	--	1.51	2.55
Medium LTPA	8.35***	6.78	29.09***	21.85	11.77***	8.15	--	--	5.71*	4.59
High LTPA	0.37	0.79	1.58	1.71	0.64	0.85	--	--	0.32	0.39
High NO_2										
Low LTPA	0.61***	0.09	--	--	0.62*	0.12	0.86	0.14	0.46***	0.08
Medium LTPA	1.06	0.26	--	--	1.12	0.43	1.55	0.36	0.83	0.17
High LTPA	0.22	0.22	--	--	0.23	0.26	0.32	0.29	0.17*	0.15

*P≤0.05 ** P≤0.01 ***P≤0.001

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-10 Associations of leisure-time physical activity (LTPA) and adverse health impact across categories of SO_2 concentration

			By Type of Neighborhood							
	Pooled		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	OR[b]	SE	OR	SE	OR	SE	OR	SE	OR	SE
Low SO_2										
Low LTPA	0.86	0.26	1.06	0.27	0.56	0.26	--	--	0.73	0.38
Medium LTPA	1.14	0.57	0.86	0.42	0.46	0.29	--	--	0.59	0.33
High LTPA	1.41	0.88	0.62	0.25	0.33*	0.18	--	--	0.43	0.20
Medium SO_2										
Low LTPA	0.49*	0.17	0.61*	0.14	0.56**	0.12	--	--	0.24***	0.08
Medium LTPA	0.78	0.55	1.41	1.73	1.30	1.42	--	--	0.56	0.55
High LTPA	0.25	0.27	0.68	0.23	0.63	0.27	--	--	0.27*	0.27
High SO_2										
Low LTPA	1.63	0.90	--	--	1.79	0.96	0.94	0.61	--	--
Medium LTPA	1.26	0.94	--	--	1.78	1.02	0.93	0.45	--	--
High LTPA	0.96	0.59	--	--	1.77	1.69	0.93	0.57	--	--

*P≤0.05 ** P≤0.01 ***P≤0.001

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-11 Associations of leisure-time physical activity (LTPA) and adverse health impact across categories of O_3 concentration

			By Type of Neighborhood							
	Pooled		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	OR[b]	SE	OR	SE	OR	SE	OR	SE	OR	SE
Low O_3										
Low LTPA	1.38	0.53	1.24	0.36	1.52	0.73	--	--	1.35	0.66
Medium LTPA	0.60	0.25	0.64	0.27	0.78	0.50	--	--	0.69	0.35
High LTPA	0.59	0.22	0.71	0.37	0.86	0.66	--	--	0.77	0.46
Medium O_3										
Low LTPA	0.36*	0.17	--	--	0.40	0.19	0.19***	0.09	--	--
Medium LTPA	0.58	0.44	--	--	0.84	0.56	0.40*	0.18	--	--
High LTPA	0.33	0.23	--	--	0.60	0.46	0.28*	0.15	--	--
High O_3										
Low LTPA	0.59	0.26	1.24	1.04	0.14***	0.03	--	--	0.29	0.29
Medium LTPA	2.04	1.99	0.53***	0.05	0.06**	0.06	--	--	0.13***	0.02
High LTPA	1.14	1.19	0.05	0.10	0.01	0.02	--	--	0.01*	0.02

*P≤0.05 ** P≤0.01 ***P≤0.001

[a] Reference is inactive group.

[b] All associations have been adjusted for confounders.

Table 5-12 Associations of leisure-time physical activity (LTPA) and adverse health impact: categorical mixture models

			By Type of Neighborhood							
	Pooled		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	OR[b]	SE	OR	SE	OR	SE	OR	SE	OR	SE
Category A: Medium Levels										
Low LTPA	0.88	0.31	0.84	0.28	1.01	0.43	--	--	0.84	0.42
Medium LTPA	0.41***	0.11	0.47**	0.14	0.56	0.22	--	--	0.46*	0.18
High LTPA	0.52***	0.11	0.66**	0.09	0.79	0.15	--	--	0.65	0.20
Category B: High NO_2 and SO_2, Low O_3										
Low LTPA	0.44***	0.09	--	--	0.47***	0.09	0.28***	0.06	--	--
Medium LTPA	0.51	0.27	--	--	0.63	0.31	0.38***	0.11	--	--
High LTPA	0.19*	0.13	--	--	0.30	0.27	0.18**	0.12	--	--
Category C: High $PM_{2.5}$ and O_3										
Low LTPA	0.95	0.53	1.67	1.45	1.39	0.96	--	--	0.42	0.43
Medium LTPA	2.92	2.19	4.28*	2.87	3.56	2.35	--	--	1.08	0.89
High LTPA	1.73	1.46	3.06	1.93	2.54	2.27	--	--	0.77	0.41

*$P \leq 0.05$ ** $P \leq 0.01$ ***$P \leq 0.001$

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-13 Associations of leisure-time physical activity (LTPA) and mental health (MCS) across categories of $PM_{2.5}$ concentrations

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low $PM_{2.5}$										
Low LTPA	3.06***	0.75	3.08***	0.75	2.95***	0.76	2.98***	0.82	3.38***	0.84
Medium LTPA	2.37***	0.62	2.21***	0.65	2.08**	0.76	2.11**	0.75	2.51***	0.69
High LTPA	3.17***	0.54	2.82***	0.54	2.69***	0.67	2.72***	0.57	3.12***	0.60
High $PM_{2.5}$										
Low LTPA	0.41	0.80	0.32	1.00	0.45	0.79	--	--	--	--
Medium LTPA	0.59	1.53	0.60	1.55	0.73	1.45	--	--	--	--
High LTPA	-1.03*	0.48	-0.91	0.51	-0.78	0.62	--	--	--	--

*P≤0.05 ** P≤0.01 ***P≤0.001

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-14 Associations of leisure-time physical activity (LTPA) and mental health (MCS) across categories of NO_2 concentration

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low NO_2										
Low LTPA	2.37***	0.71	2.32**	0.75	2.48***	0.57	3.16***	0.64	3.05***	0.67
Medium LTPA	2.63**	1.05	2.58**	0.98	2.73**	0.89	3.42***	0.99	3.31***	0.94
High LTPA	1.11	0.89	1.09	0.63	1.25*	0.58	1.93***	0.54	1.82**	0.61
Medium NO_2										
Low LTPA	-1.07	0.69	-1.80*	0.77	-0.95	0.75	--	--	-0.20	0.80
Medium LTPA	-1.95	1.00	-2.88**	1.05	-2.03	1.08	--	--	-1.28	1.01
High LTPA	0.54	0.60	-0.75***	0.15	0.10	0.29	--	--	0.85***	0.21
High NO_2										
Low LTPA	3.98***	0.75	--	--	3.95***	0.71	3.73***	1.17	4.21***	0.98
Medium LTPA	1.75*	0.86	--	--	1.69	0.88	1.47	0.92	1.96*	0.86
High LTPA	4.00***	0.60	--	--	3.88***	0.94	3.66***	0.35	4.15***	0.54

*$P \leq 0.05$ ** $P \leq 0.01$ ***$P \leq 0.001$

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-15 Associations of leisure-time physical activity (LTPA) and mental health (MCS) across categories of SO_2 concentration

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low SO_2										
Low LTPA	1.98***	0.50	1.82***	0.54	2.40***	0.48	--	--	2.53***	0.43
Medium LTPA	2.16*	1.09	2.41*	1.13	2.99**	1.13	--	--	3.12**	1.03
High LTPA	0.64	0.75	1.34	0.73	1.92*	0.92	--	--	2.05**	0.78
Medium SO_2										
Low LTPA	3.37***	0.91	3.30**	1.06	3.72***	0.77	--	--	3.93***	0.99
Medium LTPA	0.97	1.68	0.98	1.61	1.40	1.24	--	--	1.61	1.47
High LTPA	3.83***	0.67	3.78***	0.32	4.20***	0.38	--	--	4.41***	0.37
High SO_2										
Low LTPA	-0.26	1.43	--	--	-0.26	1.44	-0.18	1.70	--	--
Medium LTPA	0.06	0.50	--	--	0.05	0.52	0.12	0.47	--	--
High LTPA	0.18	0.61	--	--	0.14	0.59	0.21	0.68	--	--

*P≤0.05 ** P≤0.01 ***P≤0.001
[a]Reference is inactive group.
[b]All associations have been adjusted for confounders.

Table 5-16 Associations of leisure-time physical activity (LTPA) and mental health (MCS) across categories of O_3 concentration

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low O_3										
Low LTPA	1.05	1.48	1.69	1.31	0.89	1.27	--	--	1.61	1.46
Medium LTPA	0.98	0.98	1.09	0.63	0.30	0.64	--	--	1.02	0.81
High LTPA	1.14	1.02	0.80	0.65	<0.01	0.74	--	--	0.72	0.71
Medium O_3										
Low LTPA	2.87	1.69	--	--	2.88	1.65	2.83	1.84	--	--
Medium LTPA	2.26*	0.78	--	--	2.29**	0.78	2.24**	0.79	--	--
High LTPA	2.00	1.15	--	--	2.05	1.11	2.01	1.13	--	--
High O_3										
Low LTPA	1.08**	0.41	0.98*	0.44	1.68***	0.33	--	--	2.82***	0.46
Medium LTPA	0.93	1.64	1.21	1.75	1.91	1.67	--	--	3.05	1.90
High LTPA	-0.21	0.89	0.38	0.57	1.08	0.62	--	--	2.21***	0.44

*$P \leq 0.05$ ** $P \leq 0.01$ ***$P \leq 0.001$

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-17 Associations of leisure-time physical activity (LTPA) and mental health (MCS): categorical mixture models

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Category A: Medium Levels										
Low LTPA	3.22***	0.93	3.30***	0.86	2.92***	0.89	--	--	3.43***	1.01
Medium LTPA	2.81***	0.78	2.54***	0.70	2.15**	0.81	--	--	2.66**	0.84
High LTPA	2.69***	0.74	2.10***	0.56	1.72**	0.64	--	--	2.23***	0.68
Category B: High NO_2 and SO_2, Low O_3										
Low LTPA	3.08*	1.37	--	--	3.17**	1.22	2.69	1.71	--	--
Medium LTPA	2.11**	0.82	--	--	2.41**	0.87	1.93*	0.89	--	--
High LTPA	3.15***	0.97	--	--	3.68***	0.90	3.21***	0.64	--	--
Category C: High $PM_{2.5}$ and O_3										
Low LTPA	0.40	0.71	0.27	0.87	0.50	0.69	--	--	1.97*	0.99
Medium LTPA	0.32	1.50	0.13	1.58	0.36	1.45	--	--	1.83	1.72
High LTPA	-0.50	0.71	-0.78	0.49	-0.55	0.62	--	--	0.92*	0.39

*P≤0.05 ** P≤0.01 ***P≤0.001
[a]Reference is inactive group.
[b]All associations have been adjusted for confounders.

Table 5-18 Associations of leisure-time physical activity (LTPA) and physical health (PCS) across categories of $PM_{2.5}$ concentrations

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low $PM_{2.5}$										
Low LTPA	2.14***	0.48	2.60***	0.49	1.61*	0.63	1.54*	0.64	2.44	0.62
Medium LTPA	2.20***	0.52	2.10***	0.44	1.11*	0.48	1.04*	0.47	1.94	0.47
High LTPA	3.36***	0.69	2.71***	0.64	1.71**	0.64	1.65**	0.52	2.55	0.51
High $PM_{2.5}$										
Low LTPA	-0.62	0.44	-0.16	0.34	-0.86**	0.28	--	--	--	--
Medium LTPA	0.86	0.91	0.76	0.77	0.06	0.74	--	--	--	--
High LTPA	1.13***	0.31	0.39	0.23	-0.30*	0.14	--	--	--	--

*P≤0.05 ** P≤0.01 ***P≤0.001
[a]Reference is inactive group.
[b]All associations have been adjusted for confounders.

Table 5-19 Associations of leisure-time physical activity (LTPA) and physical health (PCS) across categories of NO_2 concentration

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low NO_2										
Low LTPA	1.28*	0.57	1.41*	0.61	0.55	0.52	0.88	0.54	1.00	0.67
Medium LTPA	2.74***	0.64	2.16***	0.59	1.29	0.67	1.63**	0.59	1.74*	0.81
High LTPA	3.09***	0.55	1.80***	0.51	0.93	0.56	1.27**	0.43	1.38*	0.55
Medium NO_2										
Low LTPA	-1.10***	0.14	-1.61***	0.19	-0.93***	0.15	--	--	0.28*	0.13
Medium LTPA	-0.62	0.34	-1.50***	0.31	-0.82	0.45	--	--	0.39	0.37
High LTPA	0.41	0.62	-1.09***	0.21	-0.41	0.30	--	--	0.80**	0.28
High NO_2										
Low LTPA	2.14***	0.66	--	--	2.01**	0.67	1.69***	0.41	2.89***	0.57
Medium LTPA	0.74	0.62	--	--	0.49	0.52	0.17	0.52	1.36*	0.57
High LTPA	2.68***	0.76	--	--	2.21**	0.70	1.90***	0.38	3.09***	0.49

*P≤0.05 ** P≤0.01 ***P≤0.001

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-20 Associations of leisure-time physical activity (LTPA) and physical health (PCS) across categories of SO_2 concentration

			By Type of Neighborhood							
	No Interaction		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low SO_2										
Low LTPA	1.06*	0.50	1.29*	0.56	0.42	0.49	--	--	0.85	0.53
Medium LTPA	2.17*	0.90	1.68*	0.85	0.81	0.88	--	--	1.24	0.86
High LTPA	2.69***	0.34	1.51***	0.32	0.64**	0.25	--	--	1.07***	0.31
Medium SO_2										
Low LTPA	1.33	0.71	1.39	0.72	-0.06	1.17	--	--	1.53	0.88
Medium LTPA	2.78*	1.25	1.43	0.90	-0.02	0.84	--	--	1.57*	0.75
High LTPA	4.55***	1.12	1.69**	0.54	0.24	0.88	--	--	1.83***	0.55
High SO_2										
Low LTPA	-0.26	0.63	--	--	-0.27	0.63	-0.32	0.61	--	--
Medium LTPA	0.47	0.59	--	--	0.48	0.56	0.43	0.74	--	--
High LTPA	0.04	0.59	--	--	0.07	0.69	0.02	0.52	--	--

*$P \leq 0.05$ ** $P \leq 0.01$ ***$P \leq 0.001$

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-21 Associations of leisure-time physical activity (LTPA) and physical health (PCS) across categories of O_3 concentration

	No Interaction		By Type of Neighborhood: Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Low O_3										
Low LTPA	0.43	0.85	1.59**	0.56	0.12	0.61	--	--	1.08	0.77
Medium LTPA	0.91	0.95	1.20*	0.54	-0.27	0.34	--	--	0.69	0.50
High LTPA	1.96	1.19	1.49*	0.58	0.02	0.34	--	--	0.97*	0.41
Medium O_3										
Low LTPA	1.56*	0.76	--	--	1.55	0.80	1.62*	0.70	--	--
Medium LTPA	1.22	1.03	--	--	1.17	1.01	1.25	1.05	--	--
High LTPA	1.38*	0.64	--	--	1.29	0.94	1.37*	0.68	--	--
High O_3										
Low LTPA	0.27	0.62	0.22	0.59	0.42	0.58	--	--	1.28*	0.62
Medium LTPA	2.40**	0.87	2.37**	0.84	2.57**	0.86	--	--	3.43***	1.00
High LTPA	2.51***	0.77	2.45***	0.32	2.65***	0.32	--	--	3.51***	0.34

$^*P \leq 0.05$ $^{**}P \leq 0.01$ $^{***}P \leq 0.001$

[a]Reference is inactive group.

