Liang et al. Sustainable Environment Research (2023) 33:1
https://doi.org/10.1186/s42834-022-00159-2

Sustainable Environment Research

RESEARCH Open Access

Effects of regional air pollutants on respiratory diseases in the basin metropolitan area of central Taiwan

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Abstract

This study divided a basin metropolitan area with high air pollution into three subareas, namely urban, suburban, and rural, on the basis of population density for a systematic analysis of the effects of local air pollutants on respiratory diseases. A panel data regression model was used to estimate the annual incidence growth rates (AIGRs) of the four respiratory diseases, namely lung cancer, chronic obstructive pulmonary disease, asthma, and pneumonia, resulting from exposure to fine particulate matter ($PM_{2.5}$, diameter of 2.5 μm or less), odd oxygen (ODO), or nonmethane hydrocarbon (NMHC). The results indicate that the prevailing wind direction is not a major factor determining the distribution of air pollutants. The spatial distributions of ODO and NMHC differed from that of $PM_{2.5}$. Three air pollutants contributed to positive AIGRs of the four diseases in the study area, but $PM_{2.5}$ which had a negative AIGR for asthma in the rural subarea. The pollutants with the strongest effects on AIGR, in descending order, were NMHC, $PM_{2.5}$, and ODO. The effect of ambient NMHC was significant and nonnegligible, especially in the urban subarea. A dimensionless potential AIGR (PAIGR) formula was established to quantitatively compare the effects of different air pollutants on the four respiratory diseases. The results indicate that ambient NMHC had the strongest effect on the incidences of the respiratory diseases, followed by that of ambient $PM_{2.5}$. The effect of ambient NMHC was significant and nonnegligible, especially in the urban subarea. The PAIGR ratio ranges of $PM_{2.5}$ to ODO and NMHC to ODO for the four diseases in urban subsarea were from 3 to 19 and from 289 to 920, respectively. This study also applied multivariate regression to assess the association among 5 aspects, namely air quality, point source, line source, area source, and socioeconomic status, and the incidences of the four respiratory diseases. The results indicate that the model has favorable fit and can thus reflect the associations of the 15 factors of 5 aspects with the four respiratory diseases in each subarea.

Keywords Air pollution, Health risks, Secondary organic aerosol, Incidence growth rate, Spatiotemporal distribution

1 Introduction

Several studies have examined diseases caused by air pollution, such as respiratory diseases [1, 2], malignant tumors [3, 4], and cardiovascular [5, 6], metabolic [7, 8], autoimmune [9, 10], and brain [11, 12] diseases. Long-term exposure to air pollutants increases all-cause mortality [13], especially by aggravating causes of many respiratory diseases, such as lung cancer [14, 15], chronic obstructive pulmonary disease (COPD) [16, 17], and asthma [18, 19]. Short-term exposure to air pollution can

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cause pneumonia, particularly in children [20, 21] and older adults [22, 23].

Numerous studies have investigated the risks associated with exposure to air pollutants such as particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO), and sulfur dioxide (SO_2) [24–27]. O_3 is a reactive oxidant causing both inflammatory and oxidative damage to the respiratory system [28]. Tian et al. [29] demonstrated that the city-specific relationship between ozone and pneumonia was stronger in older adults and not confounded by the effects of other air pollutants. The sum of O_3 and NO_2 is called "odd oxygen" which originates from atmospheric photochemical reactions [30]. Odd oxygen (ODO) varies by ozone dominance. Some studies and our previous study have verified that ODO has a strong positive relation to secondary organic aerosol (SOA). Observed O_3 and NO_2 concentrations can be used to identify ambient SOA concentration, as in this study [31]. ODO is easily absorbed by and highly toxic to the human body. Qiu et al. [32, 33] determined that airborne nonmethane hydrocarbon (NMHC) exposure increased the risk of respiratory disease–related hospital admission. Robust evidence of higher cardiorespiratory hospitalizations associated with acute exposure to ambient NMHC in many cities has been presented [27]. Thus, the effects of fine particulate matter ($PM_{2.5}$, diameter of 2.5 μm or less), ODO, and NMHC on various air pollution–related diseases differ, which warrants investigation.

Most current research focuses on the effects of individual air pollutants on disease. The quantification and comparison of the effects of major air pollutants on various diseases are still lacking. This study directly compares the effects of different air pollutants and different environmental factors on various diseases by means of dimensionless quantitative results. The study area, namely the greater Taichung area, has a population of approximately 4.4 million people and is the second largest metropolitan area in Taiwan. It is an industrial and commercially developed area with a high population density. The topography of the greater Taichung area is complicated and includes basins, mountains, hills, plains, tablelands, and rivers.

The study area has high levels of air pollution. The effect of air pollution on disease is a topic of great concern to residents. Lung cancer, COPD, asthma, and pneumonia are the four most common respiratory disorders caused by air pollution. This study performed a systematic analysis to investigate the effects of exposure to ambient $PM_{2.5}$, ODO, and NMHC on these four respiratory diseases and determine the spatiotemporal distributions of their effects. In the study areas, 61 townships were divided into 3 subareas (urban, suburban, and rural) on the basis of population density. The effects of the three air pollutants on the four respiratory diseases in these subareas were then assessed.

2 Materials and methodology

A schematic of the study flow chart is presented in Fig. 1. The study steps consisted of defining the study area, collecting data, dividing into three subareas based on population density, visualizing the spatiotemporal distribution of air pollutants and disease incidences, analyzing using two statistical methods, outputting-comparing-interpreting of the two results.

2.1 Study area and townships

The greater Taichung area comprises townships with an average altitude of lower than 800 m in Taichung City, Changhua County, and Nantou County. Figure 2 illustrates the study area, which reaches from the Daan River in the north to the Jhushuei River in the south and from the Taiwan Strait in the west to Jiji Mountain in the east.

