International Journal of
Environmental Research and Public Health

MDPI

Article

Urban Form, Air Quality, and Cardiorespiratory Mortality: A Path Analysis

Chaosu Li [1], Yan Song [2,3,*], Li Tian [4] and Wei Ouyang [5]

[1] Faculty of Innovation and Design, City University of Macau, Macau, China; chaosuli@live.unc.edu
[2] Department of City Planning, Shenzhen University, Shenzhen 518060, China
[3] Department of City and Regional Planning, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599, USA
[4] School of Architecture, Tsinghua University, Beijing 100084, China; litian262@mail.tsinghua.edu.cn
[5] School of Public Administration, Renmin University of China, Beijing 100872, China; ouyangwei@ruc.edu.cn
* Correspondence: ys@email.unc.edu

Received: 5 November 2019; Accepted: 6 February 2020; Published: 13 February 2020

check for updates

Abstract: With the unprecedented urbanization during the past three decades, air quality in many Chinese cities has been a serious issue which poses great challenges for urban sustainability. This study examines the health consequences of development patterns in China by establishing the linkage between urban form, air pollution level, and cardiorespiratory mortality rate. We assembled a dataset by compiling a series of variables from multiple sources, including China's Disease Surveillance Points (DSP) system, which forms a nationally representative sample of mortality for the year 2005, Chinese census, satellite imagery, and the Chinese National Land Use Database. After controlling for local climate, demography, socioeconomics, and other pollution factors, this study finds that urban form elements (e.g., urban density, fragmentation level, forest/green space ratio) have significant influences on $PM_{2.5}$ (atmospheric particulate matter with a diameter of less than 2.5 micrometers) concentration, thus influencing the incidence of cardiorespiratory mortality at the county level. These results may help explain how the type and pattern of development shape public health by influencing air quality and form an evidence-based land use policy to improve environmental quality and public health.

Keywords: environmental health; $PM_{2.5}$; urban form; cardiorespiratory mortality; China

1. Introduction

During recent decades, with the unprecedented urbanization, rapid economic growth, and increased usage of automobiles, air quality in many Chinese cities has been extremely poor and has become an issue associated with increasing social unrest [1–3]. Ambient concentrations of fine particular matter in Chinese cities are much higher than the national standard and bring about serious environmental issues [2,4]. Major cities in China, such as Beijing, Tianjin, Nanjing, Zhengzhou, and Jinan, frequently suffer from urban smog, with the number of days of smog pollution exceeding 130 days a year [4]. The Health Effects Institute also suggests that Chinese cities face the worst air quality across different cities around world based on an extensive research of 175 countries [5].

In effect, excessive exposure to air pollutants can lead to several negative physical health outcomes, such as cardiorespiratory diseases, lung cancer, and stroke [6–9]. In the context of China, it is also worthwhile to note cardiorespiratory diseases and lung cancer have been recorded as the leading cause of mortality in the recent decade [10]. More recently, additional empirical evidence has been accumulated in the literature that exposure to air pollutants can cause mental health issues [11–13]. The health effects of air pollution and its appropriate regulation continue to be extremely important in China. According to recent studies, a 10 $\mu g/m^3$ increase in airborne PM_{10} (atmospheric particulate matter with a diameter of less than 10 micrometers), could possibly reduce a Chinese resident' life expectancy by 0.64 years, which is equivalent to 0.89 billion life-years based on China's total population [3].

Meanwhile, there have been clear connections between urban spatial structure and air pollution. Relevant urban form policies have the potential to improve urban energy efficiency [14,15], carbon emissions [16–18], and human exposure to air pollution [19–24]. It is also worthwhile to note that relevant urban form strategies to mitigate air pollution are relevant not only because of their clear impacts on air pollutants, but also due to the potential co-benefit to combat climate change [2,3].

Currently, cities are increasingly paying more attention to urban form-related planning interventions that may shape urban air quality and public health [25–27]. Although existing studies have revealed the apparent relationship between urban form and air quality, the more comprehensive relationships among urban form, air quality, and health outcomes are not well established. In this regard, we aim to investigate the linkage between urban form, air pollution level, and public health in a more comprehensive manner and to further quantify the indirect effects of urban form on health outcome through air quality. We conduct this research in the context of China, which is of tremendous policy relevance, because the results are informative for people currently living in China and other people who are exposed to air pollution in developing countries. We first review current literature on urban form factors affecting air quality, as well as health outcomes associated with air pollution to establish the conceptual framework for this study. We present our data collection and coding, urban form measures, and the path model. We then present the results for a sample of 158 counties in China and set these in the context of existing literature. Additionally, we discuss the limitations of this study. Finally, we conclude with potential policy implications.

2. Prior Research

Connections between urban form and air quality are well established, especially in the recent literature [27]. Both simulation and empirical studies demonstrate the associations between various urban form measures and local air quality. Simulation studies usually explore different land use scenarios and support the notion that compact development improves urban air quality [28,29]. On the other hand, empirical studies in this field generally agree that urban form and land use features have modest but important impacts on urban and regional air quality [22,24,30–34]. Urban size, density, shape and contiguity (irregularity), fragmentation of urban patches, and urban forest amount and mixing level have been identified as valid urban form dimensions that can potentially capture these effects [22,24,30–37].

There has been a high degree of consensus among empirical studies that urban sprawl and fragmentary urban land use increase emissions of CO, NO_x, $PM_{2.5}$, and PM_{10} since dispersed and fragmented development could bring about a higher ratio of automobile use, longer trip length, and thus, worsen air quality [22,24,31–33,37,38]. Additionally, forest coverage level and urban-forest mixing level are significantly associated with air quality, which is evident in the literature since forests could potentially improve air quality conditions in urban areas [30,32]. Nevertheless, there are still inconsistent results within empirical studies. For example, the direction and magnitude of population density are currently disputed in the literature: Stone (2008) and Bereitschaft and Debbage (2013) suggest that higher population density is associated with lower air pollutant concentration (e.g., $PM_{2.5}$ and O_3). In contrast, Clark et al. (2011) find that higher population density is positively associated with population-weighed $PM_{2.5}$ concentrations, and Rodríguez, et al. (2016) suggest that denser cities often times suffer from higher SO_2 concentrations. More recently, Han et al. (2019) find that population density is related to $PM_{2.5}$ concentrations, indicating pollution centralization and transportation congestion effects might be larger than effects of mode-shifting associated with density, especially in high-density urban areas [39]. Additionally, different research findings of urban shape complexity are reported by different empirical studies. Bereitschaft and Debbage (2013) suggest that a higher porosity level of urban areas may lead to increased duration of vehicle travel and its associated emissions, thus increasing air pollution levels. However, other studies do not find such significant associations [24,38].