[b]All associations have been adjusted for confounders.

Table 5-22 Associations of leisure-time physical activity (LTPA) and physical health (PCS): categorical mixture models

			By Type of Neighborhood							
	Full Model		Work Unit (NH1)		Lane/Courtyard (NH2)		High-Density High Rise (NH3)		Low-Density High Rise (NH4)	
Physical Activity[a]	Beta[b]	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
Category A: Medium Levels										
Low LTPA	2.31***	0.62	2.65***	0.64	1.52	0.80	--	--	2.22**	0.92
Medium LTPA	2.36***	0.73	1.90***	0.46	0.77*	0.37	--	--	1.47**	0.51
High LTPA	3.87***	0.81	2.71***	0.49	1.58***	0.39	--	--	2.27***	0.41
Category B: High NO_2 and SO_2,Low O_3										
Low LTPA	1.45	0.80	--	--	1.49	0.79	1.30	0.73	--	--
Medium LTPA	1.34	0.97	--	--	1.45	0.92	1.26	1.08	--	--
High LTPA	1.35	0.75	--	--	1.57	0.85	1.38*	0.67	--	--
Category C: High $PM_{2.5}$ and O_3										
Low LTPA	-0.44	0.44	0.12	0.39	-0.71**	0.27	--	--	1.12**	0.35
Medium LTPA	0.92	0.99	0.63	0.82	-0.20	0.85	--	--	1.63	0.95
High LTPA	1.58**	0.53	0.35	0.33	-0.47	0.34	--	--	1.36***	0.26

*P≤0.05 ** P≤0.01 ***P≤0.001
[a]Reference is inactive group.
[b]All associations have been adjusted for confounders.

5.5 DISCUSSION

5.5.1 Main Findings

This study examined the association among physical activity levels, adverse health, and quality of life across differential residential air pollution exposures. We included neighborhood air quality in the models three ways to determine which pollutants were associated with variations in health benefits of physical activity. We were primarily interested in the results from the categorized air pollution mixture models but we also included the single-pollutant models for comparison because in some studies often data from only one pollutant are available. Although the pollutants were correlated, we also included the four pollutants in one model to see if the results were consistent.

Impacts on life due to poor health

We found evidence that on average, physical activity was associated with decreased odds of adverse health impact, but this trend could be reversed in high $PM_{2.5}$ and high O_3 environments. In Category A areas where ambient $PM_{2.5}$, NO_2, SO_2, and O_3 concentrations were classified as "medium", individuals participating in more leisure-time physical activity (LTPA) in the medium to high LTPA groups on average had lower odds of reporting adverse health impacts, as compared to those who were inactive. The low LTPA groups did not have reduced odds of reporting adverse impacts. These results are consistent with the literature citing health benefits of LTPA on general health and wellness. The results are also consistent with general public health guidelines that recommend at least 150 minutes of moderate-level (or 75 minutes of vigorous-level) of physical activity weekly to benefit health. This guideline corresponds to the medium and high LTPA groups in this study, in which we observed significant health benefits. Across the type of neighborhoods in Category A, only significant differences in the odds of reporting adverse health impacts were seen in the work unit (NH1) and low-density high-rise (NH4) neighborhoods where the health benefit was primarily in the medium LTPA group.

In Category B (high NO_2 and SO_2, low O_3), the reduction in odds of adverse health effects, especially in the high LTPA group (OR =0.19), was slightly larger than in Category A, as compared to the inactive group. In addition, some physical activity (low LTPA) is health beneficial (OR = 0.44) in the pooled model. However, despite the reduced odds of adverse health impacts in Category B neighborhoods, we do not believe the elevated NO_2 and SO_2 levels are health protective. Because the $PM_{2.5}$ levels are similar in Categories A and B, the increased health benefit could result from lowered O_3 levels in Category B, despite elevated levels of NO_2 and SO_2. In both Categories A and B, the $PM_{2.5}$ levels for neighborhoods were approximately around 62 $\mu g/m^3$. We hypothesize in Category B, the health benefits are actually obtained from decreased concentrations of $PM_{2.5}$ rather than O_3, which our exposure assessment from our land-use regression models was unable to capture. This limitation of our land-use regression models gives right-skewed $PM_{2.5}$ predictions for Xi'an and limited variability in concentrations at the lower end and made it impossible to differentiate the $PM_{2.5}$ levels between neighborhoods in these two categories. The greatest benefit from physical activity was observed in the high-density high-rise (NH3) neighborhoods where the OR ranged from 0.18 to 0.28. This difference as compared to the results from the work-unit and lane/courtyard neighborhoods could be explained by other forms of physical activity that were not included in this analysis. Our study focused on self-reported LTPA and did not compare travel behaviors in each type of neighborhood. If individuals in the work units and lane/courtyard neighborhoods participated in more active transportation modes (e.g., walking, biking, and public transit) as compared to less active ones such as driving which could be more prevalent in the high-density high-rise neighborhoods, the benefits from LTPA would be less apparent.

In addition, while most of the results were not significant at the 0.05 level, in the high $PM_{2.5}$ and high O_3 group (Category C), the direction of the results suggested that increasing levels of physicals activity may be associated with adverse health impacts, indicating the need to further explore the role of both $PM_{2.5}$ and O_3 in health outcomes. We did observe that the medium LTPA group in the work-unit neighborhoods had 4.28 the odds of reporting adverse health impacts. In this category, there was greater variability of $PM_{2.5}$ concentrations, which were correlated with O_3 levels ($r = 0.58$). Therefore, it is conceivable in Category B areas, the lower O_3 levels could correlate with lower $PM_{2.5}$ levels, which could be a potential reason why the health benefits of physical activity are even greater in Category B. The lack of significant results in Category C could result from lack of power to detect significant differences, with only 23 adults (6%) reporting "frequently" or "sometimes" having impacts due to health.

Health-related quality of life

We also examined the relationship between physical activity levels and quality of life. In general, we saw that increasing physical activity was associated with higher quality of life scores for both mental and physical health. These results are coherent with the literature that has found quality of life and health benefits of physical activity. However, we also found evidence that high $PM_{2.5}$ and high O_3 environments could reduce the quality of life benefits obtained from physical activity.

In both mental and physical models, Category C results were less significant or smaller in magnitude than those observed in Category A and B, especially in the low-density high-rise neighborhoods. The lack of significant results and reduction in health benefits of physical activity could result from the increased $PM_{2.5}$ and O_3 levels in Category C areas. The presence of statistically significant results in low-density high-rise neighborhoods in Category C demonstrates that despite the elevated $PM_{2.5}$ and O_3, the quality of life benefits of physical activity could outweigh the potential health risks of poor ambient air pollution. However, health risks from elevated $PM_{2.5}$ and O_3 are potentially more significant in the lane/courtyard neighborhoods where physical activity actually may do more harm than benefit, as seem from the 0.71 point decrease in PCS in the low LTPA group.

In the mental health model, the quality of life benefits of physical activity were only statistically significant in the low-density high-rise neighborhoods in Category C. As described in Chapter 4, these neighborhoods are newer neighborhoods with lower levels of trust among neighbors. As a result of the weaker social ties in the neighborhood, residents may derive less social and mental support from these networks as residents of the other neighborhood do. Therefore, residents with higher mental health in the low-density high-rise neighborhoods would have to obtain this support from other sources, such as physical activity. The mental health benefits of physical activity for residents of these neighborhoods seem to outweigh the potential health risks of elevated $PM_{2.5}$ and O_3 in the neighborhood. However, as with the other two health outcomes, the benefits are smaller than in Category A where $PM_{2.5}$ and O_3 levels are lower.

Categorical mixture versus single pollutant models

We found the single pollution models had inconsistent results in terms of significant tests and magnitude across the neighborhoods though there is evidence that generally, increasing physical activity is associated with improved health outcomes. The inconsistent results among the two types of models – single-pollutant and categorical-mixtures –further highlight the issues of only using single pollutants as proxies of air pollution mixtures. In this study, single pollutants were determined to be poor proxies of mixtures of pollutants. While we found significant results across our three air pollution mixture categories, based on our results across the three categories of mixtures, $PM_{2.5}$ could be the main pollutant that contributes most to the reductions in the health benefits associated with increasing levels of leisure-time physical activity.

5.5.2 Limitations

Exposure misclassification was possible at the individual and neighborhood levels. We could improve our measures of physical activity where we relied solely on self-reported measures because some individuals may over report physical activity levels. But in a large study with over 1,600 adults, personal monitoring of physical activity would have been cost-prohibitive. In addition, we focused on leisure-time physical activity rather than total physical activity which includes occupational, travel, and domestic activities. Although labor-intensive occupations were included as a confounder in the models, inclusion of active transit and domestic activities could be areas of future work. In addition, the cross-sectional design of the study may misclassify some individuals into an incorrect neighborhood air pollution category if they have recently moved.

Improved exposure assessment methods could also provide us with more conclusive results regarding the role of $PM_{2.5}$ in modifying the health benefits of physical activity. First, the data were collected at the residential neighborhood level which does not take into account time spent in other environments and other exposures. However, our models attempt to remedy this limitation by including occupational exposures as a confounder. Also, the $PM_{2.5}$ land-use regression models could be improved to provide more variability across the 20 neighborhoods. While the models are limited by the available data available – typically included data such as traffic volumes and land use were unavailable for Xi'an – LUR models for $PM_{2.5}$ could potentially be improved by including better measures of land use rather than just including measures of greenness, wetness, and brightness. Because many sources of $PM_{2.5}$ exist, improved urban land-use classification would benefit especially in a city like Xi'an where development has led to very different types of neighborhoods with different source profiles. While our air pollution sampling attempted to capture this variability, having only 19 sites, due to limitations of equipment availability and human resources, was most likely insufficient for a large diverse city like Xi'an.

In addition, future studies could increase sample sizes within neighborhoods and number of neighborhoods to capture each of the four types within the three air pollution categories. In this study, we were unable to assess across the four types of neighborhoods within the same air pollution category.

5.6 CONCLUSIONS

We found that increasingly levels of weekly leisure-time physical activity were associated with reduced odds of adverse health impacts and higher mental and physical-related quality of life. However, the health and quality of life benefits of physical activity were reduced in areas where ambient concentrations of $PM_{2.5}$ and O_3 were elevated. In addition, the physical health benefits of physical activity are potentially greatest in the new high-rise neighborhoods while the mental health benefits of physical activity are greatest in the poorer and older lane/courtyard neighborhoods.

Chapter 6 Conclusions

6.1 SUMMARY OF MAJOR FINDINGS

This dissertation explored potential linkages between urban development and health in Chinese cities. In particular, the associations between the "natural" and built environments and health were explored. Also explored was how the natural environment may modify the associations of the built environment with health.

Poor air quality is a public health concern in Xi'an but land-use regression modeling methods and new sensor technologies could assist with environmental management in rapidly changing and resource-limited areas

In Chapter 2, air pollution models were built to explore the spatial variations in $PM_{2.5}$, SO_2, NO_2, and O_3 concentrations in Xi'an. Intra-urban models for these pollutants were previously unavailable, but this chapter demonstrated the feasibility of using short-term sampling campaigns in land-use regression (LUR) methods to rapidly estimate criteria pollutant concentrations within a large city of over 800 km^2. Especially when data sources are limited for complex atmospheric transport models or existing monitoring stations are sparsely distributed over large areas, using alternative methods such as LUR to assess environmental and health risks are necessary and feasible.

In addition, new low cost and low profile environmental sensors like the PUWP can be used to assist with rapid assessments and reporting of real-time data over large areas at high resolutions. While the LUR models in Chapter 2 described using passive samplers and gravimetric methods, Chapter 3 demonstrates the validity and feasibility of using the PUWP to provide $PM_{2.5}$ data comparable to that of mature $PM_{2.5}$ measurement technologies while being several orders of magnitude lower in cost. In areas with limited resources and few personnel with the technical knowledge to operate and maintain air pollution monitoring stations, these low cost sensors provide an opportunity to increase spatiotemporal knowledge in air pollution datasets to inform where and when to focus mitigation efforts.

Interventions to improve quality of life for urban residents should be neighborhood-specific

In Chapter 4, the relationships between perceptions of built environment and quality of life were different in the work-unit, lane/courtyard, and commodity-housing neighborhoods. Higher perceptions of walkability, esthetics, and diversity of resources in the newer commodity-housing neighborhoods were significantly associated with larger increases in higher physical and mental health, as compared to those in other types of neighborhoods. In the work units, accessibility of their neighborhoods to/from other parts of the city was significantly associated with improved mental and physical health-related quality of life.

While the study is cross-sectional in nature, these results indicate quality of life in the neighborhoods could be influenced by different aspects of the built environment. Urban planners could consider improving transportation options to connect more peripherally-located work-unit neighborhoods to the city center or other commercial areas. In the commodity high-rise neighborhoods, design of the neighborhoods seems to be more important to quality of life. Therefore, urban planners should be conscious of including more pedestrian-friendly elements such as sidewalks, crosswalks, lights, trees and landscaping, not just in the gated residential complexes but throughout the surrounding neighborhood. Local governments could also help promote diversity in resources in the neighborhood by creating zoning regulations, financial incentives, and commercial real estate areas that appeal to smaller local businesses.

These differences between the older work-unit and newer commodity neighborhoods could result from differences in social capital present. While these differences need to be explored further, the strength of the social networks within a community could be crucial to supporting quality of life of its residents. As seen in Chapter 4, in the older work-unit neighborhoods where there is stronger trust between neighbors, the associations between the built environment and quality of life are smaller or less significant while these associations were larger and more significant in the newer commodity neighborhoods where residents were less likely to trust their neighbors. Improving social networks and trust within neighborhoods could be a potential target as Chinese cities develop new commodity-housing neighborhoods. For example, local community centers or the housing management could create more community engagement by organizing community events to build trust among residents. These approaches can be combined with upstream health-conscious urban planning efforts to maximize health within new Chinese neighborhoods.

Public health promotion and interventions will not be optimally effective until the urban air quality problems are mitigated

In Chapter 5, we found increasing physical activity levels generally were associated with lower odds of adverse health impacts and higher reported quality of life. However, the health benefits of physical activity were reduced in areas where ambient $PM_{2.5}$ and O_3 were elevated. Only in the low-density high-rise neighborhoods were there significant physical health benefits from LTPA in the high $PM_{2.5}$ and O_3 areas. In the lane/courtyard and work-unit neighborhoods, we also observed physical activity may actually be detrimental to one's health due to elevated $PM_{2.5}$ and O_3. These results demonstrate that public health programs promoting healthy behaviors should also consider the effects of ambient air pollution on effectiveness.

6.2 RECOMMENDATIONS FOR FUTURE WORK

This dissertation only explored a few of the associations among the built, social, and natural environments, behaviors, and health. A few areas could be of interest for future work:

Longitudinal study design: The cross-sectional design of this study limits the ability to make causal inferences about the associations among built environment, human behaviors, and health. This study could be extended into a longitudinal or panel study with follow-up visits to the 20 surveyed neighborhoods. Because changes in the built environment are occurring rapidly in Chinese cities, results generated from these longitudinal neighborhood health studies would be available within shorter time frames than in developed countries and potentially have more impact as cities are still in transition in China. Moreover, evaluations of neighborhood improvements proposed by this dissertation's findings would certainly strengthen our understanding of causal relationships and our ability to modify aspects of the environment, behavior, and health.

Objective measures of the built environment: Including objective measures of the built environment using GIS along with self-reported perceptions by residents could also provide more information about how these two measures correlate. For example, significant discrepancies between self-reported walkability and objectively measured walkability could help urban planners identify how residents use or behave within their neighborhoods and target potential areas to improve the built environment.