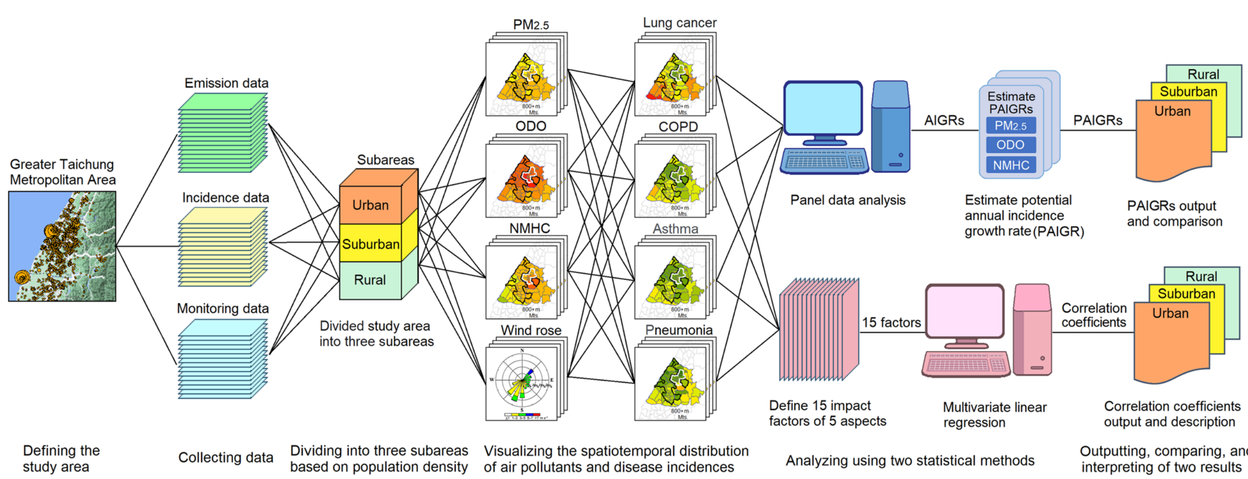


Fig. 1 Schematic of the study flow chart

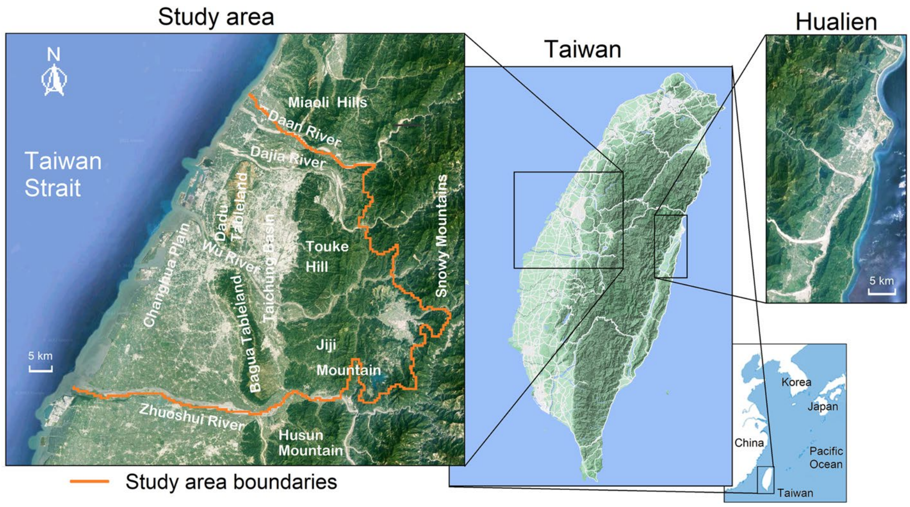


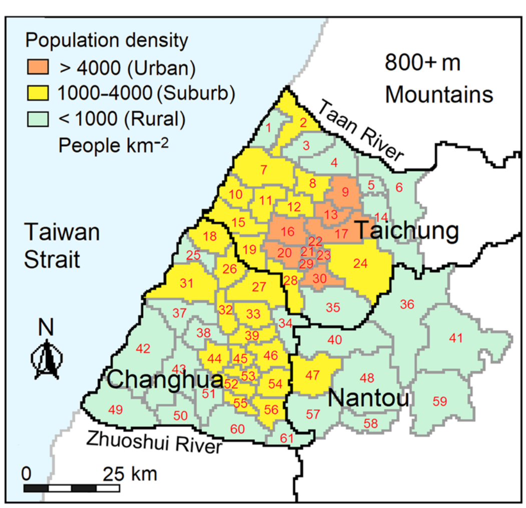
Fig. 2 Location and terrain of the study area

As of April 2022, the area with an average altitude of higher than 800 m, exclusive of mountainous areas, was approximately 3,166 km^2, and its population was 4.4 million people. The Taichung Basin is surrounded by the Miaoli Hills, Dado Tableland, Bagua Tableland, Jiji Mountain, and Touke Hill. The Wu River divides the Taichung Basin into the North Basin and South Basin. More than half of the population in the study area (approximately 2.27 million people) lives in the North Basin, the area with the highest population density. This study used data from townships in Hualien County (inset in Fig. 2) as the control data to estimate the incidence rates of the four diseases resulting from an increased per unit concentration of the three pollutants. Hualien is a county on the east coast of the island and has the best air quality in Taiwan because of its small population.

Figure 3 depicts the locations of the 61 townships in the study area. The urban, suburban, and rural subareas corresponded to areas with population densities of >4000, 1000−4000, and <1000 people km^{-2} respectively; the number of townships in each subarea was 10, 26, and 25, respectively. The urban and suburban subareas are in the North Basin and on the east side of the Changhua Plain respectively, and the rest of the study area is the rural subarea.

2.2 Data sources

Data from 2000 to 2019 were collected from the Taiwanese government. Air quality monitoring data were



1 Dann	2 Dajia	3 Waipu
4 Houli	5 Shingang	6 Dongshi
7 Qinshui	8 Shengang	9 Fengyuan
10 Wuqi	11 Shalu	12 Daya
13 Tanzi	14 Xinshe	15 Longjing
16 Xitun	17 Beitun	18 Shenkang
19 Dadu	20 Nantun	21 West
22 North	23 East	24 Taiping
25 Xianxi	26 Hemei	27 Changhua
28 Wrui	29 South	30 Dali
31 Lukang	32 Xiushui	33 Huatan
34 Fenyuan	35 Wufeng	36 Guosing
37 Fuxing	38 Puyan	39 Dacun
40 Caotun	41 Puli	42 Fangyuan
43 Erlin	44 Xihu	45 Puxin
46 Yuanlin	47 Nantou	48 Jhongliao
49 Dacheng	50 Zhutang	51 Pitou
52 Tianwei	53 Yongjing	54 Shetou
55 Beidou	56 Tianzhong	57 Mingjian
58 Jiji	59 Yuchih	60 Xizhou
61 Ershui		

Fig. 3 Locations of the 61 townships, the urban, suburban, and rural subareas

collected from the official website of Taiwan's Environmental Protection Administration (TEPA; https://data.epa.gov.tw/dataset/detail). Incidence data were extracted from the National Health Insurance Research Database (http://nhird.nhri.org.tw/), which is managed by the National Health Research Institute of Taiwan and consists of data from a large longitudinal and retrospective cohort of 1 million people randomly sampled from the total population of 23 million. The data comprise medical records including age, sex, disease diagnoses, and sociodemographic factors. The medical records collected from this database were anonymized. The data were deidentified, and patients with respiratory diseases were identified using the International Classification of Disease, Ninth Revision, Clinical Modification. Emissions data from various sources were retrieved from the Taiwan Emission Data System (TEDS 11.0; https://air.epa.gov.tw/EnvTopics/ AirQuality_6.aspx) and averaged over 2017 to 2019. Population density, salary in NT$, and medical labor force data were retrieved from Taiwan's Open Government Data Platform (https://data.gov.tw/dataset, accessible at the webpages of /8410, /103,066, and /6474, respectively). Both O_3 and NO_2 are harmful secondary air pollutants that cannot be ignored, and they are rapidly converted between each other and associated with secondary organic aerosols. Therefore, the sum of their concentrations is called "odd oxygen". In terms of health effects, O_3 and NO_2 are discussed together rather than O_3 or NO_2 alone. Ambient odd oxygen was defined as the sum of ozone and nitrogen dioxide concentrations. ODO surrogate concentration was derived from the observed odd oxygen (O_3+NO_2) concentration.

2.3 Software and statistical analysis

2.3.1 Visual and spatial analysis

Esri's ArcGIS 10.3.1, the Taiwan Township Boundary File, and Inverse Distance Weighted in the Spatial Analyst Module were used to create maps for geographic data and to analyze the spatial characteristics of the air pollutants and respiratory diseases. IBM SPSS 22.0 was used to identify associations between exposure to the three air pollutants and the respiratory diseases.

2.3.2 Panel data analysis

A panel data regression model was used to evaluate the annual incidence rate (AIR) of the four respiratory diseases resulting from exposure to the four air pollutants. The formula is as follows:

$$Y_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 Treat_{it} + \alpha_3 Airpollution_{it} + \alpha_4 I_{it} + \epsilon_{it}, t = 2000, \ldots, 2019 \quad (1)$$

where Y_{it} is the outcome for district/township i in the target area in year t. D_{it} is a vector of year dummy variables and was assigned a value of 0 for the year of 2000 and 1 otherwise. The treated areas were the target and control areas, which were assigned a $Treat_{it}$ value of 1 for each district/township of the target area and 0 otherwise. ε_{it} is a random error term, which may include pollutant-specific or year-specific components. α_0 is a constant term, and α_1, α_2, and α_3 measure the main effects at reference values that corresponded to their covariate vector, namely year dummy variables, treated target area, and concentration of air pollutants, respectively; α_4 measures the interaction between *Treat* and *Air pollution*.

Covariate vector I_{it} for the interaction terms of $Treat_{it}$, $Air\ pollution_{it}$, and D_{it} was evaluated using the following equation:

$$I_{it} = treat_{it} \times airpollution_{it} \times D_{it} \quad (2)$$

where I_{it} is the incidence per unit pollutant concentration, which was calculated using the differences in the data between the target and control areas.

2.3.3 Multivariate linear regression

There are 11 air quality monitoring stations in the study area, but the number of factories exceeds 31,000. If only exposure data (air quality monitoring data) is used in multiple regression, it may cause large bias due to insufficient data. Therefore, an ideal evaluation model of air pollution and its relationship to disease must account for the effects of air quality, point source, line source, area source, and socioeconomic status on regional morbidities. This study analyzed three factors for each of these aspects. Ambient concentrations of $PM_{2.5}$, ODO, and NMHC were used as the representative factors for air quality. Point, line, and area sources had the same representative factors, namely $PM_{2.5}$, NO_x, and NMHC emission concentrations. Population density, salary, and medical labor force were the representative factors for socioeconomic status. The evaluation model for morbidity prevalence *MP* is as follows:

$$MP = \alpha_0 + \sum_{i=1}^{3} \beta_i [AQ]_i + \sum_{j=1}^{3} \gamma_j [PS]_j + \sum_{k=1}^{3} \delta_k [LS]_k + \sum_{m=1}^{3} \zeta_m [AS]_m + \sum_{n=1}^{3} \lambda_n [SE]_n \quad (3)$$

where [*AQ*], [*PS*], [*LS*], [*AS*], and [*SE*] are the values of the factors for air quality, point source, line source, area source, and socioeconomic status, respectively. α_o is a constant term; β_i, γ_i, δ_i, $\xi_{i,}$ and λ_i are the coefficients of factors for point source, line source, area source, and socioeconomic status, respectively, which were estimated using the multivariate linear regression module of IBM SPSS 21.0.