Meanwhile, most existing research exploring the linkage between air pollution and health focus on health effects of air pollutant concentration on physical health. The majority of studies use cardiovascular or respiratory disease as a valid measure of the physical health outcome associated with air pollution. Recent studies also reveal that land use and urban form features may also affect mental health [12,40,41]. Although the empirical evidence on the impact of urban form measures on mental health is accumulating [40], the measurement of mental health is often times obscure, thus making it difficult to reveal any causal relationships. In summary, various physical and mental health outcomes of air pollution, especially physical health outcomes such as mortality and cardiorespiratory disease, have been well documented in prior studies.

It is worthwhile to note that the negative effects of air pollutant concentration on physical health have been well documented in the recent literature, especially in urban China [42–47]. Additionally, the existing literature generally agrees that cardiorespiratory causes of death are a valid measure of health outcome that have direct linkage to air quality. This study attempts to further advance the empirical understanding of how urban form shapes cardiorespiratory causes of death by influencing air quality. We attempt to explain air quality variation using urban form measures that have been well documented in the existing literature and single out the pathway of urban form measures in influencing cardiorespiratory causes of death, thus quantifying the indirect effect of each urban form measure.

3. Data and Methods

3.1. Mortality Data

Our sample of mortality is taken from the China's Disease Surveillance Points (DSP) system, which is a high-quality nationally survey conducted by the Chinese Center for Disease Control and Prevention; it contains detailed cause of death data verified by verbal autopsy (The verbal autopsy is a method of gathering health information about a deceased individual to determine his or her cause of death. Health information and a description of events prior to death are acquired from conversations or interviews with a person or persons familiar with the deceased and analyzed by health professionals or computer algorithms to assign a probable cause of death.) for a nationally representative sample of mortality of 158 counties in China in the year 2005. It is worthwhile to note that the year 2005 is the most recent year with available mortality data from the DSP system as well as nationwide $PM_{2.5}$ data and the Chinese National Land Use Database all available. In this study, we use the death category of cardiorespiratory causes of death, which have been documented by previous literature as being directly associated with air pollution [2,3]. According to International Classification of Disease Revision 9 (ICD-9) used in this study, cardiorespiratory causes of death are lung cancer, heart diseases, vascular disease, and respiratory diseases. Figure 1 shows the spatial distribution of cardiorespiratory mortality rate (incidences/100,000 population) of DSP sample sites in the year 2005, which is the variable we use later in our path model.

3.2. Urban Form Measures

Based on previous studies in this field [22–24,31–34,48,49], four measures were used to evaluate urban form in various dimensions: urban density, fragmentation level, shape complexity, and forest/green space amount.

As is identified in the previous section, urban density has been regarded as a basic urban form measure that influences local and regional air quality [22,24,38,49]. In this study, population density is calculated based on gridded geographic datasets of the population in China obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. The population density of each county is calculated by extracting the raster cells with population larger than zero and getting the total population of each county divided by the total area of the extracted cells. This measure is more precise than the traditional population density data in China because it excludes the areas without population.

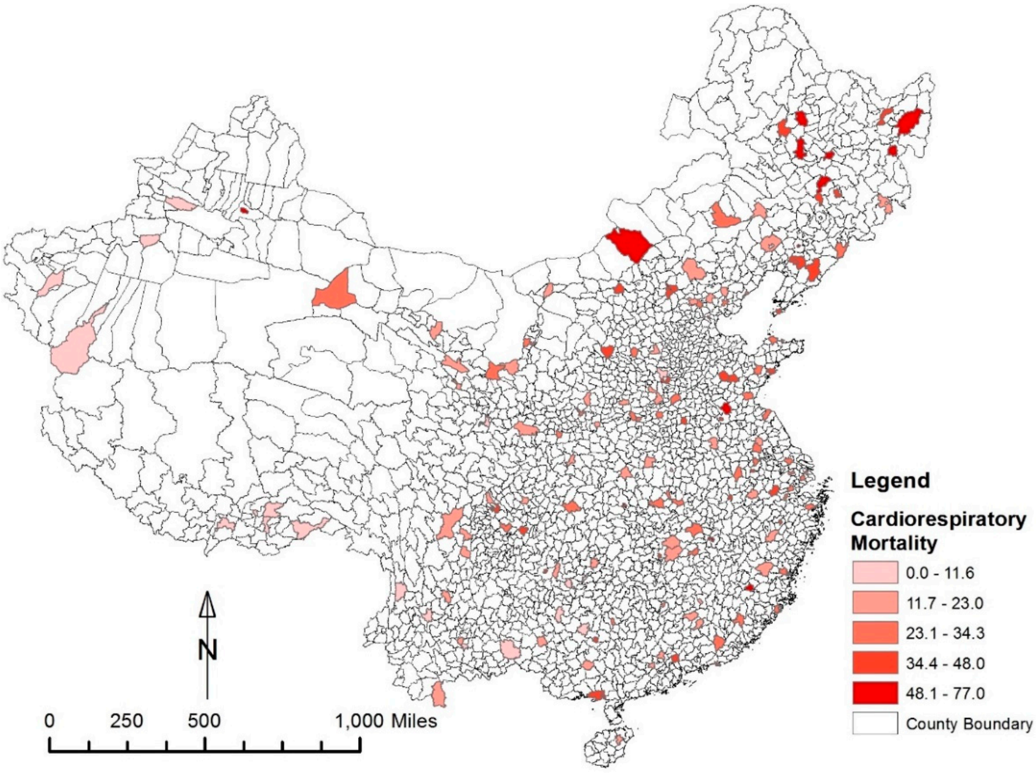

Figure 1. Spatial distribution of cardiorespiratory mortality rate (incidences/100,000 population) of Disease Surveillance Points (DSP) sample sites in the year 2005.

As is also indicated in the previous literature, the fragmentation or aggregation levels of urban landscape are significantly associated with air pollution concentration [22,24,31–33,38,50]. Thus in this study, we include the urban cohesion index, which measures the aggregation level of the urban land use, since there has been accumulated evidence showing the linkage between urban land aggregation and air quality [33]. Urban cohesion index is calculated as follows [51,52]:

$$\mathrm{CH} = \left(1 - \frac{\sum_{j=1}^{n} Pij}{\sum_{j=1}^{n} Pij\sqrt{Aij}}\right) \times \left(1 - \frac{1}{\sqrt{N}}\right)^{-1} \times 100 \tag{1}$$

where CH is the urban cohesion index, Pij is the perimeter of urban patch ij, Aij is the total area of urban patch ij, N is the total number of cells in the urban land use. In this study, we extract the urban patches from the National Land Use/Cover Database of China in the year 2005 (30 m resolution) and use Fragstats 4.2 to calculate the urban cohesion index for each county.