Continued intra-urban air pollution monitoring: This dissertation collected data during two-week campaigns in the summer and winter seasons in 2013. As the results demonstrated, the pollutants have moderate spatial variability but the temporal trends are still unclear. More sustained monitoring efforts with increased number of sites throughout Xi'an, potentially using low cost sensors, could provide information about the smaller scale differences among neighborhoods over time as the city develops and human behaviors associated with emissions (e.g., motorized transportation) evolve.

Mediating Associations: While the results of the dissertation point at neighborhood specific interventions, we have yet to fully understand why the differences we observed in associations between physical activity levels and health, or between various perceptions of built environment and health, were found. Because there are various pathways from the built environment to health, isolating the mediators of the associations between built environment and health (e.g., leisure-time physical activity, travel behaviors, social capital) could improve understanding of the potential contribution of each mediating pathway to downstream health outcomes.

Replicating this research in other cities and developing areas: Because we found that that the associations of human behaviors, environmental exposures, and health and quality of life are neighborhood-specific, this type of study should be replicated in other Chinese cities. The types of neighborhoods that co-exist in Xi'an developed at different periods of China's economic development, and development in other cities in China followed a similar pattern. However, because Xi'an is a considered a 2nd tier city, results may differ in the more economically developed cities and towns along the eastern coast and in the less developed towns in the west. While, the linkages among social, physical, and environmental factors found in this dissertation can help guide urban health research in other developing areas around the world such as parts of Africa and India, results may also be different in these regions.

6.3 CONCLUDING REMARKS

The built, natural, and social environments should be considered simultaneously as potential targets of intervention to improve quality of life and health in Chinese cities. Promoting public health should start from the design stage as urban planners consider walkability, accessibility to/from other parts of the city, and resource diversity in new neighborhoods. Even in areas where urban planning is poor and not health-conscious, we have shown that community groups or public health practitioners could potentially overcome poor built environmental design by increasing trust among neighbors through various community-building activities. Finally, targeting reductions in ambient air pollution is especially important because poor air quality could limit the health benefits from healthy behaviors like physical activities. This dissertation provides support for the concept that creating a healthy city requires collaborations across urban planning, transportation, public health, and environmental protection at all stages of development.

References

Adam, Martin, Tamara Schikowski, Anne Elie Carsin, Yutong Cai, Benedicte Jacquemin, Margaux Sanchez, Andrea Vierkötter, et al. 2015. "Adult Lung Function and Long-Term Air Pollution Exposure. ESCAPE: A Multicentre Cohort Study and Meta-Analysis." *European Respiratory Journal* 45 (1): 38–50. doi:10.1183/09031936.00130014.

Adar, Sara Dubowsky, Diane R. Gold, Brent A. Coull, Joel Schwartz, Peter H. Stone, and Helen Suh. 2007. "Focused Exposures to Airborne Traffic Particles and Heart Rate Variability in the Elderly:" *Epidemiology* 18 (1): 95–103. doi:10.1097/01.ede.0000249409.81050.46.

Andersen, Zorana Jovanovic, Audrey de Nazelle, Michelle Ann Mendez, Judith Garcia-Aymerich, Ole Hertel, Anne Tjønneland, Kim Overvad, Ole Raaschou-Nielsen, and Mark J. Nieuwenhuijsen. 2015. "A Study of the Combined Effects of Physical Activity and Air Pollution on Mortality in Elderly Urban Residents: The Danish Diet, Cancer, and Health Cohort." *Environmental Health Perspectives*, January. doi:10.1289/ehp.1408698.

Antonella Zanobetti, Meredith Franklin, Petros Koutrakis, and Joel Schwartz. 2009. "Fine Particulate Air Pollution and Its Components in Association with Cause-Specific Emergency Admissions." *Environmental Health* 8 (1): 58. doi:10.1186/1476-069X-8-58.

Atkinson, R W, A Cohen, S Mehta, and H R Anderson. 2011. "Systematic Review and Meta-Analysis of Epidemiological Time-Series Studies on Outdoor Air Pollution and Health in Asia." *Air Quality, Atmosphere & Health*. doi:10.1007/s11869-010-0123-2.

Atkinson, R. W., S. Kang, H. R. Anderson, I. C. Mills, and H. A. Walton. 2014. "Epidemiological Time Series Studies of PM2.5 and Daily Mortality and Hospital Admissions: A Systematic Review and Meta-Analysis." *Thorax*, April, thoraxjnl – 2013–204492. doi:10.1136/thoraxjnl-2013-204492.

Bai, X. M. 2008. "Urban Transition in China: Trends, Consequences and Policy Implications." In *The New Global Frontier: Urbanization, Poverty and Environment in the 21st Century*, 339–56. London: EarthScan.

Ball, Kylie, Robert W. Jeffery, David A. Crawford, Rebecca J. Roberts, Jo Salmon, and Anna F. Timperio. 2008. "Mismatch between Perceived and Objective Measures of Physical Activity Environments." *Preventive Medicine* 47 (3): 294–98. doi:10.1016/j.ypmed.2008.05.001.

Beelen, Rob, Gerard Hoek, Danielle Vienneau, Marloes Eeftens, Konstantina Dimakopoulou, Xanthi Pedeli, Ming-Yi Tsai, et al. 2013. "Development of NO2 and NOx Land Use Regression Models for Estimating Air Pollution Exposure in 36 Study Areas in Europe – The ESCAPE Project." *Atmospheric Environment* 72 (2): 10–23. doi:10.1016/j.atmosenv.2013.02.037.

Bell, Michelle L., Keita Ebisu, Brian P. Leaderer, Janneane F. Gent, Hyung Joo Lee, Petros Koutrakis, Yun Wang, Francesca Dominici, and Roger D. Peng. 2013. "Associations of PM2.5 Constituents and Sources with Hospital Admissions: Analysis of Four Counties in Connecticut and Massachusetts (USA) for Persons ≥ 65 Years of Age." *Environmental Health Perspectives*, November. doi:10.1289/ehp.1306656.

Billionnet, Cécile, Duane Sherrill, and Isabella Annesi-Maesano. 2012. "Estimating the Health Effects of Exposure to Multi-Pollutant Mixture." *Annals of Epidemiology* 22 (2): 126–41. doi:10.1016/j.annepidem.2011.11.004.

Boone-Heinonen, Janne, Barry M Popkin, Yan Song, and Penny Gordon-larsen. 2010. "Health & Place What Neighborhood Area Captures Built Environment Features Related to

Adolescent Physical Activity?” *Health & Place* 16 (6): 1280–86. doi:10.1016/j.healthplace.2010.06.015.
Briggs, David, Susan Collins, Paul Elliott, Paul Fischer, Simon Kingham, Erik Lebret, Karel Pryl, Hans van Reeuwijk, Kirsty Smallbone, and Andre van der Veen. 1997. “Mapping Urban Air Pollution Using GIS: A Regression-Based Approach.” *International Journal of Geographical Information Science* 11 (7): 699–718. doi:10.1080/136588197242158.
Cao, Junji. 2014. “Chapter 5 我国 PM2.5 研究综述 (Characterization of China’s PM2.5).” In *PM2.5 与环境 （PM2.5 and the Environment in China)*. Science Press LLC.
Cao, Shixiong, Yuan Lv, Heran Zheng, and Xin Wang. 2014. “Challenges Facing China’s Unbalanced Urbanization Strategy.” *Land Use Policy* 39: 412–15.
Casey, Romain, Jean-Michel Oppert, Christiane Weber, Hélène Charreire, Paul Salze, Dominique Badariotti, Arnaud Banos, et al. 2014. “Determinants of Childhood Obesity: What Can We Learn from Built Environment Studies?” *Food Quality and Preference* 31 (January): 164–72. doi:10.1016/j.foodqual.2011.06.003.
Cerin, Ester, Duncan J Macfarlane, Hin-Hei Ko, and Kwok-Cheung A Chan. 2007. “Measuring Perceived Neighbourhood Walkability in Hong Kong.” *Cities* 24 (3): 209–17. doi:10.1016/j.cities.2006.12.002.
Cerin, Ester, Brian E. Saelens, James F. Sallis, and Lawrence D. Frank. 2006. “Neighborhood Environment Walkability Scale: Validity and Development of a Short Form.” *Medicine & Science in Sports & Exercise* 38 (9): 1682–91. doi:10.1249/01.mss.0000227639.83607.4d.
Chan, Kam Wing, and Li Zhang. 1999. “The Hukou System and Rural-Urban Migration in China: Processes and Changes.” *The China Quarterly* 160: 818–55.
Cheng, Zhen, Jingkun Jiang, Oscar Fajardo, Shuxiao Wang, and Jiming Hao. 2013. “Characteristics and Health Impacts of Particulate Matter Pollution in China (2001–2011).” *Atmospheric Environment* 65 (February): 186–94. doi:10.1016/j.atmosenv.2012.10.022.
Chen, Yufu, Qiangguo Cai, and Haiping Tang. 2003. “Dust Storm as an Environmental Problem in North China.” *Environmental Management* 32 (4): 413–17. doi:10.1007 /s00267 -003-0042-1.
Chen, Zhu, Jin-Nan Wang, Guo-Xia Ma, and Yan-Shen Zhang. 2013. “China Tackles the Health Effects of Air Polluti.” *The Lancet* 382 (9909): 1959–60.
China Daily. 2004. “China Ends ‘Bicycle Kingdom’ as Embracing Cars.” http://www.chinadaily.com.cn/. http://www.chinadaily.com.cn/english/doc/2004-11/11/content_390685.htm.
City Mayors. 2011. “The Largest Cities in the World and Their Mayors 2011.” City Mayors Foundation. http://www.citymayors.com/statistics/largest-cities-mayors-ad2.html.
Clark, Stuart. 2014. “Scientists Warn against China’s Plan to Flatten over 700 Mountains.” The Guardian. http://www.theguardian.com/environment/2014/jun/04/scientists-warn-against-chinas-plan-to-flatten-over-700-mountains.
Démurger, Sylvie, Marc Gurgand, Shi Li, and Ximing Yue. 2009. “Migrants as Second-Class Workers in Urban China? A Decomposition Analysis.” *Journal of Comparative Economics* 37 (4): 610–28. doi:10.1016/j.jce.2009.04.008.
DeSalvo, Karen B., Nicole Bloser, Kristi Reynolds, Jiang He, and Paul Muntner. 2006. “Mortality Prediction with a Single General Self-Rated Health Question.” *Journal of General Internal Medicine* 21 (3): 267–75.

Dockery, Douglas W., C. Arden Pope, Xiping Xu, John D. Spengler, James H. Ware, Martha E. Fay, Benjamin G. Ferris, and Frank E. Speizer. 1993. "An Association between Air Pollution and Mortality in Six U.S. Cities." *New England Journal of Medicine* 329 (24): 1753–59. doi:10.1056/NEJM199312093292401.

Dominici, Francesca, Roger D. Peng, Christopher D. Barr, and Michelle L. Bell. 2010. "Protecting Human Health From Air Pollution: Shifting From a Single-Pollutant to a Multipollutant Approach." *Epidemiology* 21 (2): 187–94. doi:10.1097/EDE.0b013e3181cc86e8.

Duncan, Mitch J., Elisabeth Winkler, Takemi Sugiyama, Ester Cerin, Lorinne duToit, Eva Leslie, and Neville Owen. 2010. "Relationships of Land Use Mix with Walking for Transport: Do Land Uses and Geographical Scale Matter?" *Journal of Urban Health* 87 (5): 782–95. doi:10.1007/s11524-010-9488-7.

Durand, C P, M Andalib, G F Dunton, J Wolch, and M A Pentz. 2011. "A Systematic Review of Built Environment Factors Related to Physical Activity and Obesity Risk: Implications for Smart Growth Urban Planning." *Obesity Reviews* 12 (5): e173–82. doi:10.1111/j.1467-789X.2010.00826.x.

Evans, Jessica, Aaron van Donkelaar, Randall V. Martin, Richard Burnett, Daniel G. Rainham, Nicholas J. Birkett, and Daniel Krewski. 2013. "Estimates of Global Mortality Attributable to Particulate Air Pollution Using Satellite Imagery." *Environmental Research* 120 (January): 33–42. doi:10.1016/j.envres.2012.08.005.

Eyler, Amy A., Ross C. Brownson, Stephen J. Bacak, and Robyn A. Housemann. 2003. "The Epidemiology of Walking for Physical Activity in the United States:" *Medicine & Science in Sports & Exercise* 35 (9): 1529–36. doi:10.1249/01.MSS.0000084622.39122.0C.

Eyre, Harmon, Richard Kahn, and Rose Marie Robertson. 2004. "Preventing Cancer, Cardiovascular Disease, and Diabetes: A Common Agenda for the American Cancer Society, the American Diabetes Association, and the American Heart Association." *Diabetes Care* 27 (7).

Fan, CC. 2010. "China's Eleventh Five-Year Plan (2006-2010): From' Getting Rich First' to' Common Prosperity.'" *Eurasian Geography and Economics*. http://bellwether.metapress.com/index/76752h7r37r832m8.pdf.

Fan, C Cindy. 2010. "China's Eleventh Five-Year Plan (2006–2010): From 'Getting Rich First' to 'Common Prosperity.'" *Eurasian Geography and Economics*, no. 6. http://bellwether.metapress.com/index/76752h7r37r832m8.pdf.

Fang, Ming, Chak K. Chan, and Xiaohong Yao. 2009. "Managing Air Quality in a Rapidly Developing Nation: China." *Atmospheric Environment* 43 (1): 79–86. doi:10.1016/j.atmosenv.2008.09.064.

Feng, Jing, Thomas A Glass, Frank C Curriero, Walter F Stewart, and Brian S Schwartz. 2009. "The Built Environment and Obesity A Systematic Review of the Epidemiologic Evidence." *Health & Place* 16 (2): 175–90. doi:10.1016/j.healthplace.2009.09.008.

Fernhall, Bo, Audrey Borghi-Silva, and Abraham S. Babu. 2015. "The Future of Physical Activity Research: Funding, Opportunities and Challenges." *Progress in Cardiovascular Diseases* 57 (4): 299–305. doi:10.1016/j.pcad.2014.09.003.

