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China's potential SO_2 emissions from coal by 2050

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ABSTRACT

Coal is the dominant emitter of Sulfur Dioxide (SO_2) in some countries, comprising ~92% of total emissions in China. Mitigation of these emissions can be driven by a number of factors, such as energy-efficiency improvements, installation of scrubbers, and use of renewable energy. This study evaluates the historical reduction of overall SO_2 emission intensity from coal consumption for 30 Chinese provinces between 2000 and 2016. These trends are further combined with expected coal use from 2020 to 2050 along with scenarios of future power generation to explore China's future SO_2 emissions. The results show that provinces starting with a high emission intensity in general have higher reduction rates. By 2050, China's potential SO_2 emissions are between 3.9 Mt and 4.1 Mt, and industry mitigation efforts, such as the installation of scrubbers, appear to contribute most to abatement. Additionally, this study estimates the impact on global average temperatures from SO_2 mitigation due to the adoption of renewables in the electric sector using the MAGICC model and find an increase of ~0.01 °C by 2050. Considering the reduced abatement opportunities of desulfurization technologies and climate change effects of coal combustion, renewable energy provides the most promising option for SO_2 mitigation.

1. Introduction

China's GDP reached 10.8 trillion USD (in 2010 constant prices) by 2018, contributing 13.1% to the world economy (World Bank, 2020). This growth has led to increasing environmental pressures and attention to sustainable development. China is now the largest global energy consumer and the second-largest emitter of SO_2 behind India (Li et al., 2011, 2017a; Zhang et al., 2016). Further, coal is the largest source of energy in China, which contributes significantly to SO_2 emissions. According to Su et al. (2011), ~92% of SO_2 emissions are from coal consumption in 2007 in China. Between 2000 and 2015, coal consumption contributed ~64–73% of total energy consumption (Fig. 1(a)). Moreover, of the total primary energy consumption from coal, ~42–52% was combusted in the electric sector (Fig. 1(b)). Furthermore, SO_2 emissions from the electric sector contribute ~27%–47% of the total (Fig. 1(c)). In addition, Fig. 1(b) and (c) show that the manufacturing sector contributes a large amount to energy consumption and SO_2 emissions along with the residential consumption of coal.

Efforts to reduce SO_2 emissions take three different forms: pre-combustion measures (i.e. preferential use of low-sulfur content coal), process treatment during combustion (mainly efficiency improvements), and end-of-pipe treatment after combustion (the installation of scrubbers) (Wang et al., 2017; Cheng and Zhang, 2018). With these more technical measures, an energy transition away from coal can also reduce emissions, for example by adopting low-carbon energy like renewables or nuclear (Arvesen and Hertwich (2011, 2012); Nazari et al. (2010); Zhang et al. (2007); Xie et al. (2018)). Currently, the deployment of scrubbers is an important measure to reduce SO_2 emissions in the electric sector. However, according to Zhang et al. (2015), there is limited scope for further reduction in SO_2 emissions by installing more scrubbers at power plants. Therefore, the adoption of renewable energy is a key strategy to further reduce SO_2 emissions in the electric sector (Lu et al., 2010; Zhao et al., 2008).

In China, SO_2 emissions reduced by ~6.8% from 2000 to 2015. However, Fig. 1(a) shows that the coal consumption has more than doubled during the same time, indicating a large reduction of SO_2 emissions per unit of coal consumption over time. Based on the past reductions in SO_2 emission intensity (i.e., SO_2 emissions per unit of coal consumption), we can investigate how SO_2 emissions may decline in the future. Here, learning curves can be used to describe a relationship