Some empirical studies also identified that urban shape complexity has the potential to increase air pollution levels, since it may increase the duration of vehicle travel and its associated emissions [22]. The variable that measures the complexity of urban landscape used in this study is the commonly-used area-weighted perimeter-area ratio, with higher values indicating higher levels of urban boundary complexity [24,53]. The index is calculated as follows:

$$\mathrm{PA} = \sum_{j=1}^{n}\left[Xij \times \left(\frac{Aij}{\sum_{j=1}^{n} Aij}\right)\right] \tag{2}$$

where PA is the area-weighted perimeter–area ratio, *Aij* is the total area of urban patch *ij*, *Xij* is the perimeter of the urban patch *ij* divided by the area of the urban patch *ij*. Again, we extracted the urban patches from National Land Use/Cover Database of China and used Fragstats 4.2 software to calculate this index for each county.

The last urban form feature that has important impacts on regional air quality in prior literature is forest amount and mixing level [32]. The relevant urban form variable we used in this study is forest/green space ratio, which is calculated as forest/green space area divided by total area for each county from the National Land Use/Cover Database of China. We also calculated the forest mixing level following McCarty and Kaza [32]. Since it is highly correlated with the dummy variable which indicates if the county is urban or not, we did not include the forest mixing level variable in our final model.

3.3. Conceptual Framework

The conceptual framework of this study, shown in Figure 2, summarizes the main relationship between urban form elements, air quality, and cardiorespiratory causes of death. The expected causal relationships begin with exogenous factors. Air pollution level and cardiorespiratory causes of mortality are two endogenous factors. Urban form elements (density, fragmentation, and shape), as well as forest/green space ratio, affect air pollution, after controlling pollution from other point sources, urbanization level, socioeconomic status, and climate factors. Further, the air pollution level influences cardiorespiratory causes of death after controlling for socioeconomic factors, urbanization level, climate conditions, and the residents' age status. As stated previously, the key linkages we are interested in are urban form's potential indirect connections to cardiorespiratory causes of death through air quality. It is necessary to note that there are potential interactions in this framework which are not captured. For example, it is possible that several variables for urban form also influence exposure of people to air pollution as well as potentially influencing air pollution concentrations themselves. We leave this for future exploration.

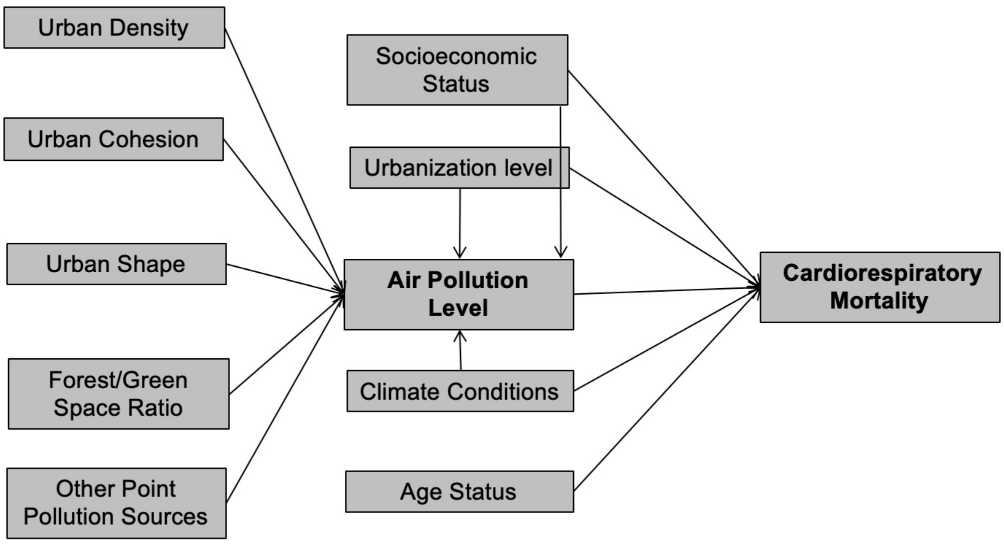

Figure 2. Conceptual framework and key relationships among urban form, air pollution level, and cardiorespiratory mortality.

3.4. Variable Coding and Descriptive Statistics

In addition to urban form variables, a dataset from multiple sources was assembled at the county level for heating degree days (Heating degree day (HDD) is a measurement designed to quantify the demand for home heating. Higher values of HDD indicate greater needs for home heating in winter months. HDD has been widely used in energy studies and has been identified in previous studies as one of the variables associated with poor air quality in Chinese cities in winter.), urban county, GDP per capita, percentage of elderly residents, and pollution company density, to account for other factors that influence $PM_{2.5}$ concentration level, and cardiorespiratory mortality, which have been identified in the previous literature and the conceptual framework (Table 1). Population-weighted concentrations of $PM_{2.5}$ were used as the measure to evaluate air quality for each county, which were calculated using Global Annual $PM_{2.5}$ Grids (http://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod/data-download4) in the year 2005 and 1 km Grid Population Dataset of China (http://www.geodoi.ac.cn/WebEn/doi.aspx?doi=10.3974/geodb.2014.01.06.v1).

Table 1. Definitions and sources of variables used in this study.

Variables	Definition	Source
Cardiorespiratory Mortality Rate	Cardiorespiratory mortality incidence per 100,000 population	China's Disease Surveillance Points (DSP) system, which forms a nationally representative sample of mortality for the year 2005.
Annual $PM_{2.5}$ [1]	Population-weighted annual average $PM_{2.5}$	Global Annual $PM_{2.5}$ Grids from MODIS [2], MISR [3] and SeaWiFS [4] Aerosol Optical Depth (AOD) with GWR [5], v1 (2005); 1 km Grid Population Dataset of China
Population Density	Total population divided by total area within the county boundary	1 km Grid Population Dataset of China; County boundary shapefile of China
Urban Cohesion Index	Patch cohesion index measures the physical connectedness of the urban patch	National Land Use/Cover Database of China 2005 (30 m × 30 m); Calculated from GIS and Fragstats
Perimeter-Area Ratio	Area-weighted Perimeter-Area Ratio measures the shape complexity of urban landscape	National Land Use/Cover Database of China 2005 (30 m × 30 m); Calculated from GIS [6] and Fragstats
Forest/Green Space Ratio	Forest/green space area divided by total area within the county boundary	National Land Use/Cover Database of China 2005 (30 m × 30 m); Calculated from GIS and Fragstats
Heating Degree days	Annual Heating Degree days of the nearest temperature station	Calculated from 2005 daily temperature data From nationwide monitoring stations
Urban County	Dummy variable indicating if the county is urban or not	China Urban Statistical Yearbook 2005
Percentage of Elderly Residents (Age > 65)	Percentage of elderly residents with age >65	China Census Data 2000
Pollution Company Density	Total number of pollution companies divided by total area within the county boundary	Calculated from GIS; Nationwide Pollution Companies Data with geo information
GDP [7] Per Capita	GDP Per Capita	1 km Grid GDP dataset of China in 2005; County boundary shapefile of China

[1] Atmospheric particulate matter with a diameter of less than 2.5 micrometers. [2] Moderate-resolution Imaging Spectroradiometer. [3] Multi-angle Imaging Spectroradiometer. [4] Sea-viewing Wide Field-of-view Sensor. [5] Geographically Weighted Regression. [6] Geographic Information System. [7] Gross Domestic Product.