Fleischer, Nancy L., Mario Merialdi, Aaron van Donkelaar, Felipe Vadillo-Ortega, Randall V. Martin, Ana Pilar Betran, and João Paulo Souza. 2014. "Outdoor Air Pollution, Preterm Birth, and Low Birth Weight: Analysis of the World Health Organization Global Survey

on Maternal and Perinatal Health.” *Environmental Health Perspectives* 122 (4): 425–30. doi:10.1289/ehp.1306837.
Frank, Lawrence D, James F Sallis, Terry L Conway, James E Chapman, Brian E Saelens, and William Bachman. 2006. “Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality.” *Journal of the American Planning Association* 72 (1): 75–87. doi:10.1080/01944360608976725.
Frank, Lawrence D., Thomas L. Schmid, James F. Sallis, James Chapman, and Brian E. Saelens. 2005. “Linking Objectively Measured Physical Activity with Objectively Measured Urban Form.” *American Journal of Preventive Medicine* 28 (2): 117–25. doi:10.1016/j.amepre.2004.11.001.
Franklin, Barry A., Robert Brook, and C. Arden Pope. 2015. “Air Pollution and Cardiovascular Disease.” *Current Problems in Cardiology*, January. doi:10.1016/j.cpcardiol.2015.01.003.
Friedmann, John. 2006. “Four Theses in the Study of China’s Urbanization.” *International Journal of Urban and Regional Research* 30 (2): 440–51.
Gao, Meiling, Junji Cao, and Edmund Seto. 2015. “A Distributed Network of Low-Cost Continuous Reading Sensors to Measure Spatiotemporal Variations of PM2.5 in Xi’an, China.” *Environmental Pollution* 199 (April): 56–65. doi:10.1016/j.envpol.2015.01.013.
Garvin, E. C., C. C. Cannuscio, and C. C. Branas. 2013. “Greening Vacant Lots to Reduce Violent Crime: A Randomised Controlled Trial.” *Injury Prevention* 19 (3): 198–203. doi:10.1136/injuryprev-2012-040439.
Gebel, Klaus, Adrian E Bauman, Takemi Sugiyama, and Neville Owen. 2011. “Mismatch between Perceived and Objectively Assessed Neighborhood Walkability Attributes Prospective Relationships with Walking and Weight Gain.” *Health & Place* 17 (2): 519–24. doi:10.1016/j.healthplace.2010.12.008.
Gebel, Klaus, Adrian Bauman, and Neville Owen. 2009. “Correlates of Non-Concordance between Perceived and Objective Measures of Walkability.” *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine* 37 (2): 228–38. doi:10.1007/s12160-009-9098-3.
Ghosh, J K C, M Wilhelm, J Su, D Goldberg, M Cockburn, M Jerrett, and B Ritz. 2012. “Assessing the Influence of Traffic-Related Air Pollution on Risk of Term Low Birth Weight on the Basis of Land-Use-Based Regression Models and Measures of Air Toxics.” *American Journal of Epidemiology* 175 (12): 1262–74. doi:10.1093/aje/kwr469.
Haight, Thaddeus J., Yue Wang, Mark J. van der Laan, and Ira B. Tager. 2010. “A Cross-Validation Deletion–substitution–addition Model Selection Algorithm: Application to Marginal Structural Models.” *Computational Statistics & Data Analysis* 54 (12): 3080–94. doi:10.1016/j.csda.2010.02.002.
Hallal, Pedro C., Lars Bo Andersen, Fiona C. Bull, Regina Guthold, William Haskell, Ulf Ekelund, Lancet Physical Activity Series Working Group, and others. 2012. “Global Physical Activity Levels: Surveillance Progress, Pitfalls, and Prospects.” *The Lancet* 380 (9838): 247–57.
Haskell, William L., I-Min Lee, Russell R. Pate, Kenneth E. Powell, Steven N. Blair, Barry A. Franklin, Caroline A. Macera, Gregory W. Heath, Paul D. Thompson, and Adrian Bauman. 2007. “Physical Activity and Public Health: Updated Recommendation for Adults from the American College of Sports Medicine and the American Heart

Association." *Medicine & Science in Sports & Exercise* 39 (8): 1423–34. doi:10.1249/mss.0b013e3180616b27.
Hazelzet, Arjan, and Bart Wissink. 2012. "Neighborhoods, Social Networks, and Trust in Post-Reform China: The Case of Guangzhou." *Urban Geography* 33 (2): 204–20. doi:10.2747/0272-3638.33.2.204.
HEI. 2010. "Outdoor Air Pollution and Health in the Developing Countries of Asia: A Comprehensive Review," 1–284.
He, Kebin, Hong Huo, and Qiang Zhang. 2002. "URBAN AIR POLLUTION IN CHINA: Current Status, Characteristics, and Progress." *Annual Review of Energy and the Environment* 27 (1): 397–431. doi:10.1146/annurev.energy.27.122001.083421.
Hennessy, Catherine Hagan, David G. Moriarty, Matthew M. Zack, Paul A. Scherr, and Robert Brackbill. 1994. "Measuring Health-Related Quality of Life for Public Health Surveillance." *Public Health Reports* 109 (5): 665.
Herring, Matthew P., Timothy W. Puetz, Patrick J. O'Connor, and Rodney K. Dishman. 2012. "Effect of Exercise Training on Depressive Symptoms among Patients with a Chronic Illness: A Systematic Review and Meta-Analysis of Randomized Controlled Trials." *Archives of Internal Medicine* 172 (2): 101–11.
Hesketh, Therese, Li Lu, and Zhu Wei Xing. 2005. "The Effect of China's One-Child Family Policy after 25 Years." *New England Journal of Medicine* 353 (11): 1171–76.
Hirsch, J. A., K. A. Moore, P. J. Clarke, D. A. Rodriguez, K. R. Evenson, S. J. Brines, M. A. Zagorski, and A. V. Diez Roux. 2014. "Changes in the Built Environment and Changes in the Amount of Walking Over Time: Longitudinal Results From the Multi-Ethnic Study of Atherosclerosis." *American Journal of Epidemiology* 180 (8): 799–809. doi:10.1093/aje/kwu218.
Hoek, Gerard, Rob Beelen, Kees De Hoogh, Danielle Vienneau, John Gulliver, Paul Fischer, and David Briggs. 2008. "A Review of Land-Use Regression Models to Assess Spatial Variation of Outdoor Air Pollution." *Atmospheric Environment* 42 (33): 7561–78. doi:10.1016/j.atmosenv.2008.05.057.
Holstius, D. M., A. Pillarisetti, K. R. Smith, and E. Seto. 2014. "Field Calibrations of a Low-Cost Aerosol Sensor at a Regulatory Monitoring Site in California." *Atmospheric Measurement Techniques Discussions* 7 (1): 605–32. doi:10.5194/amtd-7-605-2014.
Hubbard, Alan E., Jennifer Ahern, Nancy L. Fleischer, Mark Van der Laan, Sheri A. Lippman, Nicholas Jewell, Tim Bruckner, and William A. Satariano. 2010. "To GEE or Not to GEE: Comparing Population Average and Mixed Models for Estimating the Associations Between Neighborhood Risk Factors and Health." *Epidemiology* 21 (4): 467–74. doi:10.1097/EDE.0b013e3181caeb90.
Hubbell, Bryan J., Aaron Hallberg, Donald R. McCubbin, and Ellen Post. 2005. "Health-Related Benefits of Attaining the 8-Hr Ozone Standard." *Environmental Health Perspectives* 113 (1): 73–82.
Human Rights Watch. 2008. *One Year of My Blood*. Exploitation of Migrant Construction Workers in Beijing. http://books.google.com/books?id=2_cUAQAAIAAJ.
Hvistendahl, Mara. 2011. "China's Population Growing Slowly, Changing Fast." *Science* 332 (6030): 650–51. doi:10.1126/science.332.6030.650.
Ito, Kazuhiko, Samantha F. De Leon, and Morton Lippmann. 2005. "Associations between Ozone and Daily Mortality: Analysis and Meta-Analysis." *Epidemiology (Cambridge, Mass.)* 16 (4): 446–57.

Jerrett, Michael, Altaf Arain, Pavlos Kanaroglou, Bernardo Beckerman, Dimitri Potoglou, Talar Sahsuvaroglu, Jason Morrison, and Chris Giovis. 2005. "A Review and Evaluation of Intraurban Air Pollution Exposure Models." *Journal of Exposure Analysis and Environmental Epidemiology* 15 (2): 185–204. doi:10.1038/sj.jea.7500388.

Jerrett, Michael, Richard T Burnett, Renjun Ma, C Arden Pope III, Daniel Krewski, K Bruce Newbold, George Thurston, et al. 2005. "Spatial Analysis of Air Pollution and Mortality in Los Angeles." *Epidemiology* 16 (6): 727–36. doi:10.1097/01.ede.0000181630.15826.7d.

Jerrett, Michael, Richard T. Burnett, C. Arden Pope, Kazuhiko Ito, George Thurston, Daniel Krewski, Yuanli Shi, Eugenia Calle, and Michael Thun. 2009. "Long-Term Ozone Exposure and Mortality." *New England Journal of Medicine* 360 (11): 1085–95. doi:10.1056/NEJMoa0803894.

Jerrett, Michael, Rob McConnell, Jennifer Wolch, Roger Chang, Claudia Lam, Genevieve Dunton, Frank Gilliland, Fred Lurmann, Talat Islam, and Kiros Berhane. 2014. "Traffic-Related Air Pollution and Obesity Formation in Children: A Longitudinal, Multilevel Analysis." *Environmental Health* 13 (1): 49.

Jitnarin, Nattinee, Katie Heinrich, Christopher Haddock, Joseph Hughey, LaVerne Berkel, and Walker Poston. 2015. "Neighborhood Environment Perceptions and the Likelihood of Smoking and Alcohol Use." *International Journal of Environmental Research and Public Health* 12 (1): 784–99. doi:10.3390/ijerph120100784.

Johns, Douglas O., and William S. Linn. 2011. "A Review of Controlled Human SO2 Exposure Studies Contributing to the US EPA Integrated Science Assessment for Sulfur Oxides." *Inhalation Toxicology* 23 (1): 33–43. doi:10.3109/08958378.2010.539290.

Kanaroglou, Pavlos S., Michael Jerrett, Jason Morrison, Bernardo Beckerman, M. Altaf Arain, Nicolas L. Gilbert, and Jeffrey R. Brook. 2005. "Establishing an Air Pollution Monitoring Network for Intra-Urban Population Exposure Assessment: A Location-Allocation Approach." *Atmospheric Environment* 39 (13): 2399–2409. doi:10.1016/j.atmosenv.2004.06.049.

Kan, Haidong, Renjie Chen, and Shilu Tong. 2012. "Ambient Air Pollution, Climate Change, and Population Health in China." *Environment International* 42 (July): 10–19. doi:10.1016/j.envint.2011.03.003.

Kan, Haidong, Stephanie J London, Guohai Chen, Yunhui Zhang, Guixiang Song, Naiqing Zhao, Lili Jiang, and Bingheng Chen. 2008. "Season, Sex, Age, and Education as Modifiers of the Effects of Outdoor Air Pollution on Daily Mortality in Shanghai, China: The Public Health and Air Pollution in Asia (PAPA) Study." *Environmental Health Perspectives* 116 (9): 1183–88. doi:10.1289/ehp.10851.

Kan, H., G. Heiss, K. M Rose, E. Whitsel, F. Lurmann, and S. J London. 2007. "Traffic Exposure and Lung Function in Adults: The Atherosclerosis Risk in Communities Study." *Thorax* 62 (10): 873–79. doi:10.1136/thx.2006.073015.

Kenworthy, J, and G. Hu. 2002. "Transport and Urban Form in Chinese Cities." *DISP* 151 (4): 4–14.

Kim, D., SV Subramanian, and I Kawachi. 2008. "Social Capital and Physical Health." *Social Capital and Health*, 139–90.

Knuiman, M. W., H. E. Christian, M. L. Divitini, S. A. Foster, F. C. Bull, H. M. Badland, and B. Giles-Corti. 2014. "A Longitudinal Analysis of the Influence of the Neighborhood Built

Environment on Walking for Transportation: The RESIDE Study." *American Journal of Epidemiology* 180 (5): 453–61. doi:10.1093/aje/kwu171.
Lachat, Carl, Stephen Otchere, Dominique Roberfroid, Abubakari Abdulai, Florencia Maria Aguirre Seret, Jelena Milesevic, Godfrey Xuereb, Vanessa Candeias, and Patrick Kolsteren. 2013. "Diet and Physical Activity for the Prevention of Noncommunicable Diseases in Low- and Middle-Income Countries: A Systematic Policy Review." Edited by Linda J. Cobiac. *PLoS Medicine* 10 (6): e1001465. doi:10.1371/journal.pmed.1001465.
Laden, Francine, Joel Schwartz, Frank E Speizer, and Douglas W Dockery. 2006. "Reduction in Fine Particulate Air Pollution and Mortality: Extended Follow-up of the Harvard Six Cities Study." *American Journal of Respiratory and Critical Care Medicine* 173 (6): 667–72. doi:10.1164/rccm.200503-443OC.
Lam, Elegance T. P., Cindy L. K. Lam, Daniel Y. T. Fong, and Wen Wei Huang. 2013. "Is the SF-12 Version 2 Health Survey a Valid and Equivalent Substitute for the SF-36 Version 2 Health Survey for the Chinese?: Is SF-12v2 Valid Substitute for SF-36v2?" *Journal of Evaluation in Clinical Practice* 19 (1): 200–208. doi:10.1111/j.1365-2753.2011.01800.x.
Leal, C., and B. Chaix. 2011. "The Influence of Geographic Life Environments on Cardiometabolic Risk Factors: A Systematic Review, a Methodological Assessment and a Research Agenda: Geographic Life Environments and Cardiometabolic Risk Factors." *Obesity Reviews* 12 (3): 217–30. doi:10.1111/j.1467-789X.2010.00726.x.
Lin, Hui, Guibo Sun, and Rongrong Li. 2015. "The Influence of Built Environment on Walking Behavior: Measurement Issues, Theoretical Considerations, Modeling Methodologies and Chinese Empirical Studies." In *Space-Time Integration in Geography and GIScience*, 53–75. Springer. http://link.springer.com/chapter/10.1007/978-94-017-9205-9_5.
Lin, Jen-Jia, and Tzu-Pen Yu. 2011. "Built Environment Effects on Leisure Travel for Children: Trip Generation and Travel Mode." *Transport Policy* 18 (1): 246–58. doi:10.1016/j.tranpol.2010.08.008.
Li, Si-ming, Yushu Zhu, and Limei Li. 2012. "Neighborhood Type, Gatedness, and Residential Experiences in Chinese Cities: A Study of Guangzhou." *Urban Geography* 33 (2): 237–55. doi:10.2747/0272-3638.33.2.237.
Liu, Yuting, Shenjing He, Fulong Wu, and Chris Webster. 2010. "Urban Villages under China's Rapid Urbanization: Unregulated Assets and Transitional Neighbourhoods." *Habitat International* 34 (2): 135–44. doi:10.1016/j.habitatint.2009.08.003.
Li, Yuheng. 2010. "The Complexity of Urban Transformation in China: New Trends in Current Transitional Era." http://www.iphs2010.com/abs/ID520.pdf.
Lovasi, Gina S., Stephanie Grady, and A. Rundle. 2012. "Steps Forward: Review and Recommendations for Research on Walkability, Physical Activity and Cardiovascular Health." *Public Health Rev* 33 (2): 484–506.
Ludwig, Jens, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald C. Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. 2012. "Neighborhood Effects on the Long-Term Well-Being of Low-Income Adults." *Science* 337 (September).
Ludwig, Jens, Lisa Sanbonmatsu, Lisa Gennetian, Emma Adam, Greg J. Duncan, Lawrence F. Katz, Ronald C. Kessler, et al. 2011. "Neighborhoods, Obesity, and Diabetes—a Randomized Social Experiment." *New England Journal of Medicine* 365 (16): 1509–19.
Maruish, Mark E., and Michael A. DeRosa. 2009. "A Guide to the Integration of Certified Short Form Survey Scoring and Data Quality Evaluation Capabilities." QualityMetric Incorporated.

McConnell, Rob, Kiros Berhane, Frank Gilliland, Jassy Molitor, Duncan Thomas, Fred Lurmann, Edward Avol, W. James Gauderman, and John M. Peters. 2003. "Prospective Study of Air Pollution and Bronchitic Symptoms in Children with Asthma." *American Journal of Respiratory and Critical Care Medicine* 168 (7): 790–97. doi:10.1164/rccm.200304-466OC.

McCreanor, J, P Cullinan, M J Nieuwenhuijsen, J Stewart-Evans, E Malliarou, L Jarup, R Harrington, M Svartengren, I.K. Han, and P Ohman-Strickland. 2007. "Respiratory Effects of Exposure to Diesel Traffic in Persons with Asthma." *New England Journal of Medicine* 357 (23): 2348–58.

McGovern, Laura, George Miller, and Paul Hughes-Cromwick. 2014. "Health Policy Brief: The Relative Contribution of Multiple Determinants to Health Outcomes." *Health Affairs*, August.

