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Assessment of the Effect of the Three-Year Action Plan to Fight Air Pollution on Air Quality and Associated Health Benefits in Sichuan Basin, China

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Abstract: To continuously improve air quality, after implementation of the "Clean Air Action Plan, 2013–2017" (CAAP), the "Three-year Action Plan to Fight Air Pollution" (TYP) was further conducted from 2018 to 2020. However, the effectiveness of the TYP remains unclear in one of the major city-clusters of China, the Sichuan Basin. In this study, the bottom-up method was used to quantify the emission reduction during TYP based on the emissions inventory in Sichuan Basin in 2017 and the air pollution control measures adopted from 2018 to 2020 in each city. The reduction of $PM_{2.5}$ concentration and the avoided premature deaths due to implementation of air pollution control measures were assessed by using an integrated meteorology and air quality modeling system and a concentration-response algorithm. Emissions of SO_2, NOx, $PM_{2.5}$, and VOCs in the Sichuan Basin have been reduced by 42.6, 105.2, 40.2, and 136.6 Gg, respectively. The control of non-electricity industry contributed significantly to the emission reduction of all pollutants, accounting for 26–49%. In addition, the control of mobile sources contributes the most to NOx reductions, accounting for 57%. The results illustrate that the focus of air pollution control in Sichuan Basin is still industrial sources. We also found that the emission reduction of NOx, $PM_{2.5}$, and VOCs in Chengdu is significantly higher than that of other cities, which were about 3.4~15.4 times, 2.2~40.1 times, and 4.3~24.4 times that of other cities, respectively. In Sichuan Basin, the average reduction rate of $PM_{2.5}$ concentration due to air pollution control measures was 5% on average, with the highest contributions from industry, mobile source, and dust emission control. The decrease rate in each city ranges between 1~10%, and the decreasing ratios in Dazhou (10%), Chengdu (8%), and Zigong (7%) are relatively higher. The number of premature deaths avoided due to air pollution control measures in Sichuan Basin is estimated to be 22,934. Chengdu and Dazhou have benefitted most from the air pollution control measures, with 6043 and 2713 premature deaths avoided, respectively. Our results indicate that the implementation of TYP has achieved remarkable environmental and health benefits.

Keywords: Three-year Action Plan to Fight Air Pollution; health benefit; Sichuan Basin

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1. Introduction

Fine particulate matter ($PM_{2.5}$) pollution has critical impacts on human health, visibility, and climate change [1–5]. In 2013 and 2018, the Ministry of Ecology and Environment of the People's Republic of China released the "Clean Air Action Plan, 2013–2017" (hereafter "CAAP") and the "Three-year Action Plan to Fight Air Pollution, 2018–2020", aiming to improve air quality. Since then, the reduction of pollution has given rise to significant environmental effects and has led to continuous improvement of air quality across the country [6–9]. As of 2020, both the Yangtze River Delta (YRD) and Pearl River Delta (PRD) regions have met air quality standards [10] in terms of $PM_{2.5}$ concentration.

Consequently, many researchers have carried out quantitative studies to evaluate the environmental and health benefits of the prevention and control measures. On the national level, Zhang et al. (2018) [11] estimated that, during the implementation of the CAAP, anthropogenic sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon monoxide (CO), inhalable particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), black carbon (BC), and organic carbon (OC) emissions in China decreased by 59%, 21%, 23%, 36%, 33%, 28%, and 32%, respectively. In particular, the emissions of power plants and industrial sectors have been significantly reduced. Yang et al. (2016) [12] analyzed the effects of coal control strategy on energy system and local pollutant reduction for 2030, pointing out that with the co-control of both source and end-of-pipe, emissions of SO_2, NO_X, and $PM_{2.5}$ by 2030 will be reduced by 78.85%, 77.56%, and 83.32% compared to the level of 2010. Maji et al. (2018) [13] reported the $PM_{2.5}$-related long-term mortality of 161 cities in China in 2015, indicating that $PM_{2.5}$-related premature mortality was at 652,000, about 6.92% of total deaths in China of year 2015. Gautam et al. (2016) [14] suggested a lack of exposure and monitoring studies to inform personal exposure in the household and rural areas of Asian environments through a literature review. Recently, Wu et al. (2019) [15] and Ma et al. (2019) [16] evaluated the impact of the implementation of CAAP on the number of premature deaths and average life expectancy in cities across China, indicating that it helped to avoid approximately 60,213 premature deaths, and the life expectancy of cities in 2017 had increased 0.16 years compared with the 2013 level. Another recent study by Huang et al. (2021) [17] evaluated the effects of straw burning bans in China and found that after intensive implementation of straw burning bans, national total $PM_{2.5}$ emissions from open crop straw burning activities decreased by 46.9% and the number of premature deaths avoided was 4256 in China.

On regional and urban scales, Wang et al. (2016) [18] evaluated the impact of emission control measures on the air quality in the PRD region with weather research and forecasting (WRF)/community multiscale air quality (CMAQ) model system during 2006–2014. Feng et al. (2019) [19] also used the WRF/CMAQ model system to assess the influence of shipping on air quality and potential human exposure in the YRD region. Tao et al. (2019) [20] pointed out that in the autumn and winter of 2017–2018, long-term measures in Dezhou contributed 9.4% to the improvement of $PM_{2.5}$ concentration. Besides, during the autumn and winter of 2018–2019, the reduction in emissions due to long-term measures was relatively limited (5.0%). In recent years, some researchers have carried out evaluations on the effectiveness of short-term control measures adopted for major events. For example, Liu et al. (2013) [21] used air quality simulation methods and observational data to analyze the air quality improvement effects of emission reduction measures during the Guangzhou Asian Games; Li et al. (2019) [22] assessed the effectiveness of regional joint prevention and control measures during the Second World Internet Conference; and Zhan et al. (2020) [23] evaluated the effects of air pollution prevention and control measures during the "13th Five-Year Plan" (hereafter 13th FYP) period in the PRD region.