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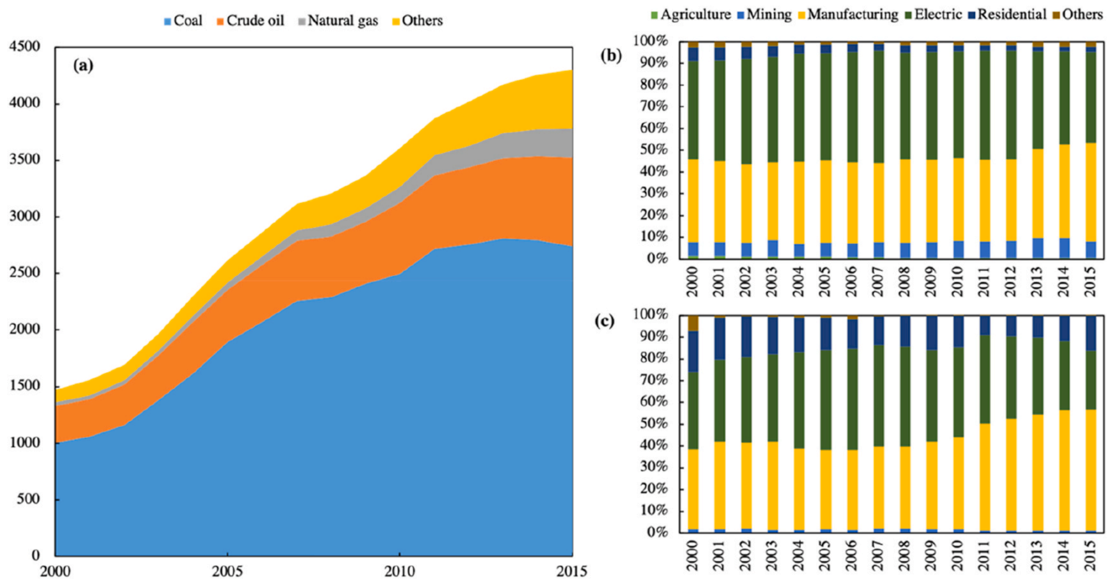

Fig. 1. (a) Energy consumption by fuel types (Unit: Mtce), shares of (b) Coal consumption and (c) SO_2 emissions in different sectors during 2000–2015.

between cost reductions and cumulative production or capacity (Pan and Köhler, 2007; Yu et al., 2011). While traditionally used in economic fields, learning curves are increasingly applied in environmental fields. For example, Guo et al. (2016) and Li et al. (2017b) used them to investigate carbon mitigation in China. Several kinds of learning mechanisms are usually identified: learning by doing, learning by researching, learning by using, learning by interacting, and economies of scale (Kahouli-Brahmi, 2008). In this study, a learning curve approach is adopted to describe how SO_2 emissions reduce with cumulative coal consumption. However, these learning mechanisms are usually applied to the learning effect of a given technology (Kahouli-Brahmi, 2008). In SO_2 mitigation efforts, many kinds of technologies are adopted, e.g., technological advancement of scrubber efficiency and energy efficiency. Also, since the technology adoption (such as the roll-out of scrubbers nationally) has played a major role in emission reduction over time, the term "adoption effect" rather than "learning effect" is used in this study.

Due to differences between provinces, improvements in SO_2 emission intensity also differ. Although adoption effects can transfer across regions, with the more polluting regions benefitting from technologies developed in the less polluting regions, there is evidence of significant policy barriers to this technology diffusion (Li et al., 2014). Therefore, it is assumed that an analysis of adoption effects on SO_2 emissions has to be made at the provincial level.

Sulfate aerosols from SO_2 emissions also have important climatic implications (Carmichael et al., 2002; Xie et al., 2016). Due to the cooling impact of aerosols, a reduction in SO_2 emissions could lead to temperature increases (Hayhoe et al., 2002; Kaufmann et al., 2011, 2006; Shindell and Faluvegi, 2010). Although most investigations of this effect have been on a global level (Ward, 2009; Ward et al., 2010), Berntsen et al. (2006) suggested that emissions reductions in different locations had different impacts on climate. Furthermore, according to Berntsen et al. (2006), the cooling climatic effect via sulfate aerosols would disappear quickly after mitigation since sulfate aerosols are short-lived components and regionally dependent. Due to the high proportion of coal consumption in China and India, Shindell and Faluvegi (2010) estimated the climatic effect of emissions from coal-fired power plants for different scenarios of coal consumption and pollution control. They found different climate responses across the Northern Hemisphere, Southern Hemisphere extratropics, and Arctic. As renewables displace coal generation, there may be a climatic effect from reducing atmospheric aerosol loading. Few studies have focused on the impact of renewable energy development on SO_2 emissions (Boudri et al., 2002; Shrestha and Timilsina, 1997; Xie et al., 2018; Yang et al., 2016), and none at the provincial level. Considering the different provincial characteristics and the negative impact of SO_2 emissions (Qian et al., 2020, 2019), including the impact of renewables is essential. To the best of our knowledge, there is no research analyzing the climatic effect of SO_2 change due to the adoption of renewable energy in specific regions.

In this study, the improvement of SO_2 emission intensities is explored based on historical information of SO_2 emissions and coal consumption. Given the importance of the electricity sector on SO_2 emissions, special attention is given to the substitution of renewable generation for coal generation into the future. For the first time, this study aims to analyze the impact of increased levels of renewable energy in the electric power sector across 30 provinces of China on the overall SO_2 emissions, as well as the impact of Chinese mitigated SO_2 emissions on the future global climate.