Michael, Yvonne L., Mandy K. Green, and Stephanie A. Farquhar. 2006. "Neighborhood Design and Active Aging." *Health & Place* 12 (4): 734–40. doi:10.1016/j.healthplace.2005.08.002.

Nasar, Jack L., Christopher Holloman, and Dina Abdulkarim. 2015. "Street Characteristics to Encourage Children to Walk." *Transportation Research Part A: Policy and Practice* 72 (February): 62–70. doi:10.1016/j.tra.2014.12.004.

National Bureau of Statistics. 2011. *China Statistical Yearbook 2011*. www.chinadataonline.org.

Ng, Shu Wen, Edward C. Norton, and Barry M. Popkin. 2009. "Why Have Physical Activity Levels Declined among Chinese Adults? Findings from the 1991–2006 China Health and Nutrition Surveys." *Social Science & Medicine* 68 (7): 1305–14. doi:10.1016/j.socscimed.2009.01.035.

Ng, S. W., A.-G. Howard, H. J. Wang, C. Su, and B. Zhang. 2014. "The Physical Activity Transition among Adults in China: 1991-2011: Physical Activity Transition in China." *Obesity Reviews* 15 (January): 27–36. doi:10.1111/obr.12127.

Ng, S. W., and B. M. Popkin. 2012. "Time Use and Physical Activity: A Shift Away from Movement across the Globe: Declines in Movement across the Globe." *Obesity Reviews* 13 (8): 659–80. doi:10.1111/j.1467-789X.2011.00982.x.

Ng, Wei-Shiuen, Lee Schipper, and Yang Chen. 2010. "China Motorization Trends: New Directions for Crowded Cities." *Journal of Transport and Land Use* 3 (3). doi:10.5198/jtlu.v3i3.151.

Norstrand, J. A., and Q. Xu. 2012. "Social Capital and Health Outcomes Among Older Adults in China: The Urban-Rural Dimension." *The Gerontologist* 52 (3): 325–34. doi:10.1093/geront/gnr072.

Oakes, J Michael. 2004. "Causal Inference and the Relevance of Social Epidemiology." *Social Science & Medicine* 58 (10): 1969–71. doi:10.1016/j.socscimed.2003.05.001.

Ogawa & Co., USA, Inc. 2001. "Protocol for Ozone Measurement Using the Ozone Passive Sampler Badge." Ogawa & Co., USA, Inc.

———. 2006. "NO, NO2, NOx and SO2 Sampling Protocol Using The Ogawa Sampler." Ogawa & Co., USA, Inc.

Ostro, Bart, Lindsey Roth, Brian Malig, and Melanie Marty. 2009. "The Effects of Fine Particle Components on Respiratory Hospital Admissions in Children." *Environmental Health Perspectives* 117 (3): 475–80. doi:10.1289/ehp.11848.

Padula, Amy M., Kathleen M. Mortimer, Ira B. Tager, S. Katharine Hammond, Frederick W. Lurmann, Wei Yang, David K. Stevenson, and Gary M. Shaw. 2014. "Traffic-Related

Air Pollution and Risk of Preterm Birth in the San Joaquin Valley of California." *Annals of Epidemiology* 24 (12): 888–95.e4. doi:10.1016/j.annepidem.2014.10.004.

Penedo, Frank J., and Jason R. Dahn. 2005. "Exercise and Well-Being: A Review of Mental and Physical Health Benefits Associated with Physical Activity." *Current Opinion in Psychiatry* 18 (2): 189–93.

Peng, Roger D., Michelle L. Bell, Alison S. Geyh, Aidan McDermott, Scott L. Zeger, Jonathan M. Samet, and Francesca Dominici. 2009. "Emergency Admissions for Cardiovascular and Respiratory Diseases and the Chemical Composition of Fine Particle Air Pollution." *Environmental Health Perspectives* 117 (6): 957–63. doi:10.1289/ehp.0800185.

Peng, Zhong-Ren, Yi Zhu, and Shunfeng Song. 2006. "Mobility of the Chinese Urban Poor – A Case Study of Hefei City." *UNR Economics Working Paper Series*. http://core.kmi.open.ac.uk/download/pdf/6272063.pdf.

Pucher, John, Zhong-ren Peng, Neha Mittal, Yi Zhu, and Nisha Korattyswaroopam. 2007. "Urban Transport Trends and Policies in China and India: Impacts of Rapid Economic Growth." *Transport Reviews* 27 (4): 379–410. doi:10.1080/01441640601089988.

Qiang Wang. 2014. "Effects of Urbanisation on Energy Consumption in China." *Energy Policy* 65 (February): 332–39. doi:10.1016/j.enpol.2013.10.005.

Rice, Mary B., Petter L. Ljungman, Elissa H. Wilker, Kirsten S. Dorans, Diane R. Gold, Joel Schwartz, Petros Koutrakis, George R. Washko, George T. O'Connor, and Murray A. Mittleman. 2015. "Long-Term Exposure to Traffic Emissions and Fine Particulate Matter and Lung Function Decline in the Framingham Heart Study." *American Journal of Respiratory and Critical Care Medicine* 191 (6): 656–64. doi:10.1164/rccm.201410-1875OC.

Saelens, Brian E., and Susan L. Handy. 2008. "Built Environment Correlates of Walking: A Review." *Medicine & Science in Sports & Exercise* 40 (Supplement): S550–66. doi:10.1249/MSS.0b013e31817c67a4.

Saelens, Brian E, James F Sallis, Jennifer B Black, and Diana Chen. 2003. "Neighborhood-Based Differences in Physical Activity: An Environment Scale Evaluation." *American Journal of Public Health* 93 (9): 1552–58.

Saelens, Brian E, James F Sallis, and Lawrence D Frank. 2003. "Environmental Correlates of Walking and Cycling: Findings from the Transportation, Urban Design, and Planning Literatures." *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine* 25 (2): 80–91.

Sallis, James F., Robert B. Cervero, William Ascher, Karla A. Henderson, M. Katherine Kraft, and Jacqueline Kerr. 2006. "An Ecological Approach to Creating Active Living Communities." *Annual Review of Public Health* 27 (1): 297–322. doi:10.1146/annurev.publhealth.27.021405.102100.

Sallis, James F., Brian E. Saelens, Lawrence D. Frank, Terry L. Conway, Donald J. Slymen, Kelli L. Cain, James E. Chapman, and Jacqueline Kerr. 2009. "Neighborhood Built Environment and Income: Examining Multiple Health Outcomes." *Social Science & Medicine* 68 (7): 1285–93. doi:10.1016/j.socscimed.2009.01.017.

Samoli, E., E. Aga, G. Touloumi, K. Nisiotis, B. Forsberg, A. Lefranc, J. Pekkanen, et al. 2006. "Short-Term Effects of Nitrogen Dioxide on Mortality: An Analysis within the APHEA Project." *The European Respiratory Journal* 27 (6): 1129–38. doi:10.1183/09031936.06.00143905.

Sarmiento, Olga L., Thomas L. Schmid, Diana C. Parra, Adriana Díaz-del-Castillo, Luis Fernando Gómez, Michael Pratt, Enrique Jacoby, José D. Pinzón, and John Duperly. 2010. “Quality of Life, Physical Activity, and Built Environment Characteristics among Colombian Adults.” *Journal of Physical Activity & Health* 7 (2): S181.

Sattelmair, Jacob, Jeremy Pertman, Eric L. Ding, Harold W. Kohl, William Haskell, and I.-Min Lee. 2011. “Dose Response between Physical Activity and Risk of Coronary Heart Disease a Meta-Analysis.” *Circulation* 124 (7): 789–95.

Schipper, L. 2006. “China Motorization Trends: Policy Options In a World of Transport Challenges.” *World Resources Institute*. http://energy.sipa.columbia.edu/events/documents/Schipper_3-8-06.pdf.

S. E. Sinisi, and M. J. van der Laan. 2014. “Deletion/Substitution/Addition Algorithm in Learning with Applications in Genomics.” *Statistical Applications in Genetics and Molecular Biology*, Article 18, 3 (1).

Shang, Yu, Zhiwei Sun, Junji Cao, Xinming Wang, Liuju Zhong, Xinhui Bi, Hong Li, Wenxin Liu, Tong Zhu, and Wei Huang. 2013. “Systematic Review of Chinese Studies of Short-Term Exposure to Air Pollution and Daily Mortality.” *Environment International* 54: 100–111.

Shi, Han, and Lei Zhang. 2006. “China’s Environmental Governance of Rapid Industrialisation.” *Environmental Politics* 15 (2): 271–92. doi:10.1080/09644010600562567.

Shi, Li. 2008a. *Rural Migrant Workers in China : Scenario , Challenges and Public Policy*.

———. 2008b. “Rural Migrant Workers in China: Scenario, Challenges and Public Policy,” 1–31.

Statistical Bureau of Shaanxi Province. 2010. *Shaanxi Statistical Yearbook 2010*. www.chinadataonline.org.

———. 2013. *Shaanxi Statistical Yearbook 2013*. www.chinadataonline.org.

Stieb, David M., Li Chen, Maysoon Eshoul, and Stan Judek. 2012. “Ambient Air Pollution, Birth Weight and Preterm Birth: A Systematic Review and Meta-Analysis.” *Environmental Research* 117 (0): 100–111. doi:10.1016/j.envres.2012.05.007.

Story, Mary, Karen M. Kaphingst, Ramona Robinson-O’Brien, and Karen Glanz. 2008. “Creating Healthy Food and Eating Environments: Policy and Environmental Approaches.” *Annual Review of Public Health* 29 (1): 253–72. doi:10.1146/annurev.publhealth.29.020907.090926.

Su, Jason G, Michael Jerrett, Bernardo Beckerman, Michelle Wilhelm, Jo Kay Ghosh, and Beate Ritz. 2009. “Predicting Traffic-Related Air Pollution in Los Angeles Using a Distance Decay Regression Selection Strategy.” *Environmental Research* 109 (6): 657–70. doi:10.1016/j.envres.2009.06.001.

Su, J G, M Jerrett, and B Beckerman. 2009. “A Distance-Decay Variable Selection Strategy for Land Use Regression Modeling of Ambient Air Pollution Exposures.” *Science of the Total Environment, The* 407 (12): 3890–98. doi:10.1016/j.scitotenv.2009.01.061.

Su, Meng, Ya-yun Tan, Qing-min Liu, Yan-jun Ren, Ichiro Kawachi, Li-ming Li, and Jun Lv. 2014. “Association between Perceived Urban Built Environment Attributes and Leisure-Time Physical Activity among Adults in Hangzhou, China.” *Preventive Medicine* 66 (September): 60–64. doi:10.1016/j.ypmed.2014.06.001.

The World Bank. 2011. “World Development Indicators: Motor Vehicles (per 1,000 People).” The World Bank. http://data.worldbank.org/indicator/IS.VEH.NVEH.P3.

The World Bank Human Development Unit. 2011. *Toward a Healthy and Harmonious Life in China: Stemming the Rising Tide of Non-Communicable Diseases*. World Bank Report Number 62318-CN. The World Bank.
United Nations. 2014. *World Urbanization Prospects: The 2014 Revision*. United Nations Department of Economic and Social Affairs Population Division.
US DHHS. 2008. *2008 Physical Activity Guidelines for Americans*. ODPHP Publication No. U0036. U.S. Department of Health and Human Services. http://www.health.gov/paguidelines/guidelines/.
US EPA. 2012. *National Ambient Air Quality Standards for Particulate Matter: Final Rule*. Federal Register, Vol. 78, No. 10, Part II: 40 CFR Parts 50, 51, 52 et al.
Van Donkelaar, Aaron, Randall V. Martin, Michael Brauer, Ralph Kahn, Robert Levy, Carolyn Verduzco, and Paul J. Villeneuve. 2010. "Global Estimates of Ambient Fine Particulate Matter Concentrations from Satellite-Based Aerosol Optical Depth: Development and Application." *Environmental Health Perspectives* 118 (6): 847–55. doi:10.1289/ehp.0901623.
Van Dyck, Delfien, Greet Cardon, Benedicte Deforche, Neville Owen, and Ilse De Bourdeaudhuij. 2011. "Relationships between Neighborhood Walkability and Adults' Physical Activity: How Important Is Residential Self-Selection?" *Health & Place* 17 (4): 1011–14. doi:10.1016/j.healthplace.2011.05.005.
Van Holle, Veerle, Benedicte Deforche, Jelle Van Cauwenberg, Liesbet Goubert, Lea Maes, Nico Van de Weghe, and Ilse De Bourdeaudhuij. 2012. "Relationship between the Physical Environment and Different Domains of Physical Activity in European Adults: A Systematic Review." *BMC Public Health* 12 (1): 807.
Vennemo, H, K Aunan, H Lindhjem, and HM Seip. 2009. "Environmental Pollution in China: Status and Trends." *Review of Environmental Economics and Policy* 3 (2): 209.
Votruba, Mark Edward, and Jeffrey R. Kling. 2009. "Effects of Neighborhood Characteristics on the Mortality of Black Male Youth: Evidence from Gautreaux, Chicago." *Social Science & Medicine* 68 (5): 814–23. doi:10.1016/j.socscimed.2008.12.018.
Wang, Chen, Guanghua Wan, and Dan Yang. 2014. "Income Inequality in the People's Republic of China: Trends, Determinants, and Proposed Remedies." *Journal of Economic Surveys*, July, n/a – n/a. doi:10.1111/joes.12077.
Wang, Donggen, and Yanwei Chai. 2009. "The Jobs–housing Relationship and Commuting in Beijing, China: The Legacy of Danwei." *Journal of Transport Geography* 17 (1): 30–38. doi:10.1016/j.jtrangeo.2008.04.005.
Wang, Donggen, Yanwei Chai, and Fei Li. 2011. "Built Environment Diversities and Activity–travel Behaviour Variations in Beijing, China." *Journal of Transport Geography* 19 (6): 1173–86. doi:10.1016/j.jtrangeo.2011.03.008.
Wang, Hong, David A. Kindig, and John Mullahy. 2005. "Variation in Chinese Population Health Related Quality of Life: Results from a EuroQol Study in Beijing, China." *Quality of Life Research* 14 (1): 119–32.
Wang, Junxiu, and Yiyin Yang. 2013. *Annual Report on Social Mentality of China (2012~2013)*. Blue Book of Social Mentality. Social Sciences Academic Press.
Wang, Shuxiao, and Jiming Hao. 2012. "Air Quality Management in China: Issues, Challenges, and Options." *Journal of Environmental Sciences* 24 (1): 2–13. doi:10.1016/S1001-0742(11)60724-9.

Watts, Jonathan. 2006. "Doctors Blame Air Pollution for China's Asthma Increases." *The Lancet* 368 (9537): 719–20.

Weichenthal, Scott, Ryan Kulka, Aimee Dubeau, Christina Martin, Daniel Wang, and Robert Dales. 2011. "Traffic-Related Air Pollution and Acute Changes in Heart Rate Variability and Respiratory Function in Urban Cyclists." *Environmental Health Perspectives* 119 (10): 1373–78. doi:10.1289/ehp.1003321.

Weinmayr, Gudrun, Elisa Romeo, Manuela De Sario, Stephan K. Weiland, and Francesco Forastiere. 2009. "Short-Term Effects of PM10 and NO2 on Respiratory Health among Children with Asthma or Asthma-like Symptoms: A Systematic Review and Meta-Analysis." *Environmental Health Perspectives* 118 (4): 449–57. doi:10.1289/ehp.0900844.

Wernham, Aaron, and Steven M. Teutsch. 2015. "Health in All Policies for Big Cities:" *Journal of Public Health Management and Practice* 21: S56–65. doi:10.1097/PHH.0000000000000130.