Table 2 presents descriptive statistics for the measures used in the analysis. Unsurprisingly, the urban form measures and the cardiorespiratory mortality rate are skewed. Therefore, we should consider the non-normality-induced bias in the model selection.

Table 2. Descriptive statistics (N = 158).

Variables	M	SD	Min	Max
Cardiorespiratory Mortality Rate (per 10,000)	27.89	14.94	0.00	77.04
Annual $PM_{2.5}$ [1] ($\mu g/m^3$)	36.94	17.27	2.17	78.36
Population Density ($/km^2$)	360.02	324.83	0.16	2132.77
Urban Cohesion Index	53.67	29.74	0.00	100.00
Perimeter-Area Ratio	28.33	9.08	0.00	40.00
Forest/Green Space Ratio (%)	28.37	26.52	0.00	89.96
Heating Degree days	2530.61	1402.21	93.80	5893.20
Urban County	0.51	-	0.00	1.00
Percentage of Elderly Residents (Age > 65)	6.97	1.91	2.73	17.31
Pollution Company Density ($/100\ km^2$)	3.44	6.68	0.00	56.17
GDP [2] Per Capita (10,000 RMB [3])	4.50	10.49	0.02	89.44

M = mean; SD = standard deviation; Min = minimum value; Max = maximum value. [1] Atmospheric particulate matter with a diameter of less than 2.5 micrometers. [2] Gross Domestic Product. [3] RMB is abbreviation for Ren Min Bi, which is the official currency of China.

3.5. Model Specification

To answer the research questions of this study, we developed a path model to account for the complexity of indirect relationships among urban form measures, air quality, and cardiorespiratory mortality, which are frequently used to model relationships in a complex system [54]. Path analysis was ideal for this analysis of urban form and cardiorespiratory mortality, since we intended to explore how urban form elements such as density, fragmentation, perimeter to area ratio, and green space, affect cardiorespiratory mortality ratio indirectly by influencing air quality.

Our path model was built based on the hypothesized linkages and conceptual framework discussed in the previous sections. Since a few of the variables in this study, especially the cardiorespiratory mortality rate, were heavily skewed, we employed the robust maximum likelihood (RML) estimation method, which corrects for non-normality-induced bias in the standard errors [55,56]. We specified urban form elements, pollution company density, percentage of elderly residents, GDP per capita, urban county, and heating degree days as exogenous variables. It should be noted that some of the exogenous variables might be correlated. Thus, we have calculated the Pearson Correlations between exogenous variables used. The results indicate that no correlation between exogeneous variables is high enough to create an instability in the parameter estimates of the path analysis: for example, the correlation between Heating Degree days and Forest/Green Space Ratio is weak (Pearson Correlation Coefficient = −0.229). Similarly, the correlation between GDP per Capita and Percentage of Elderly Residents is not strong (Pearson Correlation Coefficient = 0.206). Urban County and Percentage of Elderly Residents also presents a weak correlation (Pearson Correlation Coefficient = 0.286). Annual $PM_{2.5}$ level and cardiorespiratory mortality rate were endogenous variables. The following equations were estimated in STATA software:

$$\mathrm{CardioR_i} = \beta_{gsi}\mathrm{GDP} + \beta_{usi}\mathrm{UrbanC} + \beta_{psi}\mathrm{PM} + \beta_{hsi}\mathrm{HDD} + \beta_{esi}\mathrm{EldR} + \varepsilon_{is} \quad (3)$$

$$\begin{gathered}\mathrm{PM_i} = \beta_{gti}\mathrm{GDP} + \beta_{pti}\mathrm{PopD} + \beta_{cti}\mathrm{CohenI} + \beta_{rti}\mathrm{PerimeR} \\ + \beta_{fti}\mathrm{ForestR} + \beta_{dti}\mathrm{PollD} + \beta_{uti}\mathrm{UrbanC} + \beta_{hti}\mathrm{HDD} + \varepsilon_{it}\end{gathered} \quad (4)$$

where:

CardioR = Cardiorespiratory mortality ratio within the county
GDP = Gross domestic product per capita of the county
UrbanC = Dummy variable indicating if the county is an urban county or not
PM = Population-weighted annual average $PM_{2.5}$ within the county
HDD = Annual heating degree days of the nearest temperature station
EldR = Percentage of elderly residents within the county
PopD = Population density within the urban area of the county
CohenI = Urban Cohesion Index
PerimeR = Perimeter-Area Ratio
ForestR = Total forest/green space divided by total area within the county boundary
PollD = Total number of pollution companies divided by total area within the county boundary
ε = error coefficients
β = robust maximum likelihood estimates of independent variables.

4. Findings

The estimates of both coefficients (β) and standardized coefficients (St. β) of our path model are provided in Table 3. These estimates indicate that air quality, as measured by $PM_{2.5}$ concentration, is influenced significantly by urban form elements, pollution company density, and heating degree days (Figure 3). Our results indicate that higher population density contributes to $PM_{2.5}$ concentration at the county level. As shown in Table 3, a 10% increase in urban population density is associated with 4.0% increase in $PM_{2.5}$ concentration level. The results also suggest that there exist negative direct effects of urban cohesion index and forest/green ratio on $PM_{2.5}$ concentrations at the county level. Our model (Table 3) suggests that a standardized unit increase in urban cohesion index and forest/green space ratio would reduce the $PM_{2.5}$ concentration level by 0.16 and 0.19 of a standardized unit, respectively.

Nevertheless, our results do not reveal significant direct effects of perimeter-to-area ratio and $PM_{2.5}$ concentration. As expected, pollution company density and heating degree days are predominant factors that explains the variation of $PM_{2.5}$ concentrations at the county level: a standardized increase pollution company density and heating degree days would increase the $PM_{2.5}$ concentration directly by 0.45 and 0.12 of a standardized unit, respectively.

Table 3. The robust maximum likelihood estimates of unstandardized and standardized coefficient.