2. Methodology and data

2.1. SO_2 intensity adoption curve (SIAC)

Learning curves are usually applied to describe how the cost or environmental impact of a technology declines as it is deployed. Due to the diversity of SO_2 mitigation approaches, this study develops an adoption curve, incorporating more than technical learning alone, to investigate the change of SO_2 emission intensity. The adoption curve for SO_2 emissions per unit of coal consumption is calculated as:

$$SI = SI_0 \cdot X^{-b} \quad (1)$$

where *SI* represents the SO_2 emission intensity, i.e., SO_2 emissions per unit of coal consumption in kg/tce (tonne of coal equivalent). SI_0 denotes the initial SO_2 emissions with fixed values, which can be determined by initial coal consumption, energy structure, and SO_2 emissions. *X* represents the cumulative coal consumption in Mtce (million tonnes of coal equivalent). -*b* gives the environmental adoption coefficient of cumulative coal consumption. $b > 0$ indicates that the SO_2 emission intensity varies inversely with a change in *X* and vice versa. Theoretically, the equation includes an error term, but it is typically omitted in real-world applications (Fukui et al., 2017; Kahouli-Brahmi, 2008; Rubin et al., 2004; Yu et al., 2011). According to Eq. (1), each doubling of cumulative coal consumption results in a reduction of ($1-2^{-b}$) in SO_2

emission intensity, which is defined as the adoption rate, while the quantity 2^{-b} is defined as the progress ratio (Rubin et al., 2004).

Eq. (1) indicates the rate of change of SO_2 emission intensity caused by each marginal change of coal consumption. According to Yu et al. (2015), this study also adopts this change as the abatement potential of SO_2 emission intensity.

The SO_2 intensity change per marginal change in coal consumption can be derived by calculating the partial derivative of X in Eq. (1), which is expressed as follows:

$$\frac{\partial SI}{\partial X} = SI_0 \cdot (-b) \cdot X^{-b-1} \tag{2}$$

Once Eq. (2) is calculated, the reduction potential of SI can be obtained by multiplying Eq. (2) with the change of X, which is given as:

$$\Delta SI = \frac{\partial SI}{\partial X} \cdot \Delta X = \frac{\partial SI}{\partial X} \cdot (X_t - X_0) \tag{3}$$

In Eq. (3), $X_t$and X_0 denote the cumulative coal consumption in year t and 0, respectively. Based on Eq. (3), the SO_2 emission intensity in the future can be obtained, which can be expressed as:

$$SI_t = SI_0 + \Delta SI \tag{4}$$

Once Eq. (4) is calculated, the reduction potential of SO_2 emissions for a planned period can be obtained as:

$$\Delta S = SI_0 \cdot COAL_0 - SI_t \cdot COAL_t \tag{5}$$

In Eq. (5), $COAL_t$ and $COAL_0$ denote the coal consumption in year t and 0, respectively.

2.2. Climatic effect of SO_2 emissions

To estimate the effect of SO_2 emissions on the global mean temperature, the MAGICC6 (Model for the Assessment of Greenhouse gas Induced Climate Change version 6) model (Meinshausen et al., 2011) is adopted in this study. MAGICC6 is a reduced-complexity coupled gas-cycle climate model, which has been widely used in various studies (Jeganathan and Andimuthu, 2013; Osborn et al., 2006; Sharma et al., 2012). According to different levels of concentrations, four representative concentration pathway (RCP) emission scenarios are usually applied: RCP2.6 (Van Vuuren et al., 2007), RCP4.5 (Wise et al., 2009), RCP6.0 (Fujino et al., 2006), and RCP8.5 (Riahi et al., 2007). When investigating the climatic effect, MAGICC6 simulates the combined effect of up to 23 types of emissions. While renewable energy expansion can play multiple roles in the concentrations of different gases, desulfurization technologies only influence one: SO_2. In this study, we aimed to disentangle the climatic effect of SO_2 emissions from the confounding effect of other emissions. Therefore, a MAGICC emissions scenario was constructed where the data of SO_2 emissions is from the scenarios described below, and the other 22 annual emissions are set to zero. Otherwise, the model was run using standard parameter settings.

2.3. SO_2 mitigation in different sectors

Coal is responsible for over 90% of the SO_2 emissions in China and mainly used in the household and industrial sectors. In the household sector, coal is mainly used for cooking and heating. While in the industrial sector, it is mainly used for power generation, heat production, or other production agents (e.g. steel production). Specifically, around 42–52% of the coal is used for electricity production, which makes it a large SO_2 emitter.