Weschler, Charles J. 2006. "Ozone's Impact on Public Health: Contributions from Indoor Exposures to Ozone and Products of Ozone-Initiated Chemistry." *Environmental Health Perspectives* 114 (10): 1489–96.

Wissink, Bart, Ronald van Kempen, Yiping Fang, and Si-ming Li. 2012. "Introduction—Living in Chinese Enclave Cities." *Urban Geography* 33 (2): 161–66. doi:10.2747/0272-3638.33.2.161.

World Bank. 2015. "World Development Indicators: Total Population." *World DataBank*. http://data.worldbank.org/country/china.

World Health Organization. 2005. *WHO Air Quality Guidelines Global Update 2005: Report on a Working Group Meeting, 18–20 October 2005, Bonn, Germany*. World Health Organization. http://apps.who.int/iris/handle/10665/79170.

———. 2006. *Constitution of the World Health Organization*. Supplement Fifty-fourth Edition. Basic Documents. http://apps.who.int/iris/handle/10665/43637.

Wu, Jianguo, Wei-Ning Xiang, and Jingzhu Zhao. 2014. "Urban Ecology in China: Historical Developments and Future Directions." *Landscape and Urban Planning* 125 (May): 222–33. doi:10.1016/j.landurbplan.2014.02.010.

Xi'an Environmental Protection Bureau. 2015. "西安市空气质量发布平台 （Air Quality Visualization Platform for Xi'an)." *西安市空气质量发布平台 （Air Quality Visualization Platform for Xi'an)*. Accessed April 1. ttp://www.xaepb.gov.cn/ajax/comm/pm25/newMapindex.jsp.

Xie, Yu, and Xiang Zhou. 2014. "Income Inequality in Today's China." *Proceedings of the National Academy of Sciences* 111 (19): 6928–33.

Xu, Chenggang. 2011. "The Fundamental Institutions of China's Reforms and Development." *Journal of Economic Literature*, 1076–1151.

Yang, Gonghuan, Yu Wang, Yixin Zeng, George F. Gao, Xiaofeng Liang, Maigeng Zhou, Xia Wan, et al. 2013a. "Rapid Health Transition in China, 1990–2010: Findings from the Global Burden of Disease Study 2010." *The Lancet* 381 (9882): 1987–2015.

———. 2013b. "Rapid Health Transition in China, 1990–2010: Findings from the Global Burden of Disease Study 2010." *The Lancet* 381 (9882): 1987–2015. doi:doi:10.1016/S0140-6736(13)61097-1.

Yang, Jiawen. 2010. "Spatial and Social Characteristics of Urban Transportation in Beijing." *Transportation Research Record: Journal of the Transportation Research Board* 2193 (-1): 59–67. doi:10.3141/2193-08.

Yang, J., Q. Shen, J. Shen, and C. He. 2012. "Transport Impacts of Clustered Development in Beijing: Compact Development versus Overconcentration." *Urban Studies* 49 (6): 1315–31. doi:10.1177/0042098011410336.

Yip, Winnie, S V Subramanian, Andrew D Mitchell, Dominic T S Lee, Jian Wang, and Ichiro Kawachi. 2007. "Does Social Capital Enhance Health and Well-Being? Evidence from Rural China." *Social Science & Medicine* 64 (1): 35–49. doi:10.1016/j.socscimed.2006.08.027.

Yuanli Liu, Gonghuan Yang, Yixin Zeng, Richard Horton, and Lincoln Chen. 2013. "Policy Dialogue on China's Changing Burden of Disease." *The Lancet* 381 (9882): 1961–62. doi:10.1016/S0140-6736(13)61031-4.

Zanobetti, Antonella, Elena Austin, Brent A. Coull, Joel Schwartz, and Petros Koutrakis. 2014. "Health Effects of Multi-Pollutant Profiles." *Environment International* 71 (October): 13–19. doi:10.1016/j.envint.2014.05.023.

Zanobetti, A, J Schwartz, and D W Dockery. 2000. "Airborne Particles Are a Risk Factor for Hospital Admissions for Heart and Lung Disease." *Environmental Health Perspectives* 108 (11): 1071–77.

Zhang, Juan, and Jad Chaaban. 2013. "The Economic Cost of Physical Inactivity in China." *Preventive Medicine* 56 (1): 75–78. doi:10.1016/j.ypmed.2012.11.010.

Zhang, Junfeng, Denise L. Mauzerall, Tong Zhu, Song Liang, Majid Ezzati, and Justin V. Remais. 2010. "Environmental Health in China: Progress towards Clean Air and Safe Water." *The Lancet* 375 (9720): 1110–19.

Zhang, Yi, Wei Wu, Yuan Li, Qixing Liu, and Chaoyang Li. 2014. "Does the Built Environment Make a Difference? An Investigation of Household Vehicle Use in Zhongshan Metropolitan Area, China." *Sustainability* 6 (8): 4910–30. doi:10.3390/su6084910.

Zhao, Bin, Shuxiao Wang, Xinyi Dong, Jiandong Wang, Lei Duan, Xiao Fu, Jiming Hao, and Joshua Fu. 2013. "Environmental Effects of the Recent Emission Changes in China: Implications for Particulate Matter Pollution and Soil Acidification." *Environmental Research Letters* 8 (2): 024031. doi:10.1088/1748-9326/8/2/024031.

Zhao, Pengjun. 2010. "Sustainable Urban Expansion and Transportation in a Growing Megacity: Consequences of Urban Sprawl for Mobility on the Urban Fringe of Beijing." *Habitat International* 34 (2): 236–43. doi:10.1016/j.habitatint.2009.09.008.

Zhao, Pengjun, Bin Lu, and Gert de Roo. 2011. "The Impact of Urban Growth on Commuting Patterns in a Restructuring City: Evidence from Beijing: The Impact of Urban Growth on Commuting Patterns." *Papers in Regional Science* 90 (4): 735–54. doi:10.1111/j.1435-5957.2010.00343.x.

Zhao, Y., J. Zhang, and C. P. Nielsen. 2013. "The Effects of Recent Control Policies on Trends in Emissions of Anthropogenic Atmospheric Pollutants and CO₂ in China." *Atmospheric Chemistry and Physics* 13 (2): 487–508. doi:10.5194/acp-13-487-2013.

Zhou, Junlin, Yihan Li, Qi-kui Wang, Andrew N. Pollak, and Gerard P. Slobogean. 2014. "Status of Road Safety and Injury Burden: China." *Journal of Orthopaedic Trauma* 28: S41–42.

Zhou, Rena, Yang Li, Masahiro Umezaki, Yongming Ding, Hongwei Jiang, Alexis Comber, and Hua Fu. 2013. “Association between Physical Activity and Neighborhood Environment among Middle-Aged Adults in Shanghai.” *Journal of Environmental and Public Health* 2013: 1–7. doi:10.1155/2013/239595.

Zhou, Wenji, Bing Zhu, Dingjiang Chen, Charla Griffy-Brown, Yaoyao Ma, and Weiyang Fei. 2012. “Energy Consumption Patterns in the Process of China’s Urbanization.” *Population and Environment* 33 (2-3): 202–20. doi:10.1007/s11111-011-0133-5.

Zhou, Yixing, and Laurence J. C. Ma. 2000. “Economic Restructuring and Suburbanizaition in China.” *Urban Geography* 21 (3): 205–36. doi:10.2747/0272-3638.21.3.205.

Appendix A: Description of Air Pollution Sampling Sites

Site	Type	Environment	Sampling Height (m)	Distance to Road (m)[a]	Traffic Type
$PM_{2.5}$, NO_2, SO_2, O_3 Sites					
A01	Urban Residential	Lane/courtyard neighborhood within old city walls	2	427	Medium
A02	Urban Residential	Lane/courtyard housing within old city walls, tree-lined roads	10	255	Medium
A03	Public Library	Heavily trafficked area with street vendors and retail; Near intersection of 2nd ring road and major corridor	10	72	Heavily congested
A04	University	Balcony of office building on campus	10	116	Congested
A05	Urban Residential	High-rise residential complex, construction in area	3	57	Medium
A06	Train Station	Near city wall, high volumes of traffic	13	15	Congested
A07	University	Quiet, tree-lined campus near 2nd ring road	3	476	Congested
A08	Urban Residential	Lane/courtyard housing near tree-lined busy streets	10	113	Congested
A09	University	Quiet, tree-lined campus	3	242	Congested
A10	Urban Residential	High-rise complex	13	35	Medium
A11	Urban Residential	Work-unit complex	3	188	Congested
A12	Village	Urban village surrounded by demolition and construction	13	201	Congested
A13	Village	Quiet residential, near 3rd ring road	3	828	Light

Site	Type	Environment	Sampling Height (m)	Distance to Road (m)[a]	Traffic Type
A14	Urban Residential	High-rise complex (low-density) surrounded by villages, open spaces, and construction	18	125	Light
A15	Urban Residential	Gated medium-rise housing near subway construction	3	105	Heavily congested
A16	Roadside	Roof of office near high-rise complex, near road	13	29	Medium
A17	University	On balcony of office building in new university campus under construction	10	217	Light
A18	Urban Residential	Work-unit complex	10	164	Light
A19	Village	Quiet residential complex near new high-rise developments under construction	13	1,150	Light
NO_2, SO_2, and O_3 Sites					
B01	Urban Residential	High-rise complex near commercial area within city walls	13	14	Medium
B02	Urban Residential	Lane/courtyard complex near demolition and construction	10	139	Congested
B03	Office Building	Gated complex	3	45	Light
B04	Urban Residential	High-rise complex	6		
B05	Roadside	Near rotary next to office buildings	3	30	Congested
B06	Roadside	High-rise complex near roadway	3	5	Medium
B07	Office Building	Mix of office buildings, residential high rises, and parks	10	66	Congested

Site	Type	Environment	Sampling Height (m)	Distance to Road (m)[a]	Traffic Type
B08	University	Residential area of campus	6	298	Heavily Congested
B09	Urban Residential	High-rise complex	3	72	Medium
B10	Urban Residential	Work-unit complex	1	85	Light
B11	Village	Residential	3	90	Light
B12	Urban Residential	High-rise complex	3	90	Light
B13	Urban Residential	High-rise complex (low-density)	3	625	Light
B14	Urban Residential	High-rise complex surrounded by older neighborhoods	1	92	Congested
B15	Hospital	Surrounded by highways, near power plant	13	210	Light

[a]Roads include highways, axis, and major roads.

Appendix B: Xi'an Health Survey

Subject ID: □□ □□□□ □□

Start Time: ________

A. BACKGROUND INFORMATION

A1. Sex: (0) Male (1) Female

A2. Age: _________ years

A3. Marital status:

(0) Single

(1) Married

(2) Divorced

(3) Widowed

A4. Highest Education Level Obtained:

(0) Never attended school

(1) Elementary school

(2) Middle school

(3) Vocational Secondary

(4) High school

(5) College

(6) Vocational college

(7) Graduate School

(8) Other:_____________

A5. Household Size (including you):

_____people

A6. Number of adults (age 18 or over):

_____people

A7. Number of people with steady income (including you): _____people

A8. Household income: _____ yuan/month

A9. Individual income: _____ yuan/month

A10. Hukou:

(0) Rural (1) Urban

A11. Community Party Membership:

(0) Yes

↳A12. Joined in which year? ______

(1) No

A13. Occupation:

(0) Unemployed

(1) Student

(2) Retired

(3) Blue collar worker

(4) Farmer

(5) White collar worker (private enterprise)

(6) White collar worker (state-owned enterprise)

(7) Self employed

(8) Government employee

(9) Other: _____________

A14. Employment Benefits (select all that apply):

(0) Health insurance

(1) Retirement funds

(2) Unemployment

(3) Maternity healthcare

(4) Workplace injury insurance

(5) Real estate funds

(6) All of the above

(7) None

(8) Other:_____________

A15. How many years have you lived in the neighborhood? _____ years

A16. Do you rent or own?

(0) Rent

↳**A18. What is your monthly rent?**

_____ yuan/month

(1) Own

(2) Provided by my employer

(3) Replaced old home during redevelopment

A19. Apartment size: _____ m^2

B. ENVIRONMENTS

{Please ☒ the answer}

B1. What type of fuel do you use at home for cooking? Select all that apply:

(0) Natural gas

(1) Coal

(2) Gas

(3) Electricity

(4) Other: ___________

(5) Don't cook

(6) Don't know

B2. What type of fuel do you use at home for heating? Select all that apply:

(0) Natural Gas (Provided by city)

(1) Natural gas (individual)

(2) Coal (local community)

(3) Coal (individual)

(4) Central heating or A/C units

(5) Electric heaters

(6) Don't have/use heat

(7) Other: ___________

(8) Don't know

B3. Do you or do you have family members who smoke at home?

(0) Yes (1) No

B4. Which of the following best described the smoking habits inside your home?

(0) Smoking is not allowed in any indoor area.

(1) Smoking is only allowed in some indoor areas.

(2) No rules or restrictions.

B5. Do you have pets at home?

(0) Yes (1) No

B6. Do you use pesticides within your home?

(0) Yes (1) No (2) Don't know

B7. Are you exposed to fumes, vapors, or dust on your job?

(0) Yes (1) No (2) Don't know

B8. From birth until age 3, what kind of environment did you grow up in?

(0) Urban (1) Rural (2) Both

B9. From age 3 until age 12, what kind of environment did you grow up in?

(0) Urban (1) Rural (2) Both

B10. From age 12 until age17, what kind of environment did you grow up in?

(0) Urban (1) Rural (2) Both

C. <u>HEALTH</u>

This first question is about your health now. **Please try to answer as accurately as you can.**

C1. In general, would you say your health is… *[READ RESPONSE CHOICES]*

(Circle one number)

Excellent......1

Very good......2

Good......3

Fair......4

or Poor......5

Now I'm going to read a list of activities that you might do during a typical day. **As I read each item, please tell me if your health now limits you a lot, limits you a little, or does not limit you at all in these activities.**

C2. . . . moderate activities, such as moving a table, pushing a vacuum cleaner, bowling, or playing golf. Does your health now limit you a lot, limit you a little, or not limit you at all? *[READ RESPONSE CHOICES ONLY IF NECESSARY]*

[IF RESPONDENT SAYS S/HE DOES NOT DO ACTIVITY, PROBE: Is that because of your health?]

(Circle one number)

Yes, limited a lot......1

Yes, limited a little......2

No, not limited at all......3

C3. . . . climbing several flights of stairs. Does your health now limit you a lot, limit you a little, or not limit you at all? *[READ RESPONSE CHOICES ONLY IF NECESSARY]*

[IF RESPONDENT SAYS S/HE DOES NOT DO ACTIVITY, PROBE: Is that because of your health?]

(Circle one number)

Yes, limited a lot......1

Yes, limited a little......2

No, not limited at all......3

The following two questions ask you about your physical health and your daily activities.

C4. **During the past four weeks, how much of the time have you accomplished less than you would like as a result of your physical health?** *[READ RESPONSE CHOICES]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C5. **During the past four weeks, how much of the time were you limited in the kind of work or other regular daily activities you do as a result of your physical health?**

[READ RESPONSE CHOICES]

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

The following two questions ask about your emotions and your daily activities.

C6. **During the past four weeks, how much of the time have you accomplished less than you would like as a result of any emotional problems, such as feeling depressed or anxious?** *[READ RESPONSE CHOICES]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C7. During the past four weeks, how much of the time did you do work or other regular daily activities less carefully than usual as a result of any emotional problems, such as feeling depressed or anxious? *[READ RESPONSE CHOICES]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C8. During the past four weeks, how much did pain interfere with your normal work, including both work outside the home and housework? Did it interfere . . . *[READ RESPONSE CHOICES]*

(Circle one number)

Not at all 1

A little bit 2

Moderately 3

Quite a bit 4

or Extremely 5

The next questions are about how you feel and how things have been with you during the past four weeks. As I read each statement, please give me the one answer that comes closest to the way you have been feeling; is it all of the time, most of the time, some of the time, a little of the time, or none of the time?