	Exogenous									
Endogenous	**PopD**	**CohenI**	**PerimeR**	**ForestR**	**PollD**	**EldR**	**UrbanC**	**HDD**	**GDP**	**PM**
PM										
β	0.021	−0.093	0.210	−0.091	3.637		−0.561	0.001	−0.075	
St. β	0.396	−0.162	0.11	−0.192	0.450		−0.016	0.116	−0.043	
z	3.07	−1.72	1.28	−2.63	4.81		−0.25	2.03	−0.69	
CardioR										
β						2.199	9.845	0.001	0.160	0.129
St. β						0.259	0.303	0.115	0.103	0.136
z						3.97	4.58	1.72	0.97	2.00

PopD: Population density; CohenI: Urban Cohesion Index; PerimeR: Perimeter-Area Ratio; ForestR: Forest/green space ratio; PollD: Pollution company density; EldR: Percentage of elderly residents; UrbanC: Urban county; HDD: Heating degree days; GDP: Gross domestic product per capita; PM: Population-weighted $PM_{2.5}$; CardioR: Cardiorespiratory mortality ratio.

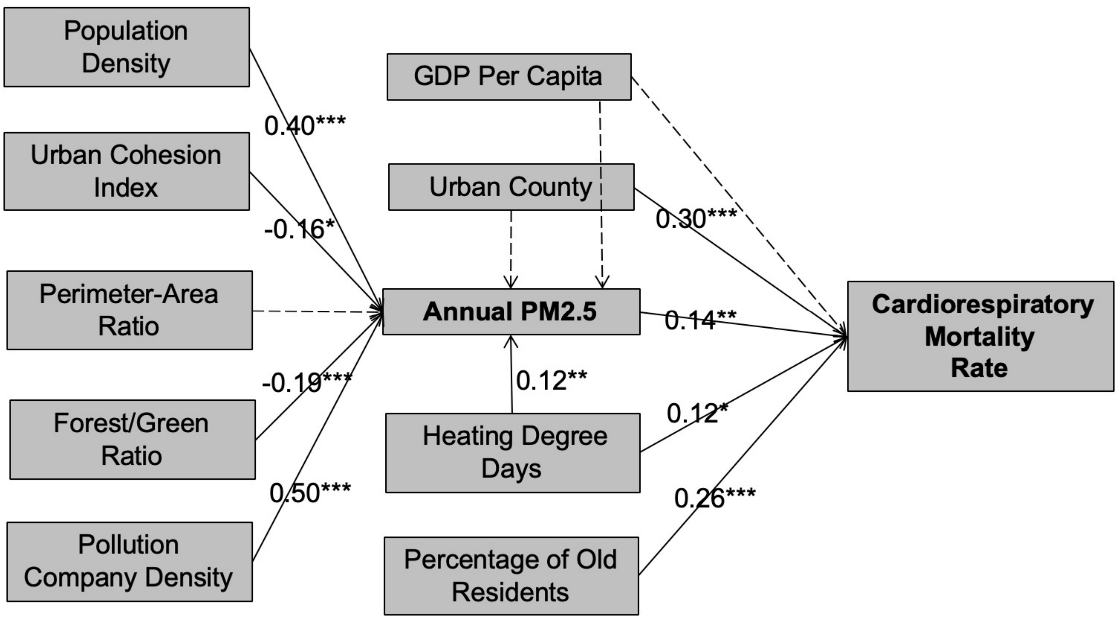

Figure 3. The estimated weights for the path model. Note: Standardized coefficient; *** denotes $P < 0.01$; ** $P < 0.05$; * $P < 0.1$. GDP: Gross Domestic Product.

It is also worthwhile to note that $PM_{2.5}$ concentration significantly affects the cardiorespiratory mortality ratio at the county level. As is shown in our model, a 10% increase in $PM_{2.5}$ concentration is associated with 1.4% increase in the cardiorespiratory mortality ratio at the county level. Similarly, as expected, the percentage of households with no tap water access, heating degree days, and urban county all have positive direct impact on cardiorespiratory mortality ratio at the county level.

The goodness-of-fit indices that are commonly used for the path model are appropriate in this analysis: the coefficient of determination (CD) is high (0.91), the root mean square error of approximations (RMSEA) is low (0.09), and the comparative fit index (CFI) and is high (0.89). These indices together suggest acceptable model fit.

The total impact of the path variables on cardiorespiratory mortality ratio is presented in Figure 4. It is worthwhile to note that the largest standardized coefficient influencing cardiorespiratory mortality ratio is urban county (0.30), followed by percentage of elderly residents (0.26), Heating Degree days

(0.14), and pollution company density (0.07). The three variables of special concern in this study, urban population density, urban cohesion index, and forest/green space ratio, also impart significant indirect impacts on cardiorespiratory mortality ratio at the county level. That is, increased urban cohesion and more forest/green space are associated with lower cardiorespiratory mortality incidence. In contrast, increased urban population density is associated with higher cardiorespiratory mortality incidence at the county level. In comparison with other variables, the impacts of urban form elements on cardiorespiratory mortality are small (−0.02 to 0.06) and indirect.

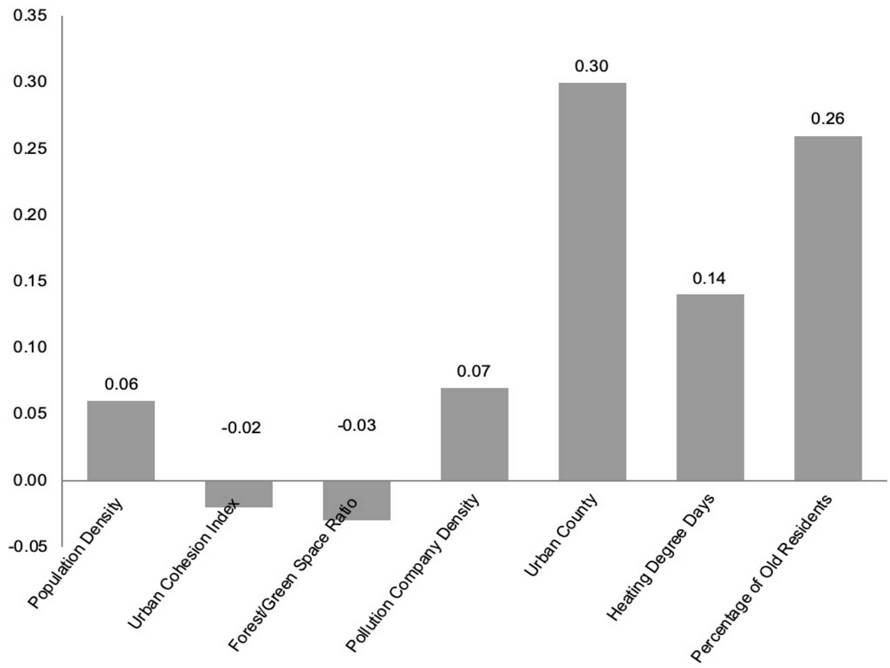

Figure 4. Standardized effects of urban form and other factors on cardiorespiratory mortality rate.

5. Discussions

The empirical evidence from this study suggests that (1) forest/green space ratio within the county boundary is associated with lower $PM_{2.5}$ concentration and thus lower cardiorespiratory mortality ratio; (2) urban cohesion level is associated with lower $PM_{2.5}$ concentration and thereby lower cardiorespiratory mortality ratio within the county indirectly; and (3) increasing urban population density is associated with higher $PM_{2.5}$ concentration.