2.3.4 Preparing wind roses

Because the Changhua air quality monitoring station (in Township 27; Fig. 2) is in the middle of the study area, its meteorological data are representative and were thus used to create an annual wind rose diagram of the study area. The Wind Chart Module of Golden Grapher 4 was used to create annual wind roses for the study area from 2005 to 2019.

3 Results

3.1 The selection of control data

The study area includes Taichung City, Changhua County, and Nantou County. In addition, Hualien County was selected as the control area. Figure 4 presents the statistical data for population, average annual income, and number of vehicles in the three target cities and counties and the control county from 2005 to 2019. The counties with the largest population, in descending order, were Taichung, Changhua, Nantou, and Hualien. However, only Taichung City had positive population growth (179,290 people year^{-1}; Fig. 3a). The population growth rates of Changhua, Nantou, and Hualien were approximately −1200, −3193, and −1445 people yr^{-1}, respectively. Taichung is the only municipality in central Taiwan. Therefore, the population concentration of Taichung is high, as expected. Unlike other counties, Taichung population is steadily growing. The growth rates of average annual income in Taichung, Changhua, Nantou, and Hualien were approximately 18,270, 9,900, 7,160, 15,620 NT$ yr^{-1}, respectively. Areas with the highest average annual income, in descending order, were Hualien, Taichung, Nantou, and Changhua (Fig. 4b). These data indicate that the people of Hualien (the control county) are well above the threshold for poverty. The number of vehicles in the four cities and county was similar to those for the entire population and therefore proportional to the population of

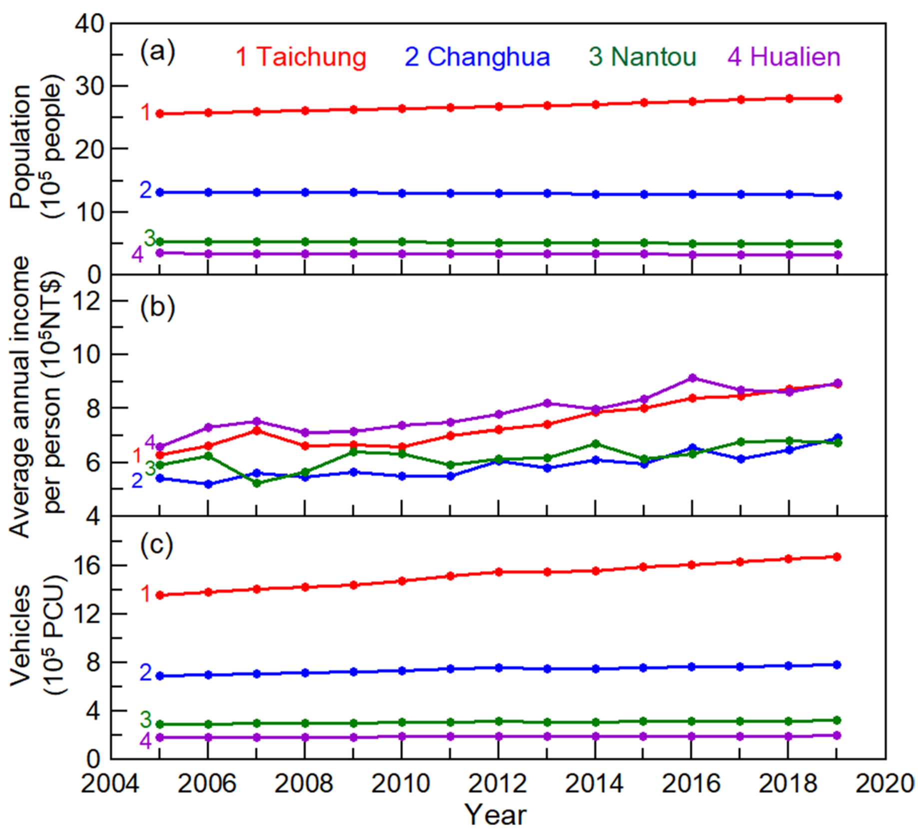


Fig. 4 Statistical data of (a) population, (b) average annual income, and (c) vehicle in three target cities/counties and the control country from 2005 to 2019. Passenger Car unit PCU (PCU) is a vehicle unit used for expressing highway capacity. A single vehicle, motorcycle, bus, and truck are considered to be 1, 0.3, 2.5, and 2.5 PCU, respectively

the city (Fig. 4a and c). Higher numbers of people and vehicles indicate more air pollutant emissions. Therefore, the air pollutant data and incidence data of Hualien County were used as control data in the study.

3.2 Annual emissions of $PM_{2.5}$, ODO, and NMHC

The emissions data from various sources were retrieved from the TEDS 11.0 of Taiwan's EPA. The TEDS is an open database that contains data on air pollutants in the atmosphere collected from various stationary and mobile pollution sources across Taiwan; these data are averaged over 3 years and published every 3 years. The TEDS 11.0 is the latest version of the database, with its data being averaged from 2017 to 2019. These data are the sum of primary pollutant emissions from stationary, mobile, and area sources, which are different from monitoring data of air quality.

Figure 5 presents bubble plots of the annual $PM_{2.5}$, NO_x, and NMHC emissions in the study area and for all of Taiwan based on the TEDS 11.0 data. The results indicate notable emission sources and high levels of emissions in the northern, central, and southern parts of western Taiwan. The results also indicate that the study area is a highly industrialized metropolitan area. A comparison of the results in Fig. 3 and the insets of Fig. 5 revealed that the main emission sources of $PM_{2.5}$, NO_x, and NMHC are located in the urban and suburban subareas. $PM_{2.5}$, NO_x, and NMHC had large emission sources, with emissions greater than 360 t yr^{-1}, in the study area. Some of the larger NMHC emissions occurred between the densely populated urban and suburban subareas. Therefore, the three air pollutants strongly affect the health of the local population.

3.3 *Spatiotemporal distributions of $PM_{2.5}$, ODO, and NMHC*

The representative annual wind roses in the northern, central, and southern of the study area are presented in Fig. 6. The results demonstrate that the annual prevailing wind directions at the three air quality stations from 2005 to 2011 were similar, which were northeast and southwest (with a wind angle range of 45 to 225°). During this period, the most frequent wind speeds, in ascending order, were 1 to 3, 3 to 5, and 5 to 7 m s^{-1}. After 2012, the prevailing wind direction was between the south and southwest. Wind speeds were mainly 1 to 3 m s^{-1}, except in 2017 and 2018, when they were 3 to 5 m s^{-1}. According to the local meteorological field, the prevailing winds between the south and southwest were dominant, followed by the northeasterly prevailing wind. The wind speed varied only slightly from year to year.

The annual concentration distribution contours and annual wind roses from 2005 to 2019 are depicted in Fig. 7. The annual average concentration of $PM_{2.5}$ significantly increased from north to south and decreased each year, especially after 2015 (Fig. 7a); air quality