Due to its complex topography and unfavorable meteorological conditions, the Sichuan Basin is one of the five most heavily polluted regions in China [3,24–26]. In 2015, 82% of cities in the Sichuan Basin failed to meet the national air quality standards, with seven days of severe pollution. Related studies show that the $PM_{2.5}$ concentration in Chengdu was higher than most major cities in China, including Beijing, Nanjing, and Shanghai [27–30]. Zigong had the highest particle pollution concentration over the whole Yangtze River economic belt of China [31]. To achieve the national air quality goal of the 13th FYP, after the completion of the CAAP, the People's Government of Sichuan Province released the "Implementation of Three-year Action Plan to fight Air Pollution (2018–2020)" (hereafter TYP). The key tasks of the TYP include adjustment of industrial, energy, transportation, and land use structure as well as imposing short-term emissions reduction during severe pollution episodes [32]. Studies have evaluated the effects of air pollution prevention and control measures in Sichuan Basin, but all of them focused on implementation of the CAAP and did not carry out the health benefit assessment. For instance, Zhou et al. (2020) [7] studied the variations of chemical components in $PM_{2.5}$ during 2012–2018 in Neijiang and found that the implementation of the CAAP has effectively controlled coal combustion and industrial emissions. The study only monitored one site, making it difficult to generalize to the whole city, and the effects of mitigation measures were not quantified. Similarly, Ma et al. (2019) [33] assessed the cost–benefit during the CAAP in Chengdu-Chongqing and pointed out that the environmental protection investment of the CAAP was RMB 74.6 billion. However, the environmental and health benefits were not evaluated in the study. Wang et al. (2020) [34] established the air pollutant emission inventory of Sichuan Province from 2013 to 2017 with a top-down approach and conducted a qualitative analysis of the impact of pollutant emission reduction on air quality using pearson correlation coefficient. Quantitative analysis of environmental benefits was also not carried out in that study.

The objective of this study is to quantitatively evaluate the impact of key tasks on $PM_{2.5}$ concentration and associated health benefits during the TYP. We first adopted a bottom-up approach to measure every city's air pollution control measures, put forward a detailed formula for calculating emissions reduction, and established an emission reduction inventory. Furthermore, by using the WRF/CMAQ model system and the concentration-response (C-R) algorithm, we quantified the impact of emission reduction measures on environmental and health benefits. The results of this study are intended to provide scientific basis for the prevention and control of air pollution during the 14th FYP.

2. Methodology

2.1. Emission Estimation

2.1.1. Baseline Emission Inventory

In this work, we collected the activity data of Sichuan Basin in 2017 (such as energy consumption, production output, solvent usage, vehicle stock, construction area, etc.), emission factors, and pollution control technologies, and established an anthropogenic air pollutants emission inventory for Sichuan Basin according to the method described by He (2018) [35] and various inventory compilation guidelines [36]. Air pollutants considered include SO_2, NO_x, CO, PM_{10}, $PM_{2.5}$, volatile organic compounds (VOCs), and ammonia (NH_3). The stationary combustion SO_2 sources are estimated using the material balance algorithm (Equation (1)), and other pollutants are estimated using the emission factor method (Equation (2)).

$$E = \sum_{i=1}^{n} C_k \times W_{i,k} \times S_{i,k} \times (1 - \eta_i) \tag{1}$$

E is the total SO_2 emissions; *i* is the *i*-th enterprise; n is the number of enterprises; k is the fuel type; *Ck* is the fuel coefficient. When *k* is coal burning, *Ck* = 17; when k is fuel oil, *Ck* = 20 [35]; W is the consumption of fuel, *t*; *S* is the sulfur content of the fuel, %; η is the removal efficiency of enterprise control measures, %.

$$E_i = \sum_{p} A_P \times EF_{pi} \times (1 - \eta_i) \tag{2}$$

where *E* is the annual pollutant emission; *i* is the type of pollutant; p is the type of emission source; *A* is the activity level; *EF* is the emission factor. Details of activity data sources, selection of emission factors, and inventory results are detailed in Xu et al. (2020) [37].

2.1.2. Emission Reduction Calculation

A detailed description of the calculation of emission reductions for each source is as follows.

(1) Industry

Industrial sources include power plants, industrial boilers, and industrial processing. The main control measures include eliminating outdated production capacity and upgrading pollutant removal technology. During the TYP, Sichuan Basin had completed a total of 6.9 million kilowatts of ultra-low emission retrofits for coal-fired units, 2 ultra-low emission retrofits for iron and steel, and 40 in-depth treatments on the cement industry. Consequently, this led to a cumulative reduction of crude steel production capacity (4.97 million tons), iron making production capacity (2,270,000 tons) as well as elimination of cement production capacity (1.86 million tons) and flat glass production (2,755,300 weight boxes). In addition, a cumulative of 565 small coal-fired boilers in built-up areas in cities at the county level and above were eliminated and transformation of 36 key enterprises' VOC efficient treatment process were completed. In addition, 3316 automobile maintenance companies adopted low-volatility water-based paints.

The emission reductions of enterprises that were eliminated or had reduced production capacity are equal to the baseline inventory emissions, whereas for those that used ultra-low emission transformation, in-depth governance and upgrades to reduce emissions were calculated based on the activity data and pollution control efficiency in 2020 using the method described in Section 2.1.1. The data were extracted from the Sichuan Province Air Quality Control Comprehensive Decision Support Platform–Emission Inventory Management System (http://103.203.219.137:31000, accessed on 30 September 2016), and they were all self-reported by enterprises. The change in pollution control efficiency is shown in Table 1. The elimination of coal-fired boilers mostly led to the use of natural gas and electricity as alternative energy sources. Therefore, emissions are zero if electricity is used as an alternative energy source. The emission reduction is equal to the emission of the original coal-fired boiler, and if natural gas is used as an alternative energy source, the calculation is carried out by the following formula.

$$\mathrm{P}_i = E_i - \frac{A_p \times Q_m}{Q_t} \times EF_t \times (1 - \eta_s) \tag{3}$$

whereby P is the emission reduction amount, t; i is the i-th enterprise; A_p is the coal consumption of the enterprise, t; Q_m is the calorific value per unit of coal, J/kg; Q_t is the calorific value per unit of natural gas consumption, J/m^3; EF_t is the emission generation coefficient of the natural gas boiler; and η_s is the pollutant removal efficiency of gas boiler, %.

Table 1. Changes of pollution control efficiency before and after renovation of key industries.

Industry	Desulfurization		Denitration		Dust Control		VOCs Control	
	Before	After	Before	After	Before	After	Before	After
Power plants	74%	95%	60%	90%	92%	99.5%	- [a]	-
Cement	14%	20%	46%	80%	90%	99.5%	-	-
Iron and steel	57%	75%	0%	70%	92%	99.5%	-	-
Petroleum processing and coking	73%	78%	13%	24%	88%	93%	38%	64%
Chemical	40%	40%	11%	18%	68%	70%	14%	34%
Furniture	-	-	-	-	-	-	35%	45%
Automobile manufacturing	-	-	-	-	-	-	59%	66%
Printing	-	-	-	-	-	-	33%	39%
Shoemaking	-	-	-	-	-	-	29%	35%
Average	52%	62%	26%	56%	86%	92%	35%	47%

[a] Means that the treatment of such pollutants is not involved.