The first two conclusions from this study are supported by existing literature, while the third one is not. The first conclusion confirms a large body of literature that has already shown green space effects to decrease air pollutant concentration [22,49]. The second conclusion also confirms a number of studies indicating that urban fragmentation is positively associated with CO, NO_x, and $PM_{2.5}$ emissions [24,31,32,34,38,49]. The third conclusion might be controversial compared with findings from previous studies. Regardless, we can still provide reasonable explanation about why urban population density can increase the $PM_{2.5}$ pollution level. Existing studies suggesting a negative association between population density and air pollution concentration are mostly simulation studies with a focus on vehicular travel [27]. If we also consider the point-source air pollution, the relationship would be different. In this case, the point-source air pollution from pollution factories and building energy consumption (especially winter heating) are very likely to be positively correlated with urban population density, thus increasing $PM_{2.5}$ concentration. This might help to further explain the fact some empirical studies also suggest a positive association between urban population density and air pollution level [33,57]. Another explanation would be transportation congestion effects associated with higher population density might outweigh the effects of transportation mode-shifting effects, especially in the context of urban China [39].

Our data do not support the finding that urban shape has significant influences on $PM_{2.5}$ concentration, which is driven mostly by transportation air pollution emission, as is well documented in the previous literature [22,24,34,38,58]. Again, this can be explained by the fact that the $PM_{2.5}$ Grids data we used in this study incorporate air pollutions from multiple sources including transportation and different point source pollution; thus, the effects of urban shape index (e.g., perimeter-to-area ratio) might not be significant.

As noted earlier, the finding that increased Heating Degree days can lead to higher cardiorespiratory mortality ratio within the county conforms to some of the empirical research which reveals that heavily subsidized coal or indoor heating in winter months in China would bring about sustained exposure to particulate matter, which in turn reduce life expectancy [3]. Nevertheless, our data do not support the notion that there is a large indirect effect though increasing the $PM_{2.5}$ concentration. Additionally, urban county can have direct impacts on cardiorespiratory mortality ratio, which is also confirmed with previous literature [27]. Since we have controlled several important urban form factors (e.g., population density, green space) and the number of pollution companies, it somehow makes sense that urban county itself does not have a significant influence on $PM_{2.5}$ concentration, thus affecting the cardiorespiratory mortality ratio at the county level. GDP per capita does not show any significant impacts on $PM_{2.5}$ concentration, which is somehow consistent with previous theories indicating the complexity of the relationship between GDP per capita and pollution level [59]. Previous studies based on major cities in China detected a negative relationship between GDP per capita and air pollution [24]. Since this study includes both urban and rural counties in China with a large variation in GDP level, the insignificant effects can be explained.

This study is subject to several limitations. First, because of data availability issues, our model does not include some important individual and household level characteristics (e.g., smoking habits, in-door air quality of the household, etc.), which might be the predominant cause of cardiorespiratory mortality. Second, the path model is built on the cross-sectional basis. Future research could consider constructing a longitudinal dataset to ensure a necessary time lag between air pollution exposure and mortality to better reveal causality. Third, this study uses cardiorespiratory mortality ratio at the county level as the only health outcome measure. Future research should explore the health impacts of the linkages in a more comprehensive way. For example, there has been study showing complex within-city tradeoffs in health outcomes associated with air pollution and physical activity. Urban form factor such as density could both affect residents' exposure to air pollution and their intention for physical activity. Another relevant issue is the scale of our analysis: this study merely analyzed effects at the county level. Nevertheless, it was possible to analyze some more detailed factors governing relationships between urban form, air pollution, and health outcomes at a finer geographical scale. To sum up, more detailed research is needed to further identify various causal pathways.

6. Conclusions and Policy Implications

This study explored the causal pathways through which various urban form elements contribute to cardiorespiratory mortality by influencing $PM_{2.5}$ concentration. We assembled a dataset by compiling a series of variables from disparate sources, including China's Disease Surveillance Points (DSP) system, Chinese census, satellite Imagery, and the National Land Cover Database, and conducted a path analysis to quantify the indirect effects of urban form features on cardiorespiratory mortality based on a nationally representative sample of 158 counties in China. The results reveal that urban form elements, including population density, urban cohesion, and forest/green space ratio, have significant impacts on $PM_{2.5}$ concentration, and are thus associated with the incidence of cardiorespiratory mortality at the county level. The results of this study also indicate that, compared with urban form elements, urbanization level of the county ("qu" vs. "xian"), percentage of elderly residents, and climate conditions (Heating Degree days) are more predominant associating factors determining cardiorespiratory mortality rate at the county level.

This study offers a cautionary note about high population density, especially in the context of dense urban environments in China, may bring about negative health consequences related to air quality. Urban planners may consider using other relevant urban form strategies such as urban greening and ventilation path to relieve the possible negative effects. It is necessary to note that when incorporating lots of greenspace into a city, planners need to adopt careful spatial planning strategies to avoid the unintended consequences of bringing greater need to travel by car due to fragmentation. In this regard, transit-oriented developments with surrounded greenspace exemplified by Copenhagen's finger plan would be a best practice case to follow [60]. Additionally, urban planners and policy makers are supposed to monitor the fragmentation level of rapid urbanizing areas on a regular basis, since fragmentary urban landscape contributes to increased urban pollution level and more cardiorespiratory mortality incidence. The study also reiterates that urban planning and design play an important role in promoting healthy cities. In this regard, a more comprehensive understanding of the complex relationships between the urban form features and public health would further guide urban planners and policy makers to the right policies and actions. More empirical work is also needed to evaluate specific urban form relevant policies and their causal pathways connecting health outcomes in various dimensions.

Author Contributions: Conceptualization—Y.S., L.T. and C.L.; Methodology—C.L.; Formal analysis—C.L.; Data curation—L.T. and Y.S.; Writing—Original draft preparation, C.L.; Writing—Review and editing, C.L., Y.S., L.T. and W.O. All authors have read and agreed to the published version of the manuscript.

Funding: This study is supported by the National Science Foundation of China (Project Numbers: 51728802; 51878367) and the Macau Foundation (Grant Number: MF1908).

Acknowledgments: We acknowledge the support from the National Science Foundation of China (Project Numbers: 51728802; 51878367) and the Macau Foundation (Grant Number: MF1908). We also want to thank Chenyu Wang for formatting the final manuscript and the anonymous reviewers for their constructive comments.