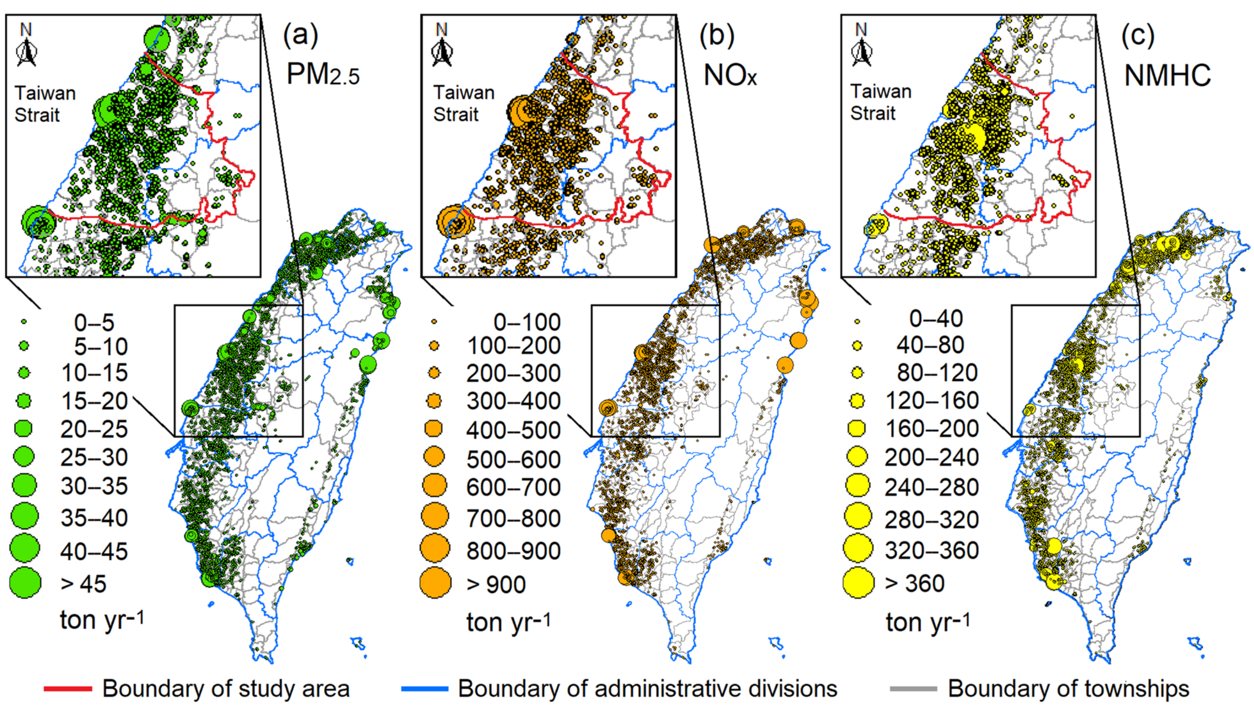


Fig. 5 Bubble plots of annual (a) $PM_{2.5}$, (b) NO_x, and (c) NMHC emissions in the study area

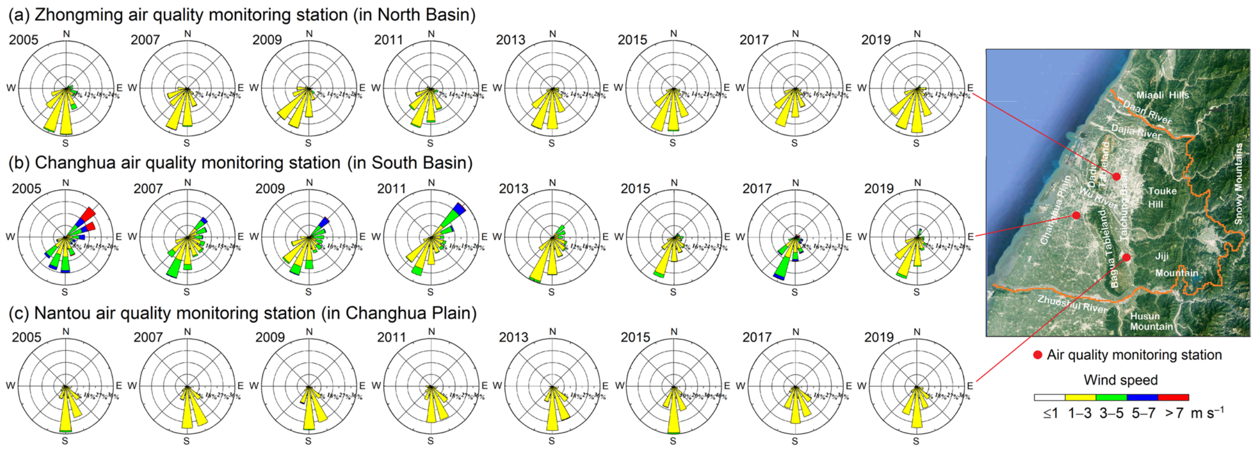


Fig. 6 The representative annual wind roses in the northern, central, and southern of the study area

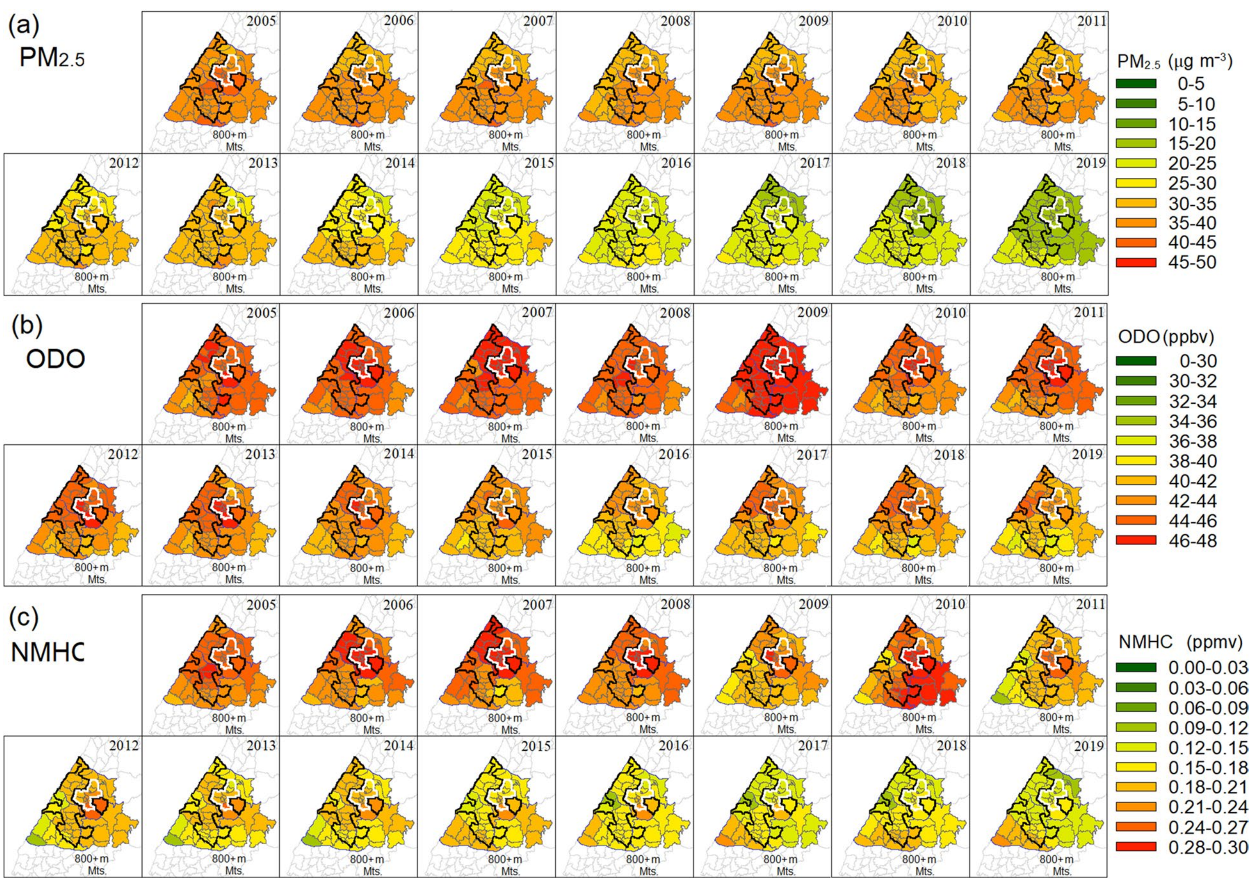


Fig. 7 Spatiotemporal distributions of $PM_{2.5}$, ODO, and NMHC in townships of study area from 2005 to 2019. The inset in each subfigure is its annual wind rose. The white and black lines are the urban and suburban boundaries, respectively

control measures in the study area were thus effective. However, the spatiotemporal distribution of $PM_{2.5}$ was independent of subarea. The local wind field did not significantly affect the PM distribution, perhaps because of the low local wind speeds. The mean wind speed between 2005 and 2019 was 1 to 3 m s^{-1}. The formation of secondary aerosol at low wind speed may also be one of the reasons affecting the distribution and high concentration of $PM_{2.5}$. All $PM_{2.5}$ concentrations were higher than the annual average standard value in Taiwan (15 μg m^{-3}); thus, the study area is moderately contaminated by $PM_{2.5}$.

ODO and NMHC exhibited an opposite spatial distribution to that of $PM_{2.5}$ (Fig. 7b and c); the highest concentrations, in descending order, were in the urban, suburban, and rural subareas. However, some high ODO and NMHC concentrations were detected in the eastern townships near the mountains, possibly because of the barrier effect of the mountains (Fig. 2). Similar to the concentration of $PM_{2.5}$, the annual average concentrations of ODO and NMHC decreased each year.

3.4 Spatiotemporal distribution of respiratory diseases

Figure 8 depicts the spatiotemporal distribution of incidence for the four respiratory diseases in the study area from 2005 to 2019. The incidence of lung cancer increased from north to south, similarly to the concentration $PM_{2.5}$. Unlike the concentrations of the pollutants, the incidence of lung cancer increased each year, which may have been a delayed effect of air pollution. The area with the highest incidence of lung cancer was the rural subarea of Changhua (Figs. 3 and 8a). However, the emissions of the three air pollutants in this area were lower than those in the urban and suburban subareas (Fig. 5a and c).