(2) Mobile source

Mobile source emission reduction measures mainly include phase-out of the old vehicles and the upgrading of oil products. During the TYP, a total of over 1.3 million old vehicles were phased out; National VI standard gasoline and diesel were fully supplied, and selling gasoline and diesel below National VI standard was prohibited. Besides, the "10 ppm ultra-low sulfur diesel" of vehicle diesel, ordinary diesel, and part of marine oil was realized. In this case, the emission reduction of obsolete vehicles is equal to the emission of the corresponding vehicle in the baseline inventory. The calculation formula for the emission reduction of fuel upgrade is as follows:

$$\mathrm{P} = \sum_{j} (EF - EF_i) \times C \times S \tag{4}$$

In this equation, P is the emission reduction; j is the vehicle type; EF is the emission factor before the fuel quality upgrade; EF_i is the emission factor after the upgrade; C is the number of motor vehicles; and S is the average mileage during the corresponding period. Data sources for activity levels and emission factors are based on Xu et al. (2020) [37].

The sulfur content of fuel was 50 ppm in 2017 and 10 ppm in 2020. The pollutant emission correction factors corresponding to different standard sulfur content are shown in Table 2 (He (2018) [35]).

Table 2. The pollutant emission correction factors corresponding to different standard and sulfur content.

Fuel	Emission Standard	Sulfur Content (ppm)	NOx	SO_2	VOCs	$PM_{2.5}$
Gasoline	Below National I	10	0.95	1	0.96	1
Gasoline	National I	10	0.95	1	0.96	1
Gasoline	National II	10	0.95	1	0.96	1
Gasoline	National III	10	0.95	1	0.96	1
Gasoline	National IV	10	0.95	1	0.96	1
Gasoline	National V	10	0.95	1	0.96	1
Gasoline	National VI	10	1	1	1	1
Gasoline	Below National I	50	1	1	1	1
Gasoline	National I	50	1	1	1	1
Gasoline	National II	50	1	1	1	1
Gasoline	National III	50	1	1	1	1
Gasoline	National IV	50	1	1	1	1
Gasoline	National V	50	1	1	1	1
Gasoline	National VI	50	1	1	1	1
Diesel	Below National I	10	0.98	1	0.96	0.77
Diesel	National I	10	0.98	1	0.96	0.77
Diesel	National II	10	0.94	1	0.96	0.85
Diesel	National III	10	0.93	1	0.96	0.8
Diesel	National IV	10	0.84	1	0.76	0.56
Diesel	National V	10	0.84	1	0.76	0.56
Diesel	National VI	10	1	1	1	1
Diesel	Below National I	50	0.98	1	1	0.78
Diesel	National I	50	0.98	1	1	0.78
Diesel	National II	50	0.94	1	1	0.87
Diesel	National III	50	0.93	1	1	0.82
Diesel	National IV	50	0.84	1	0.79	0.57
Diesel	National V	50	0.84	1	0.79	0.57
Diesel	National VI	50	1	1	1	1

(3) Dust

The main measures for dust control are to carry out special inspections, urge construction sites to implement various prevention and control measures, and at the same time increase urban road maintenance and management. Emission reductions are calculated through the improvement of the efficiency of prevention and control measures. This study obtained the dust prevention and control measures for construction sites and main roads in Chengdu, calculated the average removal efficiency of construction sites and roads compared with 2017, and obtained the improvement rate of prevention and control efficiency before and after the implementation of the TYP. The result of improvement rate is applied to other cities in the Sichuan Basin. The prevention and control measures were acquired from the Bureau of Housing and Urban-rural Development, while the prevention and control efficiency of different measures were obtained from the "Technical Guidelines for the Particulate Emission Inventories from Dust (Trial)" issued by the Ministry of Environmental Protection of the People's Republic of China. The emission reduction calculation for this category is as follows:

$$\mathrm{P} = E_i \times \frac{\eta_s - \eta_i}{\eta_i} \tag{5}$$

where P is the emission reduction amount, t; *Ei* is the baseline inventory emission amount, t; η_i is the average control efficiency in 2017; and η_s is the average control efficiency in 2020. In 2017, most dust control measures at construction sites were setting up enclosure, with an average control efficiency of 12%. In 2020, dust control measures included yard coverage and spray, with an average control efficiency of 42%.

(4) Open biomass burning

It is important to note that the open biomass burning is prohibited, and any violation is under strict supervision of local government. According to the characteristics of straw incineration, this study calculated the emission reduction based on the comprehensive utilization efficiency of straw combined with satellite data (Equation (6)). The data on comprehensive utilization efficiency of straw was obtained from the Department of Ecology and Environment of Sichuan Province.

$$\mathrm{P} = \mathrm{AD} \times EF - \mathrm{AD} \times \frac{(1-\rho_i)}{(1-\rho)} \times EF \times \frac{(m - m_i)}{m} \tag{6}$$

where P is the emission reduction amount, AD is the original straw burning amount, *EF* is the original straw emission factor, ρ is the comprehensive utilization rate of the original straw, ρ_i is the comprehensive utilization rate of the straw after the emission reduction is implemented, and m is the statistical period before emission reduction. m_i is the number of satellite fire points in the statistical period after straw burning was banned. The comprehensive utilization efficiency of straw in the Sichuan Basin was 84% in 2017 and 91% in 2020.

(5) Storage and transportation

The control measures for storage and transportation sources are mainly focused on reducing the volatilization of VOCs from gas stations through oil and gas recovery. During the TYP, the Sichuan Basin completed a total of 4299 gas stations oil and gas recovery and transformation. In this category, emission reduction is mainly affected by the efficiency of oil and gas recovery, and emission reduction is computed using Equation (5). The data on oil and gas recovery efficiency was acquired from the Sichuan Provincial Economic and Information Department, which was 50% in 2017 and 80% in 2020.