In addition, SO_2 mitigation approaches vary across sectors. In the residential sector, stove efficiency is very important (Liu et al., 2016a) whereas scrubber installation is important in the electricity sector (but scrubbers are difficult to deploy in other industrial and residential sectors (Chow, 2010; Xu et al., 2009)). For other industrial sectors, technical innovation to improve energy efficiency is an important approach. A vital solution across all sectors is to electrify and replace coal with renewable energy.

Turning to scrubbers specifically, their SO_2 removal rate has increased significantly as a result of improvements in scrubber quality and operation (Xu, 2011). According to Xu (2011), 73.2% of SO_2 emissions were removed from coal power plants with SO_2 scrubbers. Later, Hering and Poncet (2014) reported that scrubbers can remove more than 95% of SO_2 in the flue gas in the coal power plants. To promote scrubber installation, the Chinese government has implemented a series of policies, e.g., an on-grid tariff premium (Schreifels et al., 2012) and operational priority for power plants with scrubbers (Liu et al., 2016b). With the supporting policies and technological improvement in scrubbers, the proportion of coal power plants equipped with scrubbers increased from 12% in 2005 to 83% in 2010 and further to 99% by the end of 2015. However, once scrubbers are installed across the whole power fleet, and realize a removal rate of over 95%, further reductions from scrubbers becomes limited. The ultimate solution is a transition to low-emission energy generation technologies such as renewables or nuclear. Since a shift of coal to renewables is relatively easy in the power sector but more complex in other industry sectors, we tried to first investigate the expansion of renewables in the electric sector in this study.

Table 1
Annual growth and share of renewable energy in the electric sector under different scenarios.

	No policies scenario (NPS)	Current policies scenario (CPS)	Renewable energy expansion scenario (RES)	Below 2 °C scenario (B2S)
Annual growth rate of electric power				
	1.7%	1.7%	1.7%	1.4%
Share of renewable energy in power generation				
2020	25%	33%	45%	45%
2030	25%	51%	68%	68%
2040	25%	65%	80%	80%
2050	25%	78%	85%	85%

2.4. Scenarios for a shift of coal to renewables in the electric sector

To recap, it is assumed that SO_2 reductions can be driven by technological improvements or a shift to renewable energy. In order to capture the impact of transitioning to renewables, four different scenarios with different shares of renewables (driven not only by SO_2 mitigation efforts but also climate policies) are designed in this study. First, a “no policies” scenario (NPS) which assumes no change in the share of renewable energy relative to 2016. Second, a “current policies” scenario (CPS) representing the same annual growth rate of electric power as NPS, but with a larger share of renewable energy that reflects China’s nationally determined contribution to climate mitigation under the 2015 Paris Agreement. Third, a “below 2 °C” scenario (B2S), representing a lower annual growth rate of electric power and a larger share of renewable energy. Fourth, and finally, to analyze the effects of the electric demand and renewable energy on SO_2 emissions separately, a “renewable energy expansion” scenario (RES) is developed, where the annual growth rate of electric power is the same as under CPS, while the share of renewable energy is the same as under B2S. A summary of the scenarios is presented in Table 1.

In this study, data for the annual growth rate of electric power is taken from the *World and China Energy Outlook 2050* (CNPC, 2016). The *China Renewable Energy Outlook 2017* provided the trajectory for renewable energy expansion and the CPS and B2S have the same share of renewable energy in power generation. When predicting the energy development under CPS and B2S, the *China Renewable Energy Outlook 2017* assumed no construction of nuclear power plants. Analogously, this study assumed that nuclear power generation under the four scenarios is the same as in 2016. The four scenarios assume coal