The spatiotemporal distributions of the incidences of COPD and asthma differed only slightly and decreased each year. (Figure 8b and c); the areas with the highest incidences, in ascending order, were the rural, suburban, and urban subareas: a spatial distribution similar to that of the incidence of lung cancer. High COPD and asthma incidences were observed in the rural subarea despite it having the lowest density of air pollution sources (Fig. 5). The incidences of COPD and asthma in the rural subarea decreased considerably in 2018 and 2019.

The incidence of pneumonia was initially higher in the east and south but eventually increased across study area. Pneumonia is a short-term acute disease and therefore cannot result from the delayed effects of air pollution. The concentration of ODO was consistently high between 2005 and 2019 (Fig. 8b). The main component of odd oxygen is ozone. Therefore, the concentration of O_3 was also consistently high between 2005 and 2019. Ozone is a reactive oxidant causing both inflammatory and oxidative damage to the respiratory system [27]. Tian et al. [29] observed an association between hospital admissions for pneumonia and ozone exposure that was stronger for the older adult population. Therefore, the high concentrations of ozone may have increased the incidence of pneumonia in the study area. In Taiwan, the annual mean concentration of O_3 is usually consistent, but ozone event days (with an 8-h average of ≥ 71 ppb) occur, with a considerable increase noted after 2017 [18]. This increase in ozone event days may also have contributed to the increased incidence of pneumonia.

3.5 Effects of regional air pollutants on incidence of respiratory diseases

The AIRs of the four diseases caused by an increased per-unit concentration of the three pollutants were estimated using Eqs. (1) and (2), with the data from the townships of Hualien County serving as the control. The concentrations of $PM_{2.5}$, ODO, and NMHC are in μg m^{-3}, ppbv and ppmv, respectively, which are commonly used units in air quality monitoring for these three air pollutants. The annual incidence rate growth rate (AIGR) per 100,000 population per unit air pollutant concentration increments was obtained from a plot of AIR versus year.

Table 1 lists the AIGRs and the minimum and maximum error estimates based on data from 2005 to 2019. The three air pollutants were associated with a positive AIGR for lung cancer in the urban, suburban, and rural subareas, with the highest AIGR being in the urban subarea. The AIGRs were similar for the three air pollutants in the suburban and rural subareas. The AIGRs for lung cancer caused by NMHC exposure were notably high in the three subareas, with the urban AIGR being approximately twice as high as those of the suburban and rural subareas. The minimum and maximum error estimates of AIRs were the same as those of the AIGRs, with higher AIGRs having higher minimum and maximum 95% confidence intervals (95% CIs) for the AIR.

The areas in which the three air pollutants caused the largest increase in COPD AIGR, in descending order, were urban, suburban, and rural, which was the same result as that for the lung cancer AIGRs. The ratios of the AIGRs of $PM_{2.5}$, ODO, and NMHC between the urban and suburban subareas were approximately 2.01, 1.21, and 2, respectively. The AIGRs of COPD were greater than those of lung cancer in the urban and suburban subareas for all three air pollutants, especially in the urban subarea. These results demonstrate that COPD caused through exposure to the three air pollutants in the urban and suburban subareas warrants immediate attention. The order of the minimum and maximum 95% CIs of the AIRs for the three subareas was the same as those of the AIGRs. The minimum and maximum error estimates increased proportionally with AIGR. A comparison of the COPD and lung cancer AIGRs revealed that the ratios of the COPD AIGRs to the lung cancer AIGRs

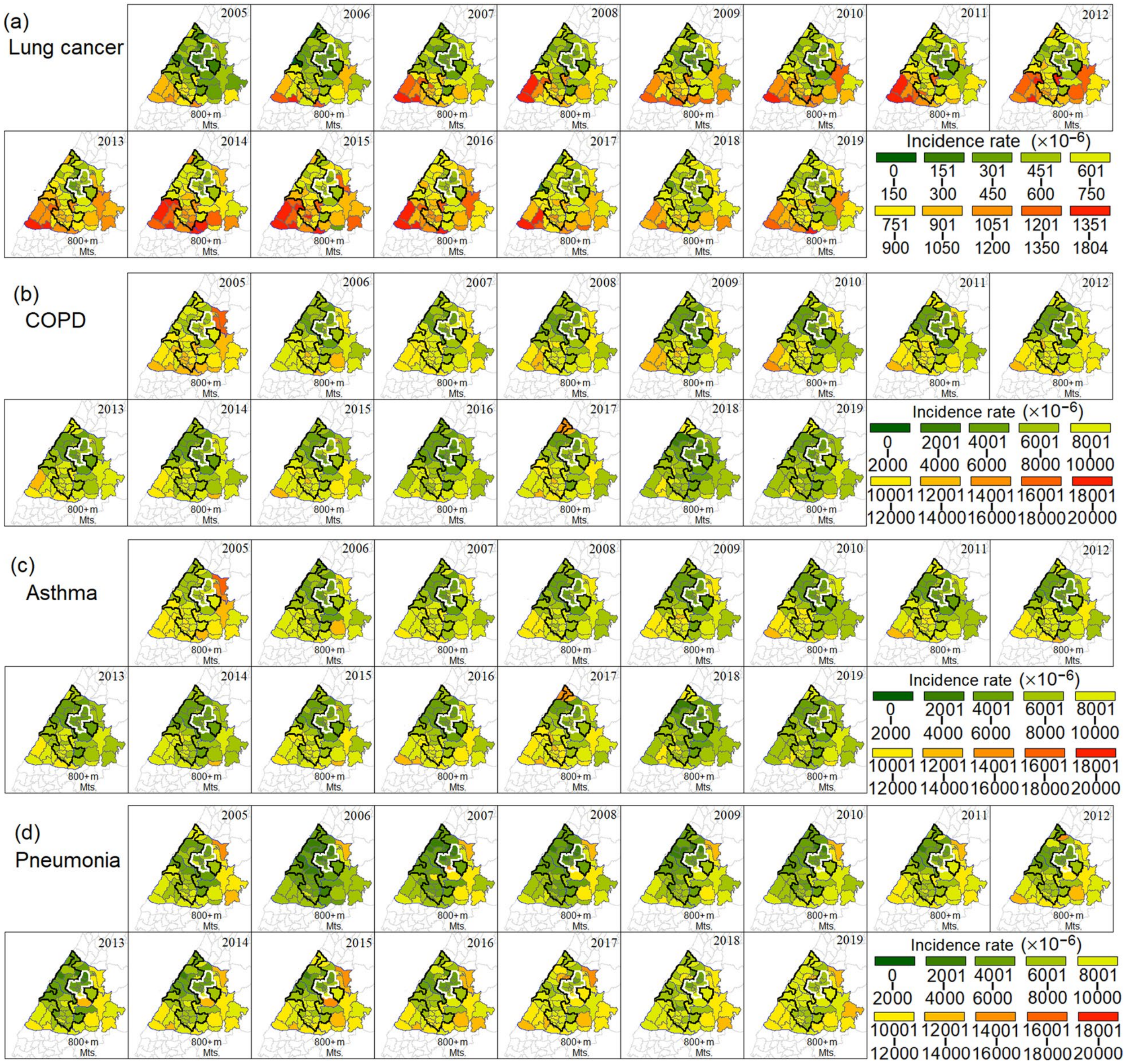


Fig. 8 Spatiotemporal distribution of incidence of the four respiratory diseases in townships of study area from 2005 to 2019. The white and black lines are the urban and suburban boundaries, respectively

were 33.09, 33.66, and 3.7 in the urban, suburban, and rural subareas, respectively. This result indicates that the effect of NMHC on the COPD AIGRs was significantly stronger than that on the lung cancer AIGRs.

The three air pollutants caused positive increases in the asthma AIGRs in the three subareas, except for $PM_{2.5}$ in the rural subarea. The areas with the highest asthma AIGRs associated with the three air pollutants, in descending order, were urban, suburban, and rural, which was the same result as that for the lung cancer and COPD AIGRs. NMHC strongly affected the asthma AIGRs in the three subareas, but the effect was slightly weaker than that on the COPD AIGRs. The strength of the effect of NMHC on lung cancer, COPD, and asthma was significantly and positively correlated with the degree of urbanization of a region. The high levels of NMHC may be attributable to the higher number of vehicles, the greater amount of vehicle exhaust emissions, and the heavier traffic flow in the urban subarea. The order of the minimum and maximum 95% CIs of the AIRs for the three subareas was the same as that of the AIGRs.