2.2. Modeling System

We applied the WRF (ver. 3.9)/CMAQ (ver. 5.0.2) modeling system to predict the air quality changes. WRF is a new generation of meso-scale weather forecast model jointly developed by the United States National Center for Atmospheric Research (NCAR) and National Centers for Environmental Prediction (NCEP), which mainly provided meteorological field drivers for air quality simulation. Moreover, LAMBERT projection was applied for the WRF model. The latitude and longitude of the projection center are 103° E and 45° N, respectively; the first parallel latitude is 25° N, and the second parallel latitude is 45° N. The meteorological simulation adopted a two-layer one-way nested simulation area with resolutions of 27 km × 27 km and 9 km × 9 km, respectively. The larger domain covers East Asia and some countries in Southeast Asia, whereas the inner domain covers the entire Sichuan Province. Furthermore, CMAQ were also configured with similar grid domains adopting the projection coordinates consistent with WRF. In addition to reducing the impact of meteorological boundary conditions on the air quality model simulation, the CMAQ model domain is slightly smaller than the WRF domain. The model simulation configurations are shown in Figure 1.

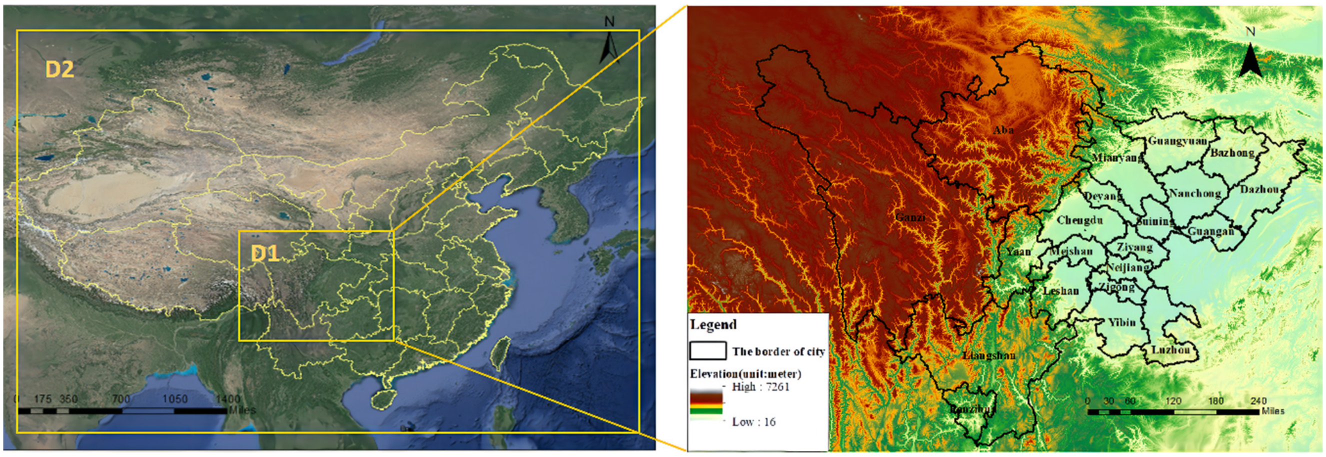

Figure 1. Modeling domain.

The CMAQ model uses meteorological input data and emission source inventory input data to simulate the transport and diffusion process of pollutants, gas-phase chemical processes, liquid phase chemical processes, and aerosol chemical processes. In this study, the CMAQ model was configured with AERO6 module for aerosol simulation; the organic aerosol utilized the SOAP; the CB05 mechanism was used for the gas phase chemistry; while the ACM2 scheme for the vertical diffusion. Additionally, the pollutant emissions were processed using the Sparse Matrix Operator Kernel Emission (SMOKE ver. 5.3) model, which mainly processes emission source inventory data such as temporal allocation, spatial allocation, vertical allocation, and speciation and then provides data that meets the format requirements of the atmospheric chemistry transmission model. The biogenic emissions are processed based on the Model of Emission of Gases and Aerosols from Nature (MEGAN ver. 2.1). We applied the baseline and reduction emission inventory developed for the Sichuan Basin as well as other regional data in the 2017 MEIC inventory developed by Tsinghua University (HTTP://meicmodel.org, accessed on 30 April 2018). This study also adopted 2017 as the base year with the simulation period focusing on four typical months (i.e., January, April, July, and October) to represent winter, spring, summer, and autumn, respectively. The average of the four months represents the annual average.

2.3. Estimation of Health Impacts

In order to estimate the health impacts resulting from long-term exposure to $PM_{2.5}$, we calculated the premature mortality due to cerebrovascular disease (stroke), ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), and lung cancer (LC) based on a widely used C-R model [38–40]:

$$\mathrm{RR(C)} = \begin{cases} 1+\alpha\left(1-e^{-\gamma(C-C_0)^{\delta}}\right),\ if\ C > C_0 \\ 1,\ esle \end{cases} \tag{7}$$

$$\mathrm{H} = \sum B \times P \times \frac{RR-1}{RR} \tag{8}$$

where RR is the relative risk; C refers to the simulated annual average $PM_{2.5}$ concentration; C_0 is the threshold value of $PM_{2.5}$ concentration for each disease; and α, γ, and δ are parameters used to describe the different shapes of the C-R curve among various diseases

(Jiang et al., 2015) [41]. The national premature mortality (H) attributable to $PM_{2.5}$ was estimated using Equation (8) [42], where B is the provincial incidence of a given health impact (https://vizhub.healthdata.org/gbdcompare/, accessed on 16 February 2020) and P is the exposed population of each city in Sichuan derived from the 2017 Statistical Yearbook.

3. Results and Discussions

3.1. Model Verification

In this work, we compared the air pollutant concentration from typical air quality monitoring stations with the corresponding grid cell hourly average pollutant concentration simulated by the CMAQ model to verify the reliability of the modeling results (Table 3). Statistical indexes include Mean Bias (MB), Mean Error (ME), Normalized Mean Bias (NMB), and Normalized Mean Error (NME) [17,22]. The NMB statistical value corresponding to $PM_{2.5}$ in most cities is within ±30%. However, the normalized mean error (NME) of the simulated value is relatively large, and the NME of some cities exceed 40%. Generally, the model underestimates the concentration of $PM_{2.5}$ in each city. We note that the underestimation of $PM_{2.5}$ is related to the underestimation of the precursor emission source inventory and the overestimation of wind speed under static wind conditions, especially wind speed, which is the main parameter that affects the accuracy of simulation results [43]. The overall model is relatively reliable and can be used to evaluate the environmental benefits of emission reduction by subsequent measures.

Table 3. Evaluation of $PM_{2.5}$ concentrations for cities in Sichuan Basin.