Conflicts of Interest: The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

1. Chan, C.K.; Yao, X. Air pollution in mega cities in China. *Atmos. Environ.* **2008**, *42*, 1–42. [CrossRef]
2. Chen, Y.; Ebenstein, A.; Greenstone, M.; Li, H. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 12936–12941. [CrossRef] [PubMed]
3. Ebenstein, A.; Fan, M.; Greenstone, M.; He, G.; Zhou, M. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 10384–10389. [CrossRef] [PubMed]
4. Xuemei, B.; Peijun, S.; Yansui, L. Realizing China's urban dream. *Nature* **2014**, *509*, 158–160.
5. HEI. *State of Global Air 2017: A Special Report on Global Exposure to Air Pollution and Its Disease Burden*; Health Effects Institute: Boston, MA, USA, 2017.
6. Gauderman, W.J.; Avol, E.; Lurmann, F.; Kuenzli, N.; Gilliland, F.; Peters, J.; McConnell, R. Childhood asthma and exposure to traffic and nitrogen dioxide. *Epidemiology* **2005**, *16*, 737–743. [CrossRef] [PubMed]
7. Brauer, M.; Lencar, C.; Tamburic, L.; Koehoorn, M.; Demers, P.; Karr, C. A cohort study of traffic-related air pollution impacts on birth outcomes. *Environ. Health Perspect.* **2008**, *116*, 680–686. [CrossRef]
8. Hoek, G.; Beelen, R.; De Hoogh, K.; Vienneau, D.; Gulliver, J.; Fischer, P.; Briggs, D. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos. Environ.* **2008**, *42*, 7561–7578. [CrossRef]
9. Raaschou-Nielsen, O.; Andersen, Z.J.; Beelen, R.; Samoli, E.; Stafoggia, M.; Weinmayr, G.; Hoffmann, B.; Fischer, P.; Nieuwenhuijsen, M.J.; Brunekreef, B. Air pollution and lung cancer incidence in 17 European cohorts: Prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *Lancet Oncol.* **2013**, *14*, 813–822. [CrossRef]

10. NCCR. *Chinese Cancer Registry Annual Report*; Military Medical Science Press: Beijing, China, 2014; Volume 17, pp. 44–47.
11. Lim, Y.-H.; Kim, H.; Kim, J.H.; Bae, S.; Park, H.Y.; Hong, Y.-C. Air pollution and symptoms of depression in elderly adults. *Environ. Health Perspect.* **2012**, *120*, 1023–1028. [CrossRef]
12. Dadvand, P.; Nieuwenhuijsen, M.J.; Esnaola, M.; Forns, J.; Basagaña, X.; Alvarez-Pedrerol, M.; Rivas, I.; López-Vicente, M.; Pascual, M.D.C.; Su, J. Green spaces and cognitive development in primary schoolchildren. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 7937–7942. [CrossRef]
13. Zheng, S.; Wang, J.; Sun, C.; Zhang, X.; Kahn, M.E. Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nat. Hum. Behav.* **2019**, *3*, 237. [CrossRef]
14. Li, C. *Essays on Climate Change Mitigation, Building Energy Efficiency, and Urban Form*; The University of North Carolina at Chapel Hill: Chapel Hill, NC, USA, 2018.
15. Holden, E.; Norland, I.T. Three challenges for the compact city as a sustainable urban form: Household consumption of energy and transport in eight residential areas in the greater Oslo region. *Urban Stud.* **2005**, *42*, 2145–2166. [CrossRef]
16. Glaeser, E.L.; Kahn, M.E. The greenness of cities: Carbon dioxide emissions and urban development. *J. Urban Econ.* **2010**, *67*, 404–418. [CrossRef]
17. Hankey, S.; Marshall, J.D. Impacts of urban form on future US passenger-vehicle greenhouse gas emissions. *Energy Policy* **2010**, *38*, 4880–4887. [CrossRef]
18. Lee, S.; Lee, B. The influence of urban form on GHG emissions in the US household sector. *Energy Policy* **2014**, *68*, 534–549. [CrossRef]
19. Borrego, C.; Martins, H.; Tchepel, O.; Salmim, L.; Monteiro, A.; Miranda, A.I. How urban structure can affect city sustainability from an air quality perspective. *Environ. Model. Softw.* **2006**, *21*, 461–467. [CrossRef]
20. Zhou, Y.; Levy, J.I. The impact of urban street canyons on population exposure to traffic-related primary pollutants. *Atmos. Environ.* **2008**, *42*, 3087–3098. [CrossRef]
21. Kahyaoğlu-Koračin, J.; Bassett, S.D.; Mouat, D.A.; Gertler, A.W. Application of a scenario-based modeling system to evaluate the air quality impacts of future growth. *Atmos. Environ.* **2009**, *43*, 1021–1028. [CrossRef]
22. Bereitschaft, B.; Debbage, K. Urban form, air pollution, and CO2 emissions in large US metropolitan areas. *Prof. Geogr.* **2013**, *65*, 612–635. [CrossRef]
23. Requia, W.J.; Roig, H.L.; Koutrakis, P.; Rossi, M.S. Mapping alternatives for public policy decision making related to human exposures from air pollution sources in the Federal District, Brazil. *Land Use Policy* **2016**, *59*, 375–385. [CrossRef]
24. Yuan, M.; Song, Y.; Huang, Y.; Hong, S.; Huang, L. Exploring the association between urban form and air quality in China. *J. Plan. Educ. Res.* **2018**, *38*, 413–426. [CrossRef]
25. Liu, Y.; Fang, F.; Li, Y. Key issues of land use in China and implications for policy making. *Land Use Policy* **2014**, *40*, 6–12. [CrossRef]
26. Su, S.; Zhang, Q.; Pi, J.; Wan, C.; Weng, M. Public health in linkage to land use: Theoretical framework, empirical evidence, and critical implications for reconnecting health promotion to land use policy. *Land Use Policy* **2016**, *57*, 605–618. [CrossRef]
27. Hankey, S.; Marshall, J.D. Urban form, air pollution, and health. *Curr. Environ. Health Rep.* **2017**, *4*, 491–503. [CrossRef] [PubMed]
28. Martins, H. Urban compaction or dispersion? An air quality modelling study. *Atmos. Environ.* **2012**, *54*, 60–72. [CrossRef]
29. Mansfield, T.J.; Rodriguez, D.A.; Huegy, J.; MacDonald Gibson, J. The effects of urban form on ambient air pollution and public health risk: A case study in Raleigh, North Carolina. *Risk Anal.* **2015**, *35*, 901–918. [CrossRef]
30. Nowak, D.J.; Crane, D.E.; Stevens, J.C. Air pollution removal by urban trees and shrubs in the United States. *Urban For. Urban Green.* **2006**, *4*, 115–123. [CrossRef]
31. Bechle, M.J.; Millet, D.B.; Marshall, J.D. Effects of income and urban form on urban NO2: Global evidence from satellites. *Environ. Sci. Technol.* **2011**, *45*, 4914–4919. [CrossRef]
32. McCarty, J.; Kaza, N. Urban form and air quality in the United States. *Landsc. Urban Plan.* **2015**, *139*, 168–179. [CrossRef]
33. Rodríguez, M.C.; Dupont-Courtade, L.; Oueslati, W. Air pollution and urban structure linkages: Evidence from European cities. *Renew. Sustain. Energy Rev.* **2016**, *53*, 1–9. [CrossRef]