C9. How much of the time during the past four weeks . . . have you felt calm and peaceful? *[READ RESPONSE CHOICES ONLY IF NECESSARY]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C10. **How much of the time during the past four weeks . . . did you have a lot of energy?** *[READ RESPONSE CHOICES ONLY IF NECESSARY]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C1. **How much of the time during the past four weeks . . . have you felt downhearted and depressed?** *[READ RESPONSE CHOICES ONLY IF NECESSARY]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C12. **During the past four weeks, how much of the time has your physical health or emotional problems interfered with your social activities like visiting with friends or relatives? Has it interfered . . .** *[READ RESPONSE CHOICES]*

(Circle one number)

All of the time 1

Most of the time 2

Some of the time 3

A little of the time 4

or None of the time 5

C13. Height: __________ cm

C14. Weight: __________ kg

C15. When you <u>don't have a cold</u>, do you sneeze, have a runny nose, or have a stuffy nose?

(0) Yes (1) No (2) Don't know

C16. In the last 12 months, how have nose problems affected your daily life?

(0) Not at all
(1) A little
(2) A lot
(3) Extremely affected

C17. In the last 12 months, have you had problems breathing when at rest?

(0) Yes (1) No (2) Don't know

C18. In the last 12 months, have you have problems breathing after exercising?

(0) Yes (1) No (2) Don't know

C19. In the last 12 months, have you woken up at night due to breathing problems?

(0) Yes (1) No (2) Don't know

C20. Have you ever been diagnosed with asthma by a doctor?

(0) Yes

(1) No, <u>*skip to question C24*</u>

(2) Don't know

C21. Do you still have asthma?

(0) Yes (1) No (2) Don't know

C22. In the last 3 months, how many asthma incidents have you experienced?

__________ incidents

(00) Don't know

C23. Do you take medication for your asthma?

(0) Yes (1) No (2) Don't know

Are you allergic to the following?

C24. Cats

(0) Yes (1) No (2) Don't know

C25. Dogs

(0) Yes (1) No (2) Don't know

C26. Pollen

(0) Yes (1) No (2) Don't know

C27. In the last 12 months, how many times have you visited the hospital for respiratory related issues?

__________times

(00) Don't know

C28. In the last 12 months, how many days of school or work have you missed for health reasons?

__________ days

(00) Don't know

E31. In the last 12 months, how often do health issues affect your daily life for ONE week or more?

(0) Frequently
(1) Sometimes
(2) Very infrequently
(3) Never
(4) Don't know

C30. Have you ever smoked?

(0) Yes (1) No, *skip to Question C36*

C31. What age did you start smoking?

______ years (00) Don't know

C32. Do you currently smoke?

(0) Yes (1) No, *skip to Question C34*

C33. On average, how many cigarettes per day do you smoke?

__________ cigarettes/day

C34. If you quit smoking, how many years did you smoke?

______ years (00) Don't know

C35. If you've already quit, on average how many cigarettes per day did you used to smoke?

__________ cigarettes/day

C36. Have you ever been diagnosed with hypertension by a doctor?

(0) Yes (1) No (2) Don't know

C37. If yes, are you using drugs to lower your blood pressure?

(0) Yes (1) No (2) Don't know

C38. Have you ever been diagnosed with diabetes by a doctor?

(0) Yes (1) No (2) Don't know

C39. Have you ever been diagnosed with myocardial infarction by a doctor?

(0) Yes (1) No (2) Don't know

C40. Including naps during the day, how many hours a day of sleep do you get? ____ hours

C41. How many hours during the day are you sedentary (e.g., watching TV, sedentary at work/school, playing video games, etc). _____ hours

Activity	**How many times per week do you participate in the following activities? (Please ☒)**								**Each time you participate, how much time do you spend on each activity (minutes)?** （0）<15 （2）31-60 （1）15-30 （3）60+	
	Never	1	2	3	4	5	6	Daily	Mon-Fri	Sat, Sun
C42.Walking										
C43. Biking										
C44. Soccer, basketball, tennis										
C45. Gymnastics, dance, acrobatics										
C46. Running, swimming										
C47. Badminton, Volleyball, Ping-pong										
C48. Exercise equipment in parks or neighborhoods										
C49. Weight training										
C50. Yoga, pilates										
C51.Wushu（gongfu、taiji）										
C52.Other：__________										

Food Type	**In the last 7 days, how frequently did you have the following foods?(Please ☒)**						**Was this frequency normal?**	
	Never	1-3 Times	4-6 Times	Once every day	Twice every day	4+ times a day	（0）Yes	（1） No
C53. Fruits								
C54. Vegetables								
C55. Meat (Pork, beef, seafood, eggs)								
C56. Daily (milk, yogurt, cheese)								
C57. Starches (rice, congee, noodles, dumplings, breads)								
C58. Desserts (cakes, ice cream)								
C59. Snacks (cookies, crackers, chips)								
C60.Alcohol (beer, wine, liquor)								
C61. Soft drinks and sodas								
C62. Fast food (KFC, McDonalds, Pizza Hut)								

D. <u>TRAVEL BEHAVIOR</u>

How many of the following do you own?

D1. Bicycle: _____

D2. Car: _____

D3. E-bike: _____

D4. Motorcycle: ____

In the SUMMER, how often do you take the following modes of transportation?

	Never	Rarely (1-2 times/week)	Sometimes (3-4 times/week)	Often (5-6 times/week)	Daily
D5. Walking	1	2	3	4	5
D6. Biking	1	2	3	4	5
D7. E-bike Bus	1	2	3	4	5
D8. Public bus	1	2	3	4	5
D9. Subway	1	2	3	4	5
D10. Private Car	1	2	3	4	5
D11. Taxi	1	2	3	4	5
D12. Company shuttle or school bus	1	2	3	4	5
D13. 3-wheeled vehicles	1	2	3	4	5

In the WINTER, how often do you take the following modes of transportation?

	Never	Rarely (1-2 times/week)	Sometimes (3-4 times/week)	Often (5-6 times/week)	Daily
D14. Walking	1	2	3	4	5
D15. Biking	1	2	3	4	5
D16. E-bike Bus	1	2	3	4	5
D17. Public bus	1	2	3	4	5
D18. Subway	1	2	3	4	5
D19. Private Car	1	2	3	4	5
D20. Taxi	1	2	3	4	5
D21. Company shuttle or school bus	1	2	3	4	5
D22. 3-wheeled vehicles	1	2	3	4	5

{If subject doesn't work or attend school, please skip to Question C25.}

D23. In the SUMMER, what mode do you most commonly use to travel to work (or school) from home? Select all that apply and include time required to travel from starting point (e.g., home) to destination (e.g., work or school).

(1) Walk ____ minutes
(2) Bike____ minutes
(3) Bus____ minutes
(4) Private car____ minutes
(5) Taxi____ minutes
(6) E-bike____ minutes
(7) Company/school bus____ minutes
(8) 3-wheeled vehicles__ minutes
(9) I don't work or attend school

D24. In the WINTER, what mode do you most commonly use to travel to work (or school) from home? Select all that apply and include time required to travel from starting point (e.g., home) to destination (e.g., work or school).

(1) Walk ____ minutes
(2) Bike____ minutes
(3) Bus____ minutes
(4) Private car____ minutes
(5) Taxi____ minutes
(6) E-bike____ minutes
(7) Company/school bus____ minutes
(8) 3-wheeled vehicles__ minutes
(9) I don't work or attend school

D25. How many trips do you take that are within 500m? ______ trips

E. NEIGHBORHOOD PERCEPTIONS

{Please use the answer placard provided for Questions C1-C31. Please circle answers.}
How long does it take to get from your home to the nearest business or facilities if you WALKED?

		<5 min	5-10 min	11-20 min	20-30 min	>30 min	Don't Know
E1	Convenience store	1	2	3	4	5	6
E2	Supermarket	1	2	3	4	5	6
E3	Street market	1	2	3	4	5	6
E4	Hardware store	1	2	3	4	5	6
E5	Clothing/shoe retail stores	1	2	3	4	5	6
E6	Pharmacy	1	2	3	4	5	6
E7	Bookstore	1	2	3	4	5	6
E8	Movie theater	1	2	3	4	5	6
E9	Library	1	2	3	4	5	6
E10	Laundromat/Dry cleaners	1	2	3	4	5	6
E11	Hair salon	1	2	3	4	5	6
E12	Bank	1	2	3	4	5	6
E13	Post Office	1	2	3	4	5	6
E14	Community Clinic	1	2	3	4	5	6
E15	Hospital	1	2	3	4	5	6
E16	Kindergarten	1	2	3	4	5	6
E17	Elementary school	1	2	3	4	5	6
E18	Other schools	1	2	3	4	5	6
E19	Fast food restaurant	1	2	3	4	5	6
E20	Chinese restaurant	1	2	3	4	5	6
E21	Non-Chinese restaurant	1	2	3	4	5	6

E22	Coffee shop	1	2	3	4	5	6
E23	Park	1	2	3	4	5	6
E24	Community Center	1	2	3	4	5	6
E25	Gym	1	2	3	4	5	6
E26	Swimming Pool	1	2	3	4	5	6
E27	Places of worship	1	2	3	4	5	6
E28	Public restroom	1	2	3	4	5	6
E29	Bakery	1	2	3	4	5	6
E30	Bus stop	1	2	3	4	5	6
E31	Subway stop	1	2	3	4	5	6

{Please use the answer placard provided for Questions C32-C65. Please circle answers.}
I will read statements describing your neighborhood to you. Please select the response that best reflects your view of the statement.

	Access to Services:	**Strongly Disagree**	**Somewhat Disagree**	**Somewhat Agree**	**Strongly Agree**
E32	Stores are within easy walking distance from my home.	1	2	3	4
E33	Shopping and commercial areas are easy to access using public transit.	1	2	3	4
E34	Parking is difficult in shopping and commercials areas.	1	2	3	4
E35	There are many places to go within easy walking distance from my home.	1	2	3	4
E36	It is easy to walk to a transit stop (bus, train) from my home.	1	2	3	4
E37	The streets in my neighborhood are hilly, making my neighborhood difficult to walk in.	1	2	3	4
E38	There are too many pedestrians making it difficult to walk on the sidewalks.	1	2	3	4
E39	There are major barriers to walking in my local area that make it hard to get from place to place (e.g., highways, railway lines, rivers)	1	2	3	4

	Street Design:	**Strongly Disagree**	**Somewhat Disagree**	**Somewha t Agree**	**Strongly Agree**
E40	The streets in my neighborhood DO NOT have many dead end streets.	1	2	3	4
E41	The distance between intersections in my neighborhood is usually short.	1	2	3	4
E42	There are many alternative routes for getting from place to place in my neighborhood. I don't have to go the same way every time.	1	2	3	4

	Pedestrian and Biking Facilities:	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree
E43	There are sidewalks on most of the streets in my neighborhood.	1	2	3	4
E44	There are parked cars on the sidewalks in my neighborhood that make walking difficult.	1	2	3	4
E45	There is a barrier (grass, dirt strip, bannister) that separates the streets from the sidewalks in my neighborhood.	1	2	3	4
E46	There is adequate lighting at night to walk in my neighborhood.	1	2	3	4
E47	There are street peddlers and stands that make walking on the sidewalks difficult in my neighborhood.	1	2	3	4
E48	There are crosswalks and traffic lights to help me cross the streets in my neighborhood.	1	2	3	4

	Neighborhood Surroundings:	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree
E49	There are trees along the streets in my neighborhood.	1	2	3	4
E50	There are many interesting things to look at while walking in my neighborhood.	1	2	3	4
E51	There are many attractive natural sights in my neighborhood (such as landscaping, views).	1	2	3	4
E52	There are attractive buildings or homes in my neighborhood.	1	2	3	4
E53	The air pollution level is high in my neighborhood.	1	2	3	4
E54	The noise levels in my neighborhood are frequently loud.	1	2	3	4
E55	There is frequently ongoing construction in my neighborhood.	1	2	3	4

	Safety	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree
E56	There is so much traffic along nearby streets that it makes it difficult or unpleasant to walk in my neighborhood.	1	2	3	4
E57	The speed of traffic on most nearby streets is usually slow due to congestion.	1	2	3	4
E58	Most drivers exceed the posted speed limit while driving in my neighborhood.	1	2	3	4
E59	There are parked vehicles that block my line of sight that makes crossing streets difficult.	1	2	3	4
E60	The traffic flows in my neighborhood make me feel unsafe to cross the streets.	1	2	3	4
E61	Walkers and bikers on the streets in my neighborhood can be easily seen by people in their homes.	1	2	3	4
E62	There is a high crime rate in my neighborhood.	1	2	3	4
E63	The crime rate in my neighborhood makes it unsafe to go on walks during the day.	1	2	3	4
E64	The crime rate in my neighborhood makes it unsafe to go on walks at night.	1	2	3	4
E65	There are few pedestrians in my neighborhood so it would be difficult to get help or assistance if necessary.	1	2	3	4

	How common are the following:	None	Very Few	Some	A Lot	All
E66	Detached single-family residences	1	2	3	4	5
E67	Apartments/condos of 1-3 stories	1	2	3	4	5
E68	Apartments/condos of 4-7 stories	1	2	3	4	5
E69	Apartments/condos of 8-12 stories	1	2	3	4	5
E70	Apartments/condos of 13-20 stories	1	2	3	4	5
E71	Apartments/condos of more than 20 stories	1	2	3	4	5

F. SOCIAL NETWORKS

F1. In an average day, how many people do you come in contact with? Include people you talk to (in person or phone), write to, or connect with over the internet.