City	Observed Average ($\mu g/m^3$)	Simulated Mean ($\mu g/m^3$)	MB ($\mu g/m^3$)	ME ($\mu g/m^3$)	NMB (%)	NME (%)
Chengdu	52.4	33.1	−19.3	27.7	−18.5	48.4
Deyang	47.3	23.9	−23.4	27.4	−37.3	48.9
Mianyang	43.1	22.9	−20.2	23.9	−35.3	44.4
Meishan	48.8	25.3	−23.6	26.4	−40.6	51.0
Ziyang	38.7	31.6	−7.2	17.1	−3.8	42.3
Leshan	52.7	32.0	−20.7	26.3	−29.4	48.6
Ya'an	44.1	22.5	−21.6	23.7	−45.1	49.6
Suining	33.3	24.9	−8.5	15.2	−11.6	38.1
Yibin	51.5	30.5	−21.1	26.7	−31.5	51.5
Zigong	36.0	17.9	−18.1	20.8	−49.7	54.6
Luzhou	48.0	30.8	−17.2	24.5	−23.9	50.9
Neijiang	44.0	32.9	−11.1	24.4	2.8	48.4
Nanchong	40.7	25.7	−14.9	19.6	−27.0	45.8
Dazhou	61.2	56.1	−5.1	28.1	7.1	49.2
Guang'an	33.1	23.0	−10.1	17.8	−11.2	43.7
Guangyuan	23.6	17.6	−0.1	7.4	9.1	49.1
Bazhong	28.4	19.1	−9.3	15.9	−11.4	49.0
Liangshan	16.4	11.4	−4.9	7.1	−29.0	42.9
Panzhihua	27.9	14.3	−13.5	13.9	−45.0	46.8
A'ba	6.0	4.3	−1.7	3.5	−12.6	56.7
Ganzi	9.7	5.2	−4.4	4.6	−45.0	46.6

3.2. Emissions Reduction

3.2.1. Emissions Reduction

The emission reduction of various measures during the TYP are shown in Table 4. The emission reduction of SO_2, NO_x, $PM_{2.5}$, and VOCs in Sichuan Basin in 2020 were 42.6, 105.2, 40.2, and 136.6 Gg, respectively, compared to the year 2017. The SO_2 emission reductions mainly came from the control of non-electric industries, industrial boilers, and ultra-low emission transformation of power plants, which accounted for 49%, 26%, and 24% of the total SO_2 emission reductions, respectively. For NO_x emissions, the mobile source contributed the highest emission reduction, accounting for 57%, followed by non-electricity industry control. The $PM_{2.5}$ emission reductions mainly came from the treatment of non-electric industries, dust sources, and open burning of straw accounting for more than 20% reductions. We also found that VOC emission reduction mainly came from control of non-electric industries as well as solvent use and mobile sources, accounting for 45%, 19%, and 15%, respectively. In general, the control of the non-electricity industry has made a remarkable contribution to the emission reduction of various pollutants, accounting for about 26–49%. This is mainly because, on the one hand, the discharge of pollutants in the non-electric industry was relatively high in 2017, with each pollutant discharge accounting for 21~49% [37]. On the other hand, the control of non-electric industries was the key task during the TYP, including the elimination of outdated production capacity, industrial kiln governance, steel and cement ultra-low emission transformation, etc.

Table 4. Emission reduction of pollution source in Sichuan Basin during TYP (Gg).

Pollution Source	SO_2	NO_x	$PM_{2.5}$	VOCs
Power ultra-low emission retrofit	10.1	7.1	1.8	0
Industrial boiler renovation	11.2	7.2	1.9	7.8
Non-electricity industry control [a]	21.0	27.4	14.2	60.9
Mobile source	0	60.5	2.2	20.0
Source of solvent	0	0	0	25.8
Dust source	0	0	10.1	0
Open burning of straw	0.3	3.0	10.0	10.1
Storage and transportation source	0	0	0	12.0
Total	42.6	105.2	40.2	136.6

[a] Non-electric industries include steel, cement, glass, petroleum processing, coking, and chemical industries.

Wang et al. (2020) [34] evaluated the effectiveness of air pollution prevention and control in the Sichuan Province during the CAAP and showed that the average annual emission reduction of SO_2 was 19.6 Gg and for VOCs was 15.4 Gg. However, in this study, we found that during the TYP, the average annual emission reduction of SO_2 and VOCs was 14.2 Gg and 45.5 Gg, respectively. Notably, the SO_2 emission reduction potential has been significantly narrowed, and the reduction of VOCs has been improved during the TYP.

Additionally, the emission reduction of pollutants in each city is shown in Figure 2. We found that, in Chengdu, the emission reductions of NO_x (26.5 Gg), $PM_{2.5}$ (6.8 Gg), and VOCs (35.7 Gg) were 3.4~15.4 times, 2.2~40.1 times, and 4.3~24.4 times higher than in the other cities (Figure 2), which is related to higher pollutant emissions [37] and is consistent with the research results of Wang et al. (2020) [34]. Further, the difference in SO_2 emission reduction among cities is relatively small. Cities such as Guang'an, Meishan, Deyang, and Dazhou have relatively high emission reductions, mainly due to measures such as ultra-low emission transformation of power plants and renovation of coal-fired boilers.

3.2.2. Emissions Reduction Verification and Implication for Uncertainties

Figure 3 shows the comparison results of pollutant emission reduction ratio and observed concentration reduction ratio of air quality stations in cities from 2017 to 2020. In most cities, the reduction ratio of SO_2, NO_x, and $PM_{2.5}$ emissions was consistent with the reduction ratio of observed concentration. However, there is a big difference between the change of emissions and observed concentration in some cities, such as Guangyuan, Leshan, Nanchong, and Yibin, where the emission reduction ratio of SO_2 is significantly higher than the observed concentration reduction. In Deyang, the NO_x emission in 2020 decreased by 14% compared with 2017, but the NO_2 observed concentration increased by 4%. In Guangyuan, the reduction rate of $PM_{2.5}$ was 6%, but the observed concentration increased by 19%.