34. Fan, C.; Tian, L.; Zhou, L.; Hou, D.; Song, Y.; Qiao, X.; Li, J. Examining the impacts of urban form on air pollutant emissions: Evidence from China. *J. Environ. Manag.* **2018**, *212*, 405. [CrossRef] [PubMed]
35. Yuan, M.; Huang, Y.; Shen, H.; Li, T. Effects of urban form on haze pollution in China: Spatial regression analysis based on PM2. 5 remote sensing data. *Appl. Geogr.* **2018**, *98*, 215–223. [CrossRef]
36. Yuan, M.; Song, Y.; Guo, L. Exploring Determinants of Urban Form in China through an Empirical Study among 115 Cities. *Sustainability* **2018**, *10*, 3648. [CrossRef]
37. Zhou, C.; Li, S.; Wang, S. Examining the Impacts of Urban Form on Air Pollution in Developing Countries: A Case Study of China's Megacities. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1565. [CrossRef] [PubMed]
38. Clark, L.P.; Millet, D.B.; Marshall, J.D. Air quality and urban form in US urban areas: Evidence from regulatory monitors. *Environ. Sci. Technol.* **2011**, *45*, 7028–7035. [CrossRef]
39. Han, S.; Sun, B. Impact of Population Density on PM2. 5 Concentrations: A Case Study in Shanghai, China. *Sustainability* **2019**, *11*, 1968. [CrossRef]
40. Evans, G.W. The built environment and mental health. *J. Urban Health* **2003**, *80*, 536–555. [CrossRef]
41. Gascon, M.; Zijlema, W.; Vert, C.; White, M.P.; Nieuwenhuijsen, M.J. Outdoor blue spaces, human health and well-being: A systematic review of quantitative studies. *Int. J. Hyg. Environ. Health* **2017**, *220*, 1207–1221. [CrossRef]
42. Chen, R.; Kan, H.; Chen, B.; Huang, W.; Bai, Z.; Song, G.; Pan, G. Association of particulate air pollution with daily mortality: The China Air Pollution and Health Effects Study. *Am. J. Epidemiol.* **2012**, *175*, 1173–1181. [CrossRef]
43. Zhou, M.; Liu, Y.; Wang, L.; Kuang, X.; Xu, X.; Kan, H. Particulate air pollution and mortality in a cohort of Chinese men. *Environ. Pollut.* **2014**, *186*, 1–6. [CrossRef]
44. Zhong, S.; Yu, Z.; Zhu, W. Study of the Effects of Air Pollutants on Human Health Based on Baidu Indices of Disease Symptoms and Air Quality Monitoring Data in Beijing, China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1014. [CrossRef] [PubMed]
45. Chen, R.; Yin, P.; Meng, X.; Wang, L.; Liu, C.; Niu, Y.; Lin, Z.; Liu, Y.; Liu, J.; Qi, J. Associations between ambient nitrogen dioxide and daily cause-specific mortality: Evidence from 272 Chinese cities. *Epidemiology* **2018**, *29*, 482–489. [CrossRef] [PubMed]
46. Wu, R.; Zhong, L.; Huang, X.; Xu, H.; Liu, S.; Feng, B.; Wang, T.; Song, X.; Bai, Y.; Wu, F. Temporal variations in ambient particulate matter reduction associated short-term mortality risks in Guangzhou, China: A time-series analysis (2006–2016). *Sci. Total Environ.* **2018**, *645*, 491–498. [CrossRef] [PubMed]
47. Wu, R.; Song, X.; Chen, D.; Zhong, L.; Huang, X.; Bai, Y.; Hu, W.; Ye, S.; Xu, H.; Feng, B. Health benefit of air quality improvement in Guangzhou, China: Results from a long time-series analysis (2006–2016). *Environ. Int.* **2019**, *126*, 552–559. [CrossRef]
48. Schweitzer, L.; Zhou, J. Neighborhood air quality, respiratory health, and vulnerable populations in compact and sprawled regions. *J. Am. Plan. Assoc.* **2010**, *76*, 363–371. [CrossRef]
49. Stone, B., Jr. Urban sprawl and air quality in large US cities. *J. Environ. Manag.* **2008**, *86*, 688–698. [CrossRef]
50. Higgins, C.D.; Adams, M.D.; Réquia, W.J.; Mohamed, M. Accessibility, air pollution, and congestion: Capturing spatial trade-offs from agglomeration in the property market. *Land Use Policy* **2019**, *84*, 177–191. [CrossRef]
51. Gustafson, E.J. Quantifying landscape spatial pattern: What is the state of the art? *Ecosystems* **1998**, *1*, 143–156. [CrossRef]
52. Pinto, A.J.; Remesar, A.B. Urban cohesion: A public space network assessment. *W@ Terfront Public Art Urban Des. Civ. Particip. Urban Regen.* **2015**, *39*, 7–25.
53. Mertes, C.M.; Schneider, A.; Sulla-Menashe, D.; Tatem, A.; Tan, B. Detecting change in urban areas at continental scales with MODIS data. *Remote Sens. Environ.* **2015**, *158*, 331–347. [CrossRef]
54. Dillon, W.R.; Goldstein, M. *Multivariate Analysismethods and Applications*; Wiley: Hoboken, NJ, USA, 1984.
55. Finney, S.J.; DiStefano, C. Non-normal and categorical data in structural equation modeling. *Struct. Equ. Model. A Second Course* **2006**, *10*, 269–314.
56. Satorra, A.; Bentler, P.M. Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika* **2010**, *75*, 243–248. [CrossRef] [PubMed]
57. Han, S.S.; Green, R.; Wang, M.Y. *Towards Low Carbon Cities in China: Urban form and Greenhouse Gas Emissions*; Routledge: Abingdon upon Thames, UK, 2014.

58. She, Q.; Peng, X.; Xu, Q.; Long, L.; Wei, N.; Liu, M.; Jia, W.; Zhou, T.; Han, J.; Xiang, W. Air quality and its response to satellite-derived urban form in the Yangtze River Delta, China. *Ecol. Indic.* **2017**, *75*, 297–306. [CrossRef]
59. Selden, T.M.; Song, D. Environmental quality and development: Is there a Kuznets curve for air pollution emissions? *J. Environ. Econ. Manag.* **1994**, *27*, 147–162. [CrossRef]
60. Knowles, R.D. Transit oriented development in Copenhagen, Denmark: From the finger plan to Ørestad. *J. Transp. Geogr.* **2012**, *22*, 251–261. [CrossRef]