Table 1 Summary of AIGE per 100,000 population per unit air pollutant concentration increments using data from 2005 to 2019

Air pollutants	Urban	Suburban	Rural
Lung cancer			
$PM_{2.5}$	0.1	0.1	0.1
	(-0.25 — 0.47; -0.20 — 1.86)	(-0.1 — 0.6; -0.7 — 3.5)	(-0.1 — 0.7; -2.2 — 11.0)
ODO	0.1	0.0	0.0
	(0.10 — 0.76; 0.01 — 1.35)	(0.0 — 0.6; -0.2 — 1.1)	(-0.6 — 0.2; -0.3 — 1.1)
NMHC	14	7	8
	(-41.9 — 56.1; 15.8 — 317.1)	(-64.0 — 27.4; -40.8 — 264.2)	(-71.2 — 25.4; -82.0 — 206.4)
COPD			
$PM_{2.5}$	1.8	0.9	0.0
	(3.2 — 25.4; 19.6 — 68.2)	(-1.6 — 14.4; -1.5 — 127.4)	(-10.3 — 5.2; -138.5 — 118.3)
ODO	0.5	0.4	0.2
	(13.5 — 44.5; 21.0 — 65.0)	(9.6 — 38.4; 16.0 — 55.3)	(-15.3 — 23.9; -18.6 — 31.1)
NMHC	478	236	28
	(1716.5 — 6247.4; 5900.5 — 17,881.6)	(916.0 — 4396.3; 1882.2 — 10,734.4)	(-1099.8 — 2423.1; -3568.9 — 3728.4)
Asthma			
$PM_{2.5}$	1.3	0.7	-0.1
	(-0.9 — 19.7; -3.1 — 41.9)	(-4.8 — 10.5; -5.8 — 116.8)	(-11.6 — 3.5; -158.0 — 109.0)
ODO	0.4	0.4	0.2
	(5.9 — 40.6; 12.2 — 55.0)	(3.3 — 35.3; 9.6 — 49.0)	(-19.7 — 22.2; -17.1 — 32.0)
NMHC	366	189	20
	(763.2 — 5507.7; 3460.3 — 15,125.4)	(306.5 — 3921.1; 1177.4 — 9495.0)	(-1143.9 — 2599.7; -3858.9 — 3157.3)
Pneumonia			
$PM_{2.5}$	0.4	0.5	0.6
	(-6.2 — -0.3; -6.7 — 16.5)	(-3.8 — 2.6; -9.9 — 35.0)	(0.3 — 5.5; -89.3 — 112.5)
ODO	0.2	0.3	0.2
	(-3.5 — 1.6; -8.0 — 4.2)	(-3.4 — 2.2; -7.0 — 5.5)	(-5.8 — 1.1; -2.3 — 11.8)
NMHC	44	49	69
	(-718.0 — 45.8; -1273.0 — 1976.9)	(-535.9 — 269.3; -1349.5 — 1410.4)	(-409.5 — 410.9; -359.9 — 2454.1)

The numbers in parentheses are the minimum and maximum error estimates of yearly AIR from 2005 to2019

Pneumonia is an acute lung infection resulting from bacteria, viruses, mycoplasmas, and fungus. Air pollution can weaken the immune function of the respiratory system, increasing susceptibility to pneumonia [34]. The areas in which the three air pollutants had the strongest effects on pneumonia AIGRs, in descending order, were rural, suburban, and urban, which is the opposite pattern to those of the lung cancer, COPD, and asthma AIGRs (Table 1). However, the differences in the effects among the subareas were nonsignificant. This was also the same order for the AIGRs of the other diseases: NMHC > $PM_{2.5}$ > ODO.

3.6 Comparison of the effects of regional air pollutants on respiratory diseases

Because the scale and variable ranges of the three air pollutants differed, the AIGRs of the three pollutants (Table 1) could not be directly used to compare their effects on the four diseases. Therefore, the AIGRs were converted into a new parameter independent of concentration and variable ranges. This study used potential AIGR (PAIGR) per 100,000 population to solve this problem. The concentration-independent variable interval of each air pollutant was the difference between the highest and lowest values (Hualien) for annual average air pollutants, which is the maximum variation in air pollutant concentration. PAIGR per one hundred thousand population for air pollutant i in zone j in terms of the ratio of the AIGR to variable interval VI is expressed by the following equation:

$$PAIGR_{ij} = AIGR_{ij} \times VI_i \tag{4}$$

where $PAIGR$ is independent of the air pollutant concentration.

Box-whisker plots of the annual concentrations of the three air pollutants in the urban, suburban, and rural subareas and in Hualien (control area) between 2005 and 2019 are presented in Fig. 9; *VI* in the subareas was obtained using these results. *VI* for $PM_{2.5}$, ODO, and NMHC was 27 μg m^{-3}, 15 ppb, and 0.2 ppm, respectively.

Because PAIGR is a relative quantity independent of the concentration (or scale) of each air pollutant, it can be used to compare the effects of the three pollutants on a disease. Table 2 lists the PAIGRs per 100,000 population for the four diseases associated with exposure to the three air pollutants based on data from 2005 to 2019. The air pollutants with the strongest effects on lung cancer PAIGR, in descending order, were NMHC, $PM_{2.5}$, and ODO, with the urban subarea being most affected. For the lung cancer PAIGRs in the urban subarea, the ratio of $PM_{2.5}$ to ODO to NMHC was approximately 19:1:289. The areas in which the air pollutants had the strongest effects on COPD PAIGR, in descending order, were urban, suburban, and rural. The effect of NMHC on the COPD PAIGRs was considerable in each subarea. The ratios of $PM_{2.5}$ to ODO to NMHC in the urban, suburban, and rural subareas were approximately 3.5:1:920, 2:1:550, and 0:1:166, respectively. The areas in which the pollutants had the strongest effects on asthma PAIGR, in descending order, were urban, suburban, and rural. NMHC had the strongest effect on asthma in the urban subarea. The areas in which the pollutants had the strongest effects on pneumonia PAIGR, in descending order, were urban, suburban, and rural. The ratios of $PM_{2.5}$ to ODO to NMHC for the urban, suburban, and rural subareas were approximately 2.9:1:291, 1.8:1:163, and 2.5:1:286, respectively.

Table 2 Summary of PAIGE per 100,000 population obtained by Eq. (2) using data of 2005−2019

Air pollutants	Urban	Suburban	Rural
Lung cancer			
$PM_{2.5}$	0.95	0.05	0.06
ODO	0.05	0.04	0.04
NMHC	14	7	8
COPD			
$PM_{2.5}$	1.81	0.90	0.00
ODO	0.52	0.43	0.17
NMHC	478	236	28
Asthma			
$PM_{2.5}$	1.28	0.66	-0.05
ODO	0.04	0.36	0.15
NMHC	366	189	20
Pneumonia			
$PM_{2.5}$	0.43	0.54	0.61
ODO	0.15	0.30	0.24
NMHC	44	49	69

NMHC had the most harmful effects, followed by $PM_{2.5}$. The increases in all-cause mortality of lung cancer, COPD, and asthma were due to long-term air pollutant exposure. The study area is a metropolitan basin with a population of 4.4 million, and about half of the population (approximately 2.27 million people) lives in the urban subarea. Therefore, this area contains the most vehicles, which emit

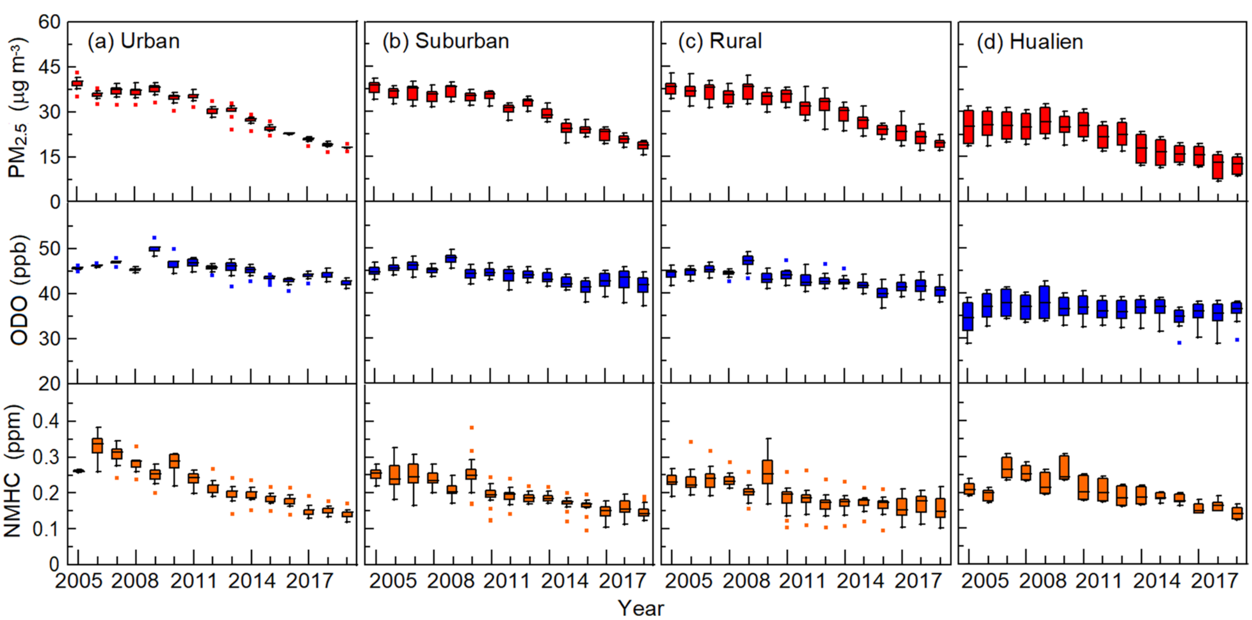


Fig. 9 Box-whisker plots of annual concentrations of the three air pollutants in (a) Urban, (b) Suburban, (c) Rural, and (d) Hualien (control area) from 2005 to 2019