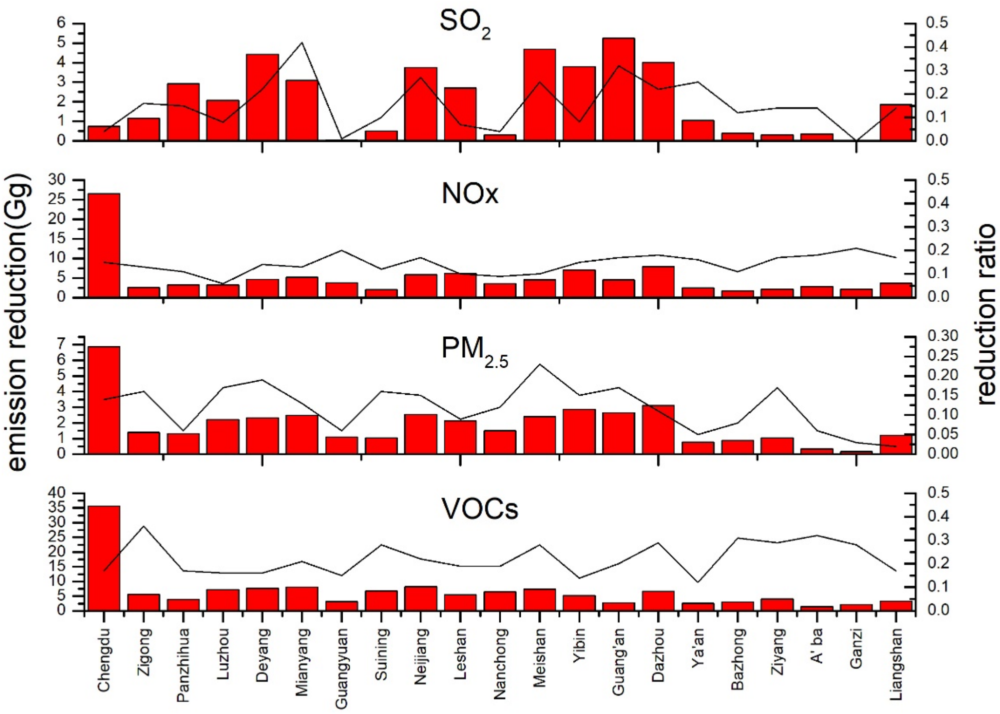

Figure 2. Pollutant emission reduction and reduction ratio in each city.

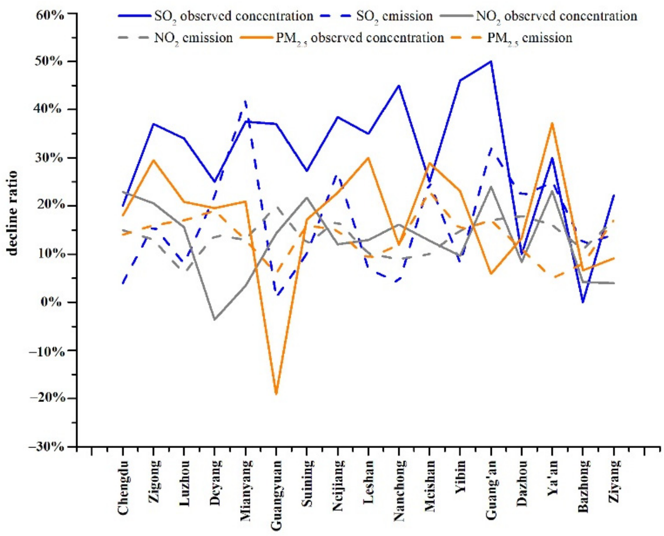

Figure 3. Comparison of emission reduction ratio and observed concentration reduction ratio.

The difference between pollutant emissions and observed concentrations can be attributed to many factors. On one hand, after pollutants are emitted, they will undergo a series of chemical reactions. The reaction process is greatly affected by the real atmosphere, which may be the reason for the large difference between the pollutant emission and the observed concentration of individual cities [11,44,45]. On the other hand, uncertainties in both the observation and the calculation of emission reduction can also contribute to the discrepancies. Relevant studies have shown that the observed NO_2 concentrations relied on chemiluminescence measurements, which may significantly overestimate NO_2 concentrations [46], leading to differences between changes in emissions and observed observations. For emission reduction calculations, there are generally less uncertainties for pollutants (e.g., SO_2 and NO_x) whose emissions are dominated by large sources. However, for pollutants (e.g., $PM_{2.5}$) whose emissions are contributed by scattered emitting sources, there is greater uncertainty [11]. The results calculated by the bottom-up method are relatively accurate [47], but non-compliance with regulations due to lack of inspection will lead to differences between estimated and real-world efficiencies of pollutant emission control facilities [48], which will affect the calculation of emission reduction. In addition, it is difficult to verify the effectiveness of measures such as phasing out coal-fired boilers and improving oil and gas recovery efficiency of gas stations, which may lead to higher uncertainty ranges in emission reduction calculations.

3.3. Impact on $PM_{2.5}$ Concentration

We conducted two simulations with baseline emission inventory and reduced inventory (using 2017 weather conditions for both simulations) to quantify the contribution of emission control measures to $PM_{2.5}$ concentration. Additionally, the average value of simulated concentration in the grid cells corresponding to the location of the typical air quality monitoring stations was considered as the average value of the city. As a result, the decrease proportions of $PM_{2.5}$ concentration caused by the TYP measures in each city are shown in Figure 4.

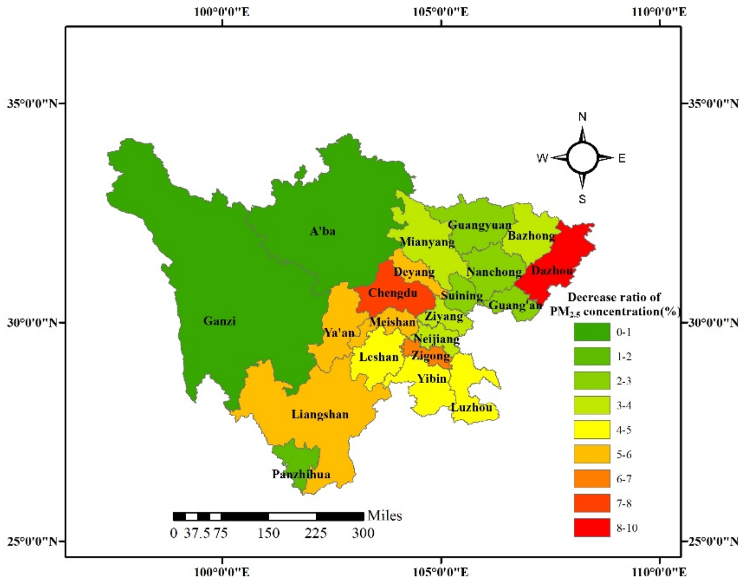

Figure 4. Decrease ratios of $PM_{2.5}$ concentration due to implementation of TYP.