(0) 0-4 people
(1) 5-9 people
(2) 10-19 people
(3) 20-40 people
(4) 50-99 people
(5) 100+ people

F2. Within the people you interact with on a daily basis, are most from work? Circle one:

(0) Almost all are from work
(1) Most are from work
(2) About half are from work
(3) Most of them are NOT from work
(4) Almost all are NOT from work
(5) Not relevant

{Please use the answer placard provided for Questions F3-F44. Please circle answers.}

How do you rate the number of people in each of the following six (6) categories? Please circle one for each:		A few	Less than average	Average	More than average	A lot
F3	Your family members	1	2	3	4	5
F4	Your relatives	1	2	3	4	5
F5	People in your neighborhood	1	2	3	4	5
F6	Your friends	1	2	3	4	5
F7	Your coworkers/fellows	1	2	3	4	5
F8	Your country fellows/old classmates	1	2	3	4	5

With how many people in each of the following categories do you keep routine contact?		None	Few	Some	Most	All
F9	Your family members	1	2	3	4	5
F10	Your relatives	1	2	3	4	5
F11	People in your neighborhood	1	2	3	4	5
F12	Your friends	1	2	3	4	5
F13	Your coworkers/fellows	1	2	3	4	5
F14	Your country fellows/old classmates	1	2	3	4	5

Among the people in the each of following six (6) categories, how many can you trust?		None	Few	Some	Most	All
F15	Your family members	1	2	3	4	5
F16	Your relatives	1	2	3	4	5
F17	People in your neighborhood	1	2	3	4	5
F18	Your friends	1	2	3	4	5
F19	Your coworkers/fellows	1	2	3	4	5
F20	Your country fellows/old classmates	1	2	3	4	5

	Among people in each of the following six (6) categories, how many will definitely help you upon your request?	None	Few	Some	Most	All
F21	Your family members	1	2	3	4	5
F22	Your relatives	1	2	3	4	5
F23	People in your neighborhood	1	2	3	4	5
F24	Your friends	1	2	3	4	5
F25	Your coworkers/fellows	1	2	3	4	5
F26	Your country fellows/old classmates	1	2	3	4	5

	When people in all the six categories are considered, how many possess the following assets/resources?	None	Few	Some	Most	All
F27	Certain political power	1	2	3	4	5
F28	Wealth or own a company	1	2	3	4	5
F29	Influential	1	2	3	4	5
F30	Good reputation	1	2	3	4	5
F31	Has high school or higher education	1	2	3	4	5
F32	Has a professional job	1	2	3	4	5

How do you rate the number of the following two types of groups/organization in your community?		A few	Less than average	Average	More than average	A lot
F33	Government, political, economic and social groups/organization (e.g., political parties, women's groups, village committees, trade unions, cooperate associations, volunteer groups, etc).	1	2	3	4	5
F34	Cultural, recreational and leisure groups and organizations (e.g., religious country fellows alumni, sport, music, dances, crafts, games, etc.)	1	2	3	4	5

Do you participate in activities for how many of each of these two types of groups/organization in your community?		None	Few	Some	Most	All
F35	Government, political, economic and social groups/organization (e.g., political parties, women's groups, village committees, trade unions, cooperate associations, volunteer groups, etc).	1	2	3	4	5
F36	Cultural, recreational and leisure groups and organizations (e.g., religious country fellows alumni, sport, music, dances, crafts, games, etc.)	1	2	3	4	5

Among each of the two types of groups and organizations, how many represent your rights and interests?		None	Few	Some	Most	All
F37	Government, political, economic and social groups/organization (e.g., political parties, women's groups, village committees, trade unions, cooperate associations, volunteer groups, etc).	1	2	3	4	5
F38	Cultural, recreational and leisure groups and organizations (e.g., religious country fellows alumni, sport, music, dances, crafts, games, etc.)	1	2	3	4	5

Among each of the two types of groups and organizations, how many will help you upon your request?		None	Few	Some	Most	All
F39	Government, political, economic and social groups/organization (e.g., political parties, women's groups, village committees, trade unions, cooperate associations, volunteer groups, etc).	1	2	3	4	5
F40	Cultural, recreational and leisure groups and organizations (e.g., religious country fellows alumni, sport, music, dances, crafts, games, etc.)	1	2	3	4	5

When all groups and organizations in the two categories are considered, how many possess the following assets and resources?		None	Few	Some	Most	All
F41	Significant power for decision making	1	2	3	4	5
F42	Solid financial basis	1	2	3	4	5
F43	Broad social connections	1	2	3	4	5
F44	Great social influence	1	2	3	4	5

This is the end of the survey. Thank you for your participation and cooperation!
NOTE TO INTERVIEWER: Please ask the participant if he/she would like to be contacting regarding future studies. Please record response on the cover sheet.}
End time: ___________

Appendix C: Photos of types of Chinese neighborhoods

Figure C-1 Work-unit neighborhoods (NH1)

Figure C-2 Lane and courtyard neighborhoods (NH2)

Figure C-3 Commodity neighborhoods: High-density high-rise neighborhoods (NH3)

Figure C-4 Commodity neighborhoods: Low-density high-rise neighborhoods (NH4)

Appendix D: Chapter 4 Model Results

This appendix supplements Chapter 5 regression results for the categorical air pollution mixture models. Tables include regression coefficients for the covariates included as confounders. The reference categories for physical activity level, household income, and neighborhood type are inactive, less than 2000 yuan per month, and work-unit neighborhoods, respectively.

Table D-1 Full regression results for associations of neighborhood variables and MCS

MCS	Walking		Diversity		Access		Safety		Esthetics		Streets	
Covariates	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
NH Variable	0.21	0.60	0.99	0.68	4.11**	1.46	2.78**	0.88	0.26	0.80	1.03	0.59
Age	0.01	0.02	0.02	0.02	0.00	0.01	0.01	0.02	0.01	0.02	0.01	0.02
Female	0.01	0.25	0.29	0.32	-0.10	0.27	0.04	0.23	0.04	0.27	0.12	0.26
College	-0.64	0.63	-0.62	0.65	-0.45	0.71	-0.67	0.65	-0.62	0.54	-0.63	0.69
Hukou	0.30	0.70	0.11	0.84	0.43	0.69	0.34	0.69	0.00	0.64	0.28	0.72
Household Income (¥/month)												
2000-3999	0.96	0.71	0.78	0.65	.0.29	0.61	0.73	0.66	0.83	0.71	0.50	0.58
4000-5999	0.30	0.60	0.67	0.58	-0.07	0.65	0.09	0.69	0.34	0.59	0.16	0.60
6000+	1.58*	0.66	1.63*	0.65	1.25*	0.57	1.41*	0.59	1.43*	0.65	1.49*	0.60
Missing	2.58***	0.76	2.69***	0.70	2.63**	0.84	2.44**	0.95	2.44***	0.75	2.51***	0.78
Type of Neighborhood												
Lane/courtyard (NH2)	0.30	0.70	0.83	2.65	11.34*	5.05	8.75*	4.35	-2.50	2.44	4.55	2.75
High-density high rise (NH3)	0.30***	0.70	-4.78	3.28	-8.54	5.53	-6.16	5.46	1.32	2.00	2.53	2.49
Low-density high rise (NH4)	0.30	0.70	-0.56	2.68	3.86	5.11	6.04	3.61	-2.68	2.84	1.04	2.42
Interactions												
Variable x NH2	1.80**	0.69	0.60	0.99	-3.14	1.65	-2.40	1.45	2.02*	0.97	-0.74	0.75
Variable x NH3	3.68***	1.10	1.47	1.20	2.88	1.72	2.00	1.85	-0.30	0.90	-0.70	0.75
Variable x NH4	1.09	1.11	0.36	1.00	-1.24	1.56	-2.13	1.27	1.11	1.09	-0.26	0.84
Constant	52.20***	1.80	49.60***	1.39	41.55***	5.22	45.20***	3.50	52.17***	1.23	49.89***	1.38

*P≤0.05 ** P≤0.01 ***P≤0.001

Table D-2 Full regression results for associations of neighborhood variables and PCS

PCS	Walking		Diversity		Access		Safety		Esthetics		Streets	
Covariates	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE	Beta	SE
NH Variable	0.32	0.54	0.46	0.50	3.24***	0.39	0.37	0.19	1.12***	0.31	0.34	0.73
Age	-0.20***	0.01	-0.20***	0.01	-0.20***	0.01	-0.20***	0.01	-0.21***	0.01	-0.20***	0.01
Female	-0.49	0.59	-0.35	0.70	-0.57	0.58	-0.49	0.58	-0.47	0.62	-0.43	0.64
College	0.71*	0.35	0.44	0.48	0.73*	0.33	0.68	0.37	0.49	0.52	0.67	0.36
Hukou	-0.18	0.50	-0.44	0.43	-0.12	0.53	-0.25	0.51	-0.37	0.52	-0.24	0.47
Household Income (¥/month)												
2000-3999	1.14*	0.46	1.39***	0.42	0.78	0.56	1.20**	0.43	1.54**	0.50	1.04*	0.50
4000-5999	1.58*	0.62	2.29***	0.56	1.46*	0.60	1.77***	0.53	2.18***	0.53	1.69**	0.55
6000+	2.79***	0.49	3.39***	0.82	2.66***	0.45	2.94***	0.47	3.35***	0.76	2.84***	0.53
Missing	-0.18*	0.40	1.48***	0.37	1.08**	0.37	1.19***	0.33	1.44***	0.33	1.11**	0.37
Type of Neighborhood												
Lane/courtyard (NH2)	2.77	2.17	-0.17	1.92	12.62***	2.55	-0.83	3.58	2.78	2.27	1.92	3.14
High-density high rise (NH3)	-3.67	1.93	0.78	1.14	4.65	2.51	-8.96**	2.89	0.26	0.99	-3.13	2.44
Low-density high rise (NH4)	1.57	2.06	-2.62	1.47	0.55	2.55	1.56	6.08	0.30	1.09	1.60	2.58
Interactions												
Variable x NH2	-0.45	0.58	0.62	0.62	-3.92***	0.70	0.82	1.08	-0.43	0.64	-0.15	0.83
Variable x NH3	1.49*	0.64	0.10	0.49	-1.26	0.76	3.43***	0.93	0.34	0.35	1.34	0.77
Variable x NH4	-0.32	0.62	1.16	0.61	0.02	0.85	-0.42	2.09	0.06	0.32	-0.32	0.72
Constant	58.36***	2.35	58.54***	1.75	50.51***	1.66	58.56***	1.33	56.98***	1.11	58.40***	2.01

*P≤0.05 ** P≤0.01 ***P≤0.001

Appendix E: Chapter 5 Model Results

The reference categories for physical activity level, household income, and neighborhood type are inactive, less than 2000 yuan per month, and lane/courtyard neighborhoods, respectively.

Table E-1 Full regression results for associations of leisure-time physical activity (LTPA) and adverse health impact: categorical mixture models

	Category A: Medium Levels		Category B: High NO_2 and SO_2, Low O_3		Category C: High $PM_{2.5}$ and O_3	
Covariates	OR	SE	OR	SE	OR	SE
LTPA Levels						
Low LTPA	1.01	0.43	0.47***	0.09	1.39	0.96
Medium LTPA	0.56	0.22	0.63	0.31	3.56	2.35
High LTPA	0.79	0.15	0.30	0.27	2.54	2.27
Interactions						
LPTA x Work Unit (NH1)	0.83	0.09	--	--	1.20	0.36
LTPA x High-density high rise (NH3)	--	--	0.60	0.18	--	--
LTPA x Low-density high rise (NH4)	0.82	0.09	--	--	0.30**	0.13
Age	1.04**	0.01	1.06***	0.01	1.02	0.01
Female	0.55***	0.10	2.28	1.16	1.95*	0.64
College	1.52	0.45	0.39***	0.11	0.12***	0.03
Urban Hukou	2.07	0.86	0.97	0.31	6.82	9.37
Household Income (¥/month)						
2000-3999	0.79	0.22	0.71	0.35	0.99	0.41
4000-5999	0.54	0.26	0.45	0.22	0.03**	0.05
6000+	0.33*	0.17	0.62	0.24	0.47	0.22
Missing	0.43**	0.12	0.38	0.36	0.58	0.32
Manual Labor Occupation	0.47*	0.14	1.72	1.10	0.17**	0.11
Current Smoker	1.05	0.39	0.67	0.14	2.62	1.30
Seasonal Allergies	1.08	0.18	2.15	1.54	4.47***	1.88
Occupational Exposure	1.59	0.44	1.04	0.56	1.55	0.89
Type of Neighborhood						
Work Unit (NH1)	1.63	0.56	--	--	1.95*	0.54
High-density high rise (NH3)	--	--	1.51	0.61	--	--
Low-density high rise (NH4)	0.73	0.37	--	--	27.26***	8.66
Constant	0.02***	0.02	0.02***	0.01	0.001***	0.002

*P≤0.05 ** P≤0.01 ***P≤0.001

Table E-2 Full regression results for associations of leisure-time physical activity (LTPA) and mental health (MCS): categorical mixture models

	Category A: Medium Levels		Category B: High NO_2 and SO_2, Low O_3		Category C: High $PM_{2.5}$ and O_3	
Covariates	Beta	SE	Beta	SE	Beta	SE
LTPA Levels						
Low LTPA	2.92***	0.89	3.17**	1.22	0.50	0.69
Medium LTPA	2.15**	0.81	2.41**	0.87	0.36	1.45
High LTPA	1.72**	0.64	3.68***	0.90	-0.55	0.62
Interactions						
LPTA x Work Unit (NH1)	0.39	0.24	--	--	-0.23	0.23
LTPA x High-density high rise (NH3)	--	--	0.01	0.54	--	--
LTPA x Low-density high rise (NH4)	0.51*	0.23	--	--	1.47	0.38
Age	-0.01	0.03	0.01	0.03	0.01	0.02
Female	-0.02	0.65	-0.95	0.53	0.28	0.69
College	-0.01	0.75	-0.93	0.57	-1.00	0.88
Urban Hukou	-0.22	-/49	1.79	1.45	0.22	1.57
Household Income (¥/month)						
2000-3999	1.48	1.24	1.60	1.33	-0.49	0.71
4000-5999	1.02	1.25	0.63	0.94	0.14	0.73
6000+	1.28	1.23	-0.17	1.55	2.07**	0.74
Missing	3.85***	0.70***	4.79***	0.90	2.25**	0.83
Manual Labor Occupation	1.06	0.88	0.47	0.90	0.54	0.66
Current Smoker	0.58	0.50	0.49	0.40	-0.18	1.08
Seasonal Allergies	-2.05	1.32	-0.34	2.75	-1.25	0.91
Occupational Exposure	-2.30***	0.70	-2.77	1.51	-2.24*	1.14
Type of Neighborhood						
Work Unit (NH1)	-3.14***	0.95	--	--	-2.43*	1.17
High-density high rise (NH3)	--	--	0.01	0.54	--	--
Low-density high rise (NH4)	-2.09**	0.79	--	--	-5.70***	0.39
Constant	54.73***	1.10	52.68***	2.54	56.59***	0.50

*P≤0.05 ** P≤0.01 ***P≤0.001

Table E-3 Full regression results for associations of leisure-time physical activity (LTPA) and physical health (PCS): categorical mixture models

	Category A: Medium Levels		Category B: High NO_2 and SO_2, Low O_3		Category C: High $PM_{2.5}$ and O_3	
Covariates	Beta	SE	Beta	SE	Beta	SE
LTPA Levels						
Low LTPA	1.52	0.80	1.49	0.79	-0.71**	0.27
Medium LTPA	0.77*	0.37	1.45	0.92	-0.20	0.85
High LTPA	1.58***	0.39	1.57	0.85	-0.47	0.34
Interactions						
LPTA x Work Unit (NH1)	1.13**	0.41	--	--	0.83***	0.18
LTPA x High-density high rise (NH3)	--	--	-0.19	0.25	--	--
LTPA x Low-density high rise (NH4)	0.69**	0.26	--	--	1.83***	0.21
Age	-0.19***	0.03	-0.24***	0.03	-0.21***	0.02
Female	0.20	0.43	-0.21	0.42	0.33	0.79
College	0.95	0.99	0.46	0.73	-0.17	0.41
Urban Hukou	0.30	0.66	1.51	1.45	-0.52	0.43
Household Income (¥/month)						
2000-3999	1.68	1.07	1.51	0.77	1.36	0.99
4000-5999	1.60	1.52	1.04	0.89	3.03***	0.17
6000+	2.52*	1.19	2.85***	0.22	3.34***	0.80
Missing	2.13*	0.91	1.19*	0.52	2.20***	0.25
Manual Labor Occupation	1.22*	0.48	-2.45*	1.07	2.67***	0.71
Current Smoker	2.67***	0.65	1.61**	0.56	0.62	0.85
Seasonal Allergies	-0.98**	0.66	-1.76*	0.88	-2.64***	0.80
Occupational Exposure	-1.76***	0.62	0.18	0.63	-1.57***	0.34
Type of Neighborhood						
Work Unit (NH1)	-2.60*	1.07	--	--	-2.99***	0.50
High-density high rise (NH3)	--	--	1.42***	0.37	--	--
Low-density high rise (NH4)	-0.46	0.82	--	--	-4.10***	0.57
Constant	57.32***	1.94	58.80***	2.13	63.07***	1.26

*P≤0.05 ** P≤0.01 ***P≤0.001