large amounts of NMHC (Figs. 3 and 4c). This explains why the effects of the three air pollutants on the three chronic diseases were strongest in the urban subarea. The effects of the three air pollutants on acute pneumonia differed little among the urban, suburban, and rural subareas.

3.7 Effects of the fifteen factors on regional incidence

The effects of air quality, point source, line source, area source, and socioeconomic status on regional incidence were estimated using the multivariate linear regression module of SPSS. Air quality comprised the ambient concentrations of $PM_{2.5}$, ODO, and NMHC; the point, line, and area sources comprised the emissions of $PM_{2.5}$, NO_x, and NMHC; socioeconomic status comprised population density, salary, and medical labor force.

3.7.1 Lung cancer

The multivariate regression coefficients for the effects of the 15 factors on the incidence of lung cancer are listed in Table 3. The correlations of the 15 factors with lung cancer incidence differed significantly among the subareas, especially in terms of the positive and negative correlations. Thus, each of the 15 factors played distinct roles in the subareas. Some independent variables (factors) in the urban subarea were excluded in the statistical estimation because they did not contribute significantly to the R^2 values when R^2 was 1. The results indicate that β_1, γ_1, ξ_2, and λ_3 had positive correlation coefficients with the incidence of lung cancer and that the rest of the factors had negative correlation coefficients or were excluded. The greatest positive and negative correlation coefficients, in descending order, were those of γ_1, λ_3, ξ_2, and β_1 and those of β_3, ξ_1, ξ_3, γ_3, λ_2, and λ_1, respectively. $PM_{2.5}$ from point sources had a coefficient of 2.35, which was more than 2.6 times the coefficients of other factors and this merits attention.

In the suburban subarea, the increase in incidence resulting from NO_x from point sources was large, with a coefficient more than 5.1 times greater than those of the other factors. The main point sources of NO_x were mostly located in the suburban subarea, with a few located in the urban subarea (Fig. 4b). The suburban subarea had the largest distribution of ambient ODO (Fig. 7b). The marked increase in the incidence of lung cancer may be attributable to high NO_x emissions from point sources in this subarea. Notably, the maximum reduction factor of incidence was observed for $PM_{2.5}$ emitted from point sources. However, a high ambient $PM_{2.5}$ concentration was not observed in the suburban subarea, and the $PM_{2.5}$ concentration in the study area decreased significantly and rapidly, especially in the suburban subarea (Fig. 7a).

Table 3 Summary of the multivariate regression coefficients of 15 factors in the incidences of lung cancer

Coefficients	Urban	Suburban	Rural
Constant coefficient, α_0	0.00	0.00	0.00
Air quality aspect			
$PM_{2.5}$, β_1	0.69	-0.16	-0.52
ODO, β_2	-*	0.07	-0.39
NMHC, β_3	-1.60	0.35	0.68
Point source aspect			
$PM_{2.5}$, γ_1	2.35	-11.17	-0.11
NO_x, γ_2	-	10.99	0.57
NMHC, γ_3	-1.20	0.44	-0.66
Line source aspect			
$PM_{2.5}$, δ_1	-	-0.21	4.92
NO_x, δ_2	-	-0.55	-3.35
NMHC, δ_3	-	2.15	-1.94
Area source aspect			
$PM_{2.5}$, ξ_1	-1.52	0.44	0.45
NO_x, ξ_2	0.90	-1.73	0.35
NMHC, ξ_3	-1.34	-0.47	-0.11
Social economics aspect			
Population density, λ_1	-0.15	-0.25	0.12
Salary, λ_2	-0.53	0.07	-0.78
Medical manpower, λ_3	1.02	-0.14	-0.22
R-squared	1	0.90	0.87
p-values	-**	0.00	0.00

* An independent variable that was excluded by SPSS statistical estimation when $R^2=1$

** The *p*-value is infinitely small

A high ambient $PM_{2.5}$ concentration was noted in the rural subarea. The results demonstrate that the $PM_{2.5}$ emitted from line sources had the highest effect on the incidence rate increase in rural areas at more than 7.2 times that of other factors (Fig. 6a). The ambient NMHC concentration in the rural subarea was lower than that in the other two subareas, possibly because of the NMHC factors in all aspects of the rural subarea except for air quality being negatively correlated. Factors λ_3, λ_2, and λ_1 were positively correlated with lung cancer in the urban, suburban, and rural subareas, respectively. The rest of the factors had low negative correlation coefficients. The regional medical labor force is dependent on the supply and demand of resources for treating diseases; the positive correlation coefficient for medical manpower ($\lambda_3=1.016$) indicates high demand in the urban subarea.

3.7.2 COPD

Table 4 lists the multivariate regression coefficients for the effects of the 15 factors on the incidence of COPD. As with lung cancer incidence, when R^2 was 1, the SPSS statistical estimates excluded some independent variables (factors) for the urban subarea. Factors β_1, γ_1, and ξ_2 were the three main positively correlated factors for the urban subarea, and factor λ_3 was a minor positively correlated factor (Table 4). Factors γ_3, ξ_1, and λ_1 had high negative correlation coefficients, especially factor ξ_1, which had the highest, −2.49.

Most of the factors were positively associated with the incidence of COPD in the suburban subarea. The results shows that the values of γ_2 (5.01) and δ_2 (4.82) indicating these two factors in the suburban subarea were main causes of the high COPD incidence. In the rural subarea, nine factors were negatively associated with COPD incidence, particularly factor δ_1, which had the highest coefficient, −4.46. δ_2 and δ_3 were the two main causes of the high COPD incidence in the rural subarea. For the socioeconomic aspect, the factors λ_3 in the three subareas and λ_2 in the suburban and rural subareas exhibited weak positive correlations with COPD incidence.

3.7.3 Asthma

The multivariate regression coefficients for the effects of the 15 factors on the incidence of asthma are listed in Table 5. A comparison of the results (Tables 4 and 5) revealed that the 15 factors exhibited the same positive and negative relationships with the incidence of both COPD and asthma, except for medical labor force λ_3 in the urban subarea. This result may be attributable to both COPD and asthma being chronic respiratory diseases with similar outcomes in the study area. For air quality and point, line, and area sources, the ratios of asthma incidence to COPD incidence in the urban, suburban, and rural subareas ranged from 0.70 to 1.03 (average = 0.91), 0.54 to 1.06 (average = 0.95), and 0.55 to 1.35 (average = 1.03), respectively. This result indicates that the contributions of the four aspects to the incidences of both COPD and asthma were similar in the three subareas. For the socioeconomic aspect, the ratios of asthma incidence to COPD incidence in the urban, suburban, and rural subareas ranged from −0.75 to 1.01 (average = 0.40), 0.94 to

Table 4 Summary of the multivariate regression coefficients of 15 factors for COPD

Coefficients	Urban	Suburban	Rural
Constant coefficient, α_0	-0.05	0.01	0.02
Air quality aspect			
$PM_{2.5}$, β_1	2.56	0.17	-0.16
ODO, β_2	-*	0.08	-0.27
NMHC, β_3	-0.55	0.07	-0.14
Point source aspect			
$PM_{2.5}$, γ_1	1.98	-5.12	1.04
NO_x, γ_2	-	5.01	-0.92
NMHC, γ_3	-1.47	-0.21	-0.67
Line source aspect			
$PM_{2.5}$, δ_1	-	-9.90	-4.46
NO_x, δ_2	-	4.82	3.36
NMHC, δ_3	-	7.44	1.07
Area source aspect			
$PM_{2.5}$, ξ_1	-2.49	0.30	0.52
NO_x, ξ_2	1.64	-2.89	-0.72
NMHC, ξ_3	-0.43	0.19	-0.10
Social economics aspect			
Population density, λ_1	-1.14	-0.39	-0.02
Salary, λ_2	-0.39	0.09	0.22
Medical manpower, λ_3	0.03	0.18	0.10
R-squared	1	0.901	0.753
p-values	-**	0.003	0.063