Evidently, the average reduction rate of $PM_{2.5}$ concentration in the Sichuan Basin is 5%, i.e., a decrease of 1.9 $\mu g/m^3$. From 2017 to 2020, the reduction rate of observed $PM_{2.5}$ concentration was 17%, which was higher than the reduction rate of $PM_{2.5}$ caused by pollution emission reduction (5%). The differences are mainly attributed to changes in meteorology, the occurrence of COVID-19 and uncertainties in model simulation. First, the contribution of meteorological changes to $PM_{2.5}$ concentration can reach −70~55% [49–51], and the contribution in the Sichuan Basin from 2000 to 2017 was ±10% [49]. The quantitative contribution of meteorological changes to $PM_{2.5}$ concentration during the TYP needs to be further studied. Second, during the COVID-19 period in 2020, anthropogenic emissions significantly decreased, resulting in a decrease in the concentration of pollutants (e.g., $PM_{2.5}$, SO_2, and NO_2) in most parts of the country [49,52]. The decrease of observed $PM_{2.5}$ concentrations during the TYP can be partly attributed to the epidemic. Lastly, current air quality models are dependent on a priori knowledge [43], which still have substantial bias in simulating air pollutant concentrations, particularly in reproducing $PM_{2.5}$ concentrations [53,54]. In this study, the model simulation underestimated $PM_{2.5}$ concentration, which may understate the contribution of pollution emission reduction to the $PM_{2.5}$ concentration improvement.

The reduction rate in each city ranges between 1~10%, corresponding to absolute decrease of 0.1~4.1 $\mu g/m^3$. Cities including Dazhou, Chengdu, and Zigong have relatively high decline ratios, with 10%, 8%, and 7%, respectively. We also noted that the decrease in $PM_{2.5}$ concentration in each city is closely related to the emission reduction for pollutants. For example, Dazhou, which has the largest decrease, has a relatively high emission reduction for all pollutants. Furthermore, the emission reductions of SO_2, NO_x, $PM_{2.5}$, and VOCs are located in the province. No. 4, No. 2, No. 2, and No. 6 (Figure 2) indicate that the $PM_{2.5}$ concentration of each city is mainly affected by local emissions, which is consistent with the study by Li et al. (2019) [22] in the YRD region. It is worth noting that emission reductions of all pollutants of Zigong are relatively low, all located at the bottom 10 of the Sichuan Basin (Figure 2). The emission reduction ratios of SO_2 and NO_x based on 2017 are relatively low, but the emission reduction ratios of $PM_{2.5}$ and VOCs are at the sixth and first place, respectively (Figure 2). This shows that in addition to the $PM_{2.5}$ emissions, VOCs emissions have a greater impact on the concentration of $PM_{2.5}$ [55]. In addition, related studies show that Zigong is greatly affected by regional transmission, and the emission reduction of surrounding cities has a significant impact on $PM_{2.5}$ in Zigong [56].

Further analysis on the contribution of various measures to the improvement of $PM_{2.5}$ concentration are shown in Figure 5. We found that, during the implementation of TYP, non-electricity industry control and emission reduction measures contributed relatively highly to $PM_{2.5}$ improvement at 2.1%, followed by mobile source emission control and dust control, each at 1.2%. The contribution of various measures to the improvement of $PM_{2.5}$ concentration is consistent with its emission reduction.

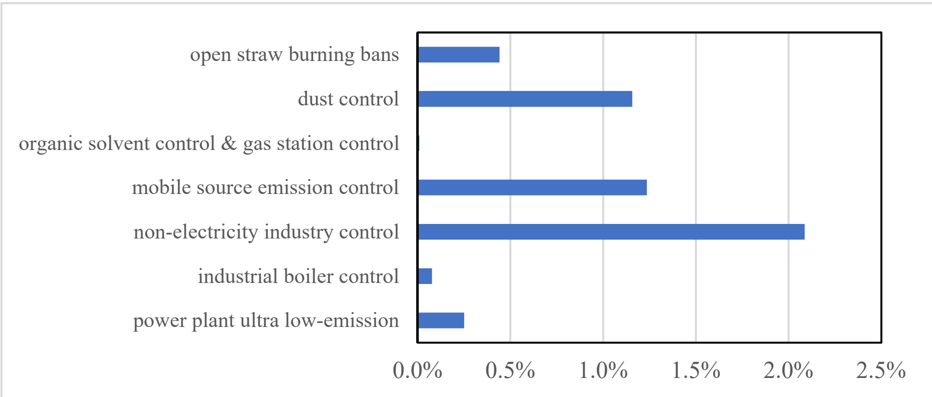

Figure 5. Contributions of each measure in the TYP to $PM_{2.5}$ improvement.

At present, the focus of the reduction of air pollutants in the Sichuan Basin is still based on industrial sources, taking into account both mobile sources and dust sources. With deepening of governance, the potential for industrial emission reduction will be narrowed, and the impact of mobile source emission reduction on air quality improvement will become increasingly prominent [23].

3.4. Impact on Human Health

In 2017, the number of premature deaths caused by $PM_{2.5}$ pollution in the Sichuan Basin was 743,351 (Table 5). Among them, stroke and IHD largely accounted for 59% and 29%, respectively. In the cities, Chengdu had 2.9–156.2 times higher number of premature deaths than other cities, accounting for 21% of the total premature deaths, followed by Neijiang, Dazhou, and Nanchong, all accounting for about 7% of the total premature deaths. The number of premature deaths in cities such as A'ba, Ganzi, and Panzhihua was lower than 10,000. The number of premature deaths appears correlated with the city's $PM_{2.5}$ concentration and population.

Table 5. The number of premature deaths in each city in 2017 and the number of premature deaths avoided after the implementation of TYP (persons).

City	Number of Premature Deaths in 2017					The Number of Premature Deaths Avoided after the Implementation of TYP				
	COPD	IHD	Stroke	LC	Total	COPD	IHD	Stroke	LC	Total
Chengdu	16,355	43,834	81,176	14,526	155,890	876	1279	3093	794	6043
Zigong	3599	9152	17,107	3201	33,059	159	214	438	143	955
Panzhihua	713	2226	3701	626	7266	11	20	62	10	103
Luzhou	4007	10,917	20,105	3556	38,585	135	201	500	123	958
Deyang	4913	13,494	24,769	4358	47,534	201	303	773	183	1461
Mianyang	4758	13,349	24,257	4216	46,579	132	205	542	120	999
Guangyuan	1394	4984	6696	1203	14,277	40	88	272	37	437
Suining	2260	6811	11,751	1992	22,815	51	88	259	47	444
Neijiang	5553	15,548	28,282	4921	54,303	154	238	627	140	1158
Leshan	3755	10,069	18,644	3335	35,802	124	181	432	113	849
Nanchong	4935	14,012	25,291	4370	48,607	104	163	442	94	803
Meishan	3348	9327	17,009	2968	32,651	139	215	564	127	1044
Yibin	4752	12,654	23,477	4222	45,104	156	224	526	142	1049
Guang'an	2430	7404	12,638	2139	24,611	55	97	291	51	494
Dazhou	5154	14,288	26,120	4570	50,133	360	557	1468	328	2713
Ya'an	1215	3396	6184	1077	11,873	51	79	208	46	383
Bazhong	2230	7062	11,548	1956	22,796	71	133	411	66	681
Ziyang	1855	5687	9646	1632	18,820	57	101	305	52	516
A'ba	112	553	242	90	998	2	8	13	2	25
Ganzi	261	1014	1124	222	2622	3	7	20	3	33
Liangshan	2833	10,096	13,651	2446	29,025	164	362	1111	150	1787
Sichuan Basin	76,431	215,877	383,416	67,626	743,351	3046	4761	12,358	2769	22,934