* An independent variable that was excluded by SPSS statistical estimation when $R^2 = 1$

** The *p*-value approaches zero

Table 5 Summary of the multivariate regression coefficients of five aspects for asthma

Coefficients	Urban	Suburban	Rural
Constant coefficient, α_0	-0.05	0.01	0.03
Air quality aspect			
$PM_{2.5}$, β_1	2.64	0.17	-0.15
ODO, β_2	-*	0.05	-0.36
NMHC, β_3	-0.43	0.05	-0.17
Point source aspect			
$PM_{2.5}$, γ_1	1.90	-5.06	1.01
NO_x, γ_2	-	4.95	-0.90
NMHC, γ_3	-1.47	-0.23	-0.67
Line source aspect			
$PM_{2.5}$, δ_1	-	-9.67	-3.65
NO_x, δ_2	-	4.68	2.95
NMHC, δ_3	-	7.32	0.59
Area source aspect			
$PM_{2.5}$, ξ_1	-2.51	0.28	0.54
NO_x, ξ_2	1.66	-2.85	-0.73
NMHC, ξ_3	-0.30	0.18	-0.10
Social economics aspect			
Population density, λ_1	-1.15	-0.38	-0.04
Salary, λ_2	-0.37	0.10	0.27
Medical manpower, λ_3	-0.02	0.17	0.15
R-squared	1	0.898	0.769
p-values	-**	0.004	0.047

* An independent variable that was excluded by SPSS statistical estimation when $R^2 = 1$

** The *p*-value approaches zero

1.12 (average = 1.01), and 1.22 to 2.38 (average = 1.71), respectively.

3.7.4 Pneumonia

Table 6 lists the multivariate regression coefficients of the effects of the 15 factors on the incidence of COPD. The excluded independent variables (factors) for the urban subareas, processed through SPSS statistical estimation, were the same as those for the three other respiratory diseases. The coefficients indicate considerable variation between the positive and negative relationships, especially for the suburban subarea. Factors β_1, β_3, and ξ_3 were positively correlated for the urban subarea, with coefficients higher than 3.2. Factor γ_3 was slightly positively correlated, with coefficient of 0.22. Factors γ_1 and λ_1 had high negative correlation coefficients, especially factor γ_1, which had the highest coefficient, − 1.72.

In the suburban subarea, factors γ_2 and δ_1 had the highest and second-highest positive correlations, with values of 13.9 and 7.74, respectively. Factors γ_1 and δ_2 had the highest and second-highest negative correlations, with values of − 14.1 and − 5.47, respectively. Therefore, the reduction of point-source NO_x emissions and line-source $PM_{2.5}$ emissions prevented pneumonia infection. Factors δ_2 and δ_3 had the two highest positive correlations for the rural subarea, with values of 2.97 and 2.42, respectively. The value of factor δ_1 was − 5.59, which was the highest negative correlation coefficient. These results indicate that the three factors of the line source aspect influenced the incidence of pneumonia. In the study area, two express highways and two freeways with heavy traffic flow are located in the rural subarea.

Table 6 Summary of the multivariate regression coefficients of five aspects for pneumonia

Coefficients	Urban	Suburban	Rural
Constant coefficient, α_0	-0.13	0.03	0.02
Air quality aspect			
$PM_{2.5}$, β_1	3.20	-0.58	-0.24
ODO, β_2	-*	-0.06	-0.00
NMHC, β_3	3.68	0.04	0.12
Point source aspect			
$PM_{2.5}$, γ_1	-1.72	-14.07	-0.35
NO_x, γ_2	-	13.94	-0.13
NMHC, γ_3	0.22	0.09	0.19
Line source aspect			
$PM_{2.5}$, δ_1	-	7.74	-5.59
NO_x, δ_2	-	-5.47	2.97
NMHC, δ_3	-	-2.32	2.42
Area source aspect			
$PM_{2.5}$, ξ_1	-0.48	-0.56	0.10
NO_x, ξ_2	0.83	0.54	-0.02
NMHC, ξ_3	3.60	-0.03	-0.11
Social economics aspect			
Population density, λ_1	-1.24	-0.27	-0.01
Salary, λ_2	-0.59	-0.36	0.29
Medical manpower, λ_3	0.18	0.68	-0.65
R-squared	1	0.687	0.830
p-values	-**	0.276	0.011

* An independent variable that was excluded by SPSS statistical estimation when $R^2 = 1$

** The *p*-value approaches zero

4 Discussion

The wind field in the study area exhibited northeast and southwest monsoon characteristics. The average annual wind speed was between 1 and 5 m s^{-1} (frequency > 80%) between 2005 and 2019. The prevailing wind direction was not a major factor determining the distribution of air pollutants. The concentrations of the three pollutants decreased each year. The spatial distribution of $PM_{2.5}$ in the three subareas was similar and not significantly affected by the local wind field. The spatial distributions of ODO and NMHC differed from that of $PM_{2.5}$, and the subareas with the highest concentrations, in descending order, were urban, suburban, and rural. This result may be explained by the fact that both ODO and NMHC are precursors of $PM_{2.5}$ (Fig. 7). In addition, the mountain barrier effect results in higher concentrations of air pollutants in the surrounding areas.

The spatial distribution of the incidences of the four respiratory diseases was the same as that of $PM_{2.5}$, which gradually increased from north to south (Figs. 7 and 8). The order of their spatial distributions in subareas was rural > suburban > urban, which was opposite to those of ODO and NMHC. A reduction in the precursors increased $PM_{2.5}$ concentrations, thereby increasing the incidence of respiratory disease.

The panel data regression model was used to evaluate the AIRs of the four respiratory diseases. The change in AIGR was obtained by plotting AIR by years. All three air pollutants lead to positive AIGRs for all four diseases in the three subareas, except for $PM_{2.5}$, which was associated with a negative asthma AIGR in the rural subarea. The areas with the highest AIGRs for lung cancer, COPD, and asthma, in descending order, were urban, suburban, and rural. The areas with the highest AIGRs for pneumonia, in descending order, were rural, suburban, and urban. The air pollutants that most strongly affected the AIGRs of the four respiratory diseases, in descending order, were NMHC, $PM_{2.5}$, and ODO, which may be attributable to the effects of high numbers of vehicles, high amounts of exhaust emissions, and heavy traffic flow in the urban subarea.

This study developed a new parameter, PAIGR, and its estimation formula to quantitatively compare the effects of the three air pollutants on the respiratory diseases. The results shows that NMHC is the most serious on the four respiratory diseases, followed by $PM_{2.5}$. Therefore, the impact from NMHC was significant and cannot be ignored, especially in urban subarea.

The 15 factors had positive or negative correlations with each disease. The socioeconomic factors (i.e., population density, salary, and medical labor force) had low coefficients for the positive and negative correlations with incidence of the four diseases, indicating that they have little effect on incidence.

5 Conclusion

The study area has serious air pollution problems because of its high industrial and population densities. The results indicate that ambient NMHC had the strongest effects on the incidence of respiratory diseases, followed by those of ambient $PM_{2.5}$. The effect of ambient NMHC was significant and cannot be ignored, especially in the urban subarea. This study also used multivariate regression to assess the association between the 15 factors of the five aspects and the incidences of the four respiratory diseases. The results revealed a favorable goodness of fit. They also indicated that the socioeconomic aspect had little effect on the disease incidences.

Acknowledgements

The authors would like to thank the Ministry of Science and Technology of the Republic of China, Taiwan, for financially supporting this research under Contract No. MOST 109-2221-E-035-025. The authors would like to thank Dr. Bing-Yen Wang, Division of Thoracic Surgery, Department of Surgery, Changhua Christian Hospital, Changhua, Taiwan, for providing the medical expertise of this research.

Authors' contributions

Chen-Jui Liang: Conceptualization, Methodology, Investigation, Writing-Original draft preparation. Ping-Yi Lin: Software, Validation, Investigation. Ying-Chieh Chen: Visualization, Data curation. Jeng-Jong Liang: Supervision, Writing- Reviewing and Editing. All authors read and approved the final manuscript.

Funding

This work was supported by the Ministry of Science and Technology of Taiwan (MOST 109-2221-E-035-025).

Availability of data and materials

All data generated or analyzed during this study are available within the article and its supplementary materials.

Declarations

Competing interests

The authors declare they have no competing interests.

Received: 9 August 2022 Accepted: 14 November 2022
Published online: 13 January 2023

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