After implementation of TYP, the number of premature deaths avoided due to the reduction of $PM_{2.5}$ concentration in the Sichuan Basin was 22,934, and the number of deaths avoided due to stroke and IHD accounted for about 54% and 21% of the former number, respectively. Consequently, we found relatively high number of avoided premature deaths in Chengdu (6043) and Dazhou (2713), accounting for 26% and 12% of the Sichuan Basin, respectively. This is related to the large decrease in $PM_{2.5}$ concentration. Although the $PM_{2.5}$ concentration decline of Zigong was relatively high, the number of premature deaths avoided due to the improvement of $PM_{2.5}$ concentration was only 955. This is mainly attributed to its small population, which was about 2.9 million at the end of 2017, accounting for only 3% of the total population of the Sichuan Basin (Sichuan Provincial Bureau of Statistics, http://tjj.sc.gov.cn/tjnj/cs/2018/indexch.htm, accessed on 15 November 2018).

The results of Ding et al. (2019) [57] showed that between 2013 and 2017 in the Sichuan Basin, the number of premature deaths avoided due to the decrease of $PM_{2.5}$ concentration was 19,000, and the average number of premature deaths avoided was 3900 each year. However, in our study, we found that during the TYP in the Sichuan Basin (2018–2020), the average annual number of premature deaths avoided due to a decrease in $PM_{2.5}$ concentration was 7600, which is significantly greater than the results of 2013–2017. The dynamic changes of population and $PM_{2.5}$ concentration significantly affect the health assessment result [58]. The main difference between these two studies could be better explained by the difference in mortality rate applied in the calculations. In our study, we obtained the mortality rate for 2017 of each city (ranging from 0.05% to 0.09%) from the Sichuan Statistical Yearbook. On the contrary, Ding et al. (2019) [57] divided the death toll in Sichuan Province by the total population in the China Statistical Yearbook to obtain a death rate of 0.006%.

The product of urban population and the observed concentration of $PM_{2.5}$ is used to express the degree of pollution exposure risk [59]. The range of changes in the degree of $PM_{2.5}$ exposure risk in cities before and after the implementation of the TYP is shown in Figure 6. The increase in the number of urban residents combined with a drop in $PM_{2.5}$

concentrations resulted in a 16% drop in $PM_{2.5}$ exposure in the Sichuan Basin after the TYP was implemented. In most cities, population exposure levels of $PM_{2.5}$ decreased by 3% to 48%. However, the degree of $PM_{2.5}$ exposure in Guangyuan, A'ba, and Liangshan increased by 21%, 49%, and 9%, respectively, mainly because their observed $PM_{2.5}$ concentration increased in 2020 compared with 2017.

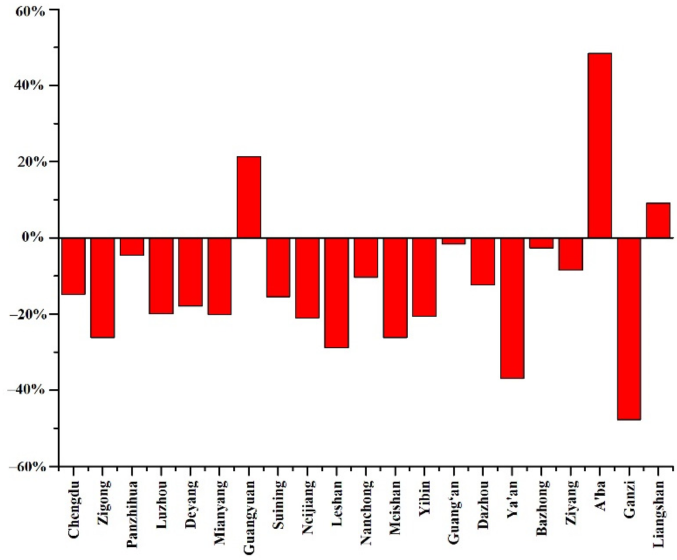

Figure 6. The change of $PM_{2.5}$ exposure risk before and after the implementation of the TYP.

4. Conclusions

In this study, emission reductions of the Sichuan Basin were calculated during the TYP. The WRF/CMAQ model and C-R algorithm were used to simulate the impact of pollution reduction on $PM_{2.5}$ concentration and the health benefits.

After implementation of the TYP, the emissions of SO_2, NO_x, $PM_{2.5}$, and VOCs in Sichuan Basin were reduced by 42.6, 105.2, 40.2, and 136.6 Gg, respectively. During the TYP, the emission reduction of the Sichuan Basin was still mainly focused on industry. It was found that the control of the non-electricity industry contributed significantly to the emission reduction of all pollutants, accounting for 26~49% of the total number. The pollutant emission reduction ratios are consistent with the observed concentration reduction ratios in most cities.

The average decline ratio of $PM_{2.5}$ concentration in the Sichuan Basin due to implementation of TYP was around 5% on average, and the decreasing rate of each city ranges between 1~10%. Cities including Dazhou, Chengdu, and Zigong had relatively high decline rates. Non-electric industry governance (2.1%), mobile source emission control (1.2%), and dust control (1.2%) have relatively high contributions to the improvement of $PM_{2.5}$ over the Sichuan Basin area.

The implementation of the TYP during 2018–2020 also generates significant health benefits. The number of premature deaths avoided due to the decrease of $PM_{2.5}$ concentration in the Sichuan Basin is estimated to be 22,934. Chengdu and Dazhou had the most avoided premature deaths due to a significant decline in $PM_{2.5}$ concentration and their large population, which accounted for 26% and 12% in the Sichuan Basin.

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