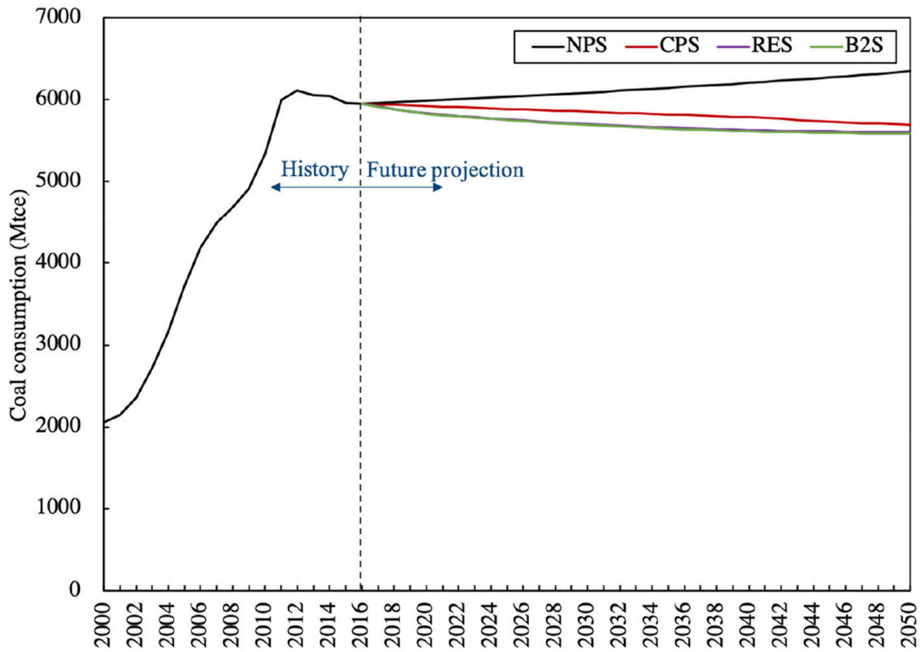

Fig. 2. Coal consumption under four scenarios in 2000–2050.

Table 2
Annualized growth rate assumptions for thermal power generation under four scenarios.

	2016–2020	2020–2030	2030–2040	2040–2050
NPS	1.7%	1.7%	1.7%	1.7%
CPS	−1.3%	−1.5%	−1.8%	−3.2%
RES	−6.4%	−4.0%	−3.3%	−1.3%
B2S	−6.7%	−4.2%	−3.6%	−1.7%

Table 3
Descriptive statistics at the provincial level.

Index	Unit	Sample size[a]	Min	Max	Mean	SD
SO_2 emission intensity	kg/tce	510	1.2	26.7	6.0	3.9
Cumulative coal consumption	Mtce	510	2.8	6993.7	1107.9	1238.9

[a] The sample size is the number of observations on 30 provinces for 17 years (during 2000–2016).

consumption by other sectors is the same as in 2016. As shown in Fig. 2, coal consumption increases under NPS but decreases in the others. Additionally, Table 2 shows that decreasing thermal power generation under the B2S is always larger than those under the NPS over the same period (thermal power includes coal, petroleum, natural gas, etc., though we only consider coal consumption as thermal power in this study). Furthermore, coal consumption under RES and B2S is almost the same and shows that the impact on reducing electricity demand on coal consumption is minor compared to the renewable transition.

2.5. Data sources

This study analyzes the SO_2 emission intensity of 30 provinces and municipalities in China during 2000–2016. SO_2 emissions and coal consumption data are obtained from the *China Statistical Yearbook* (NBS, 2017a) and the *China Energy Statistical Yearbook* (NBS, 2017b), respectively. When estimating the effect of renewable energy expansion in the electric sector on overall SO_2 emissions, electricity generation data from different sources are needed from the *China Electric Power Yearbook* (IEA, 2016). Conversion factors for coal (kgce/kg) and electricity (kgce/KWh) are adopted from the *China Energy Statistical Yearbook*[1] (NBS, 2017b). SO_2 emission intensities and cumulative coal consumption for 30 provinces during 2000–2016 are shown in Table 3.

In order to facilitate the calculation in this study, Eq. (1) is linearized using a natural logarithmic transformation:

$$\ln(SI) = \ln(SI_0) - b\ \ln(X) \tag{6}$$

When estimating the coefficients, the initial step is to check the data stability. In this study, the SO_2 emission intensity and cumulative coal consumption data are tested to be stationary with two unit root tests Levin, Lin & Chu (Levin et al., 2002) and ADF-Fisher (Maddala and Wu, 1999) (see Table S1 for results). Furthermore, the F-test results shown in Table S2 suggest a model arrangement with both variable intercepts and coefficients. Considering the differences in economic development, resource endowment, and other technical levels among provinces, it is reasonable to express Eq. (6) as:

$$ln\left(SI_{i,t}\right) = \ln\left(SI_{i,0}\right) - b_{1i} ln\left(X_{i,t}\right) \tag{7}$$

where i = 1, 2, …, 30 represent the 30 provinces and time t = 2000, 2005, …, 2016. The other variables in Eq. (7) are the same as in Eq. (1).

3. Results and discussions

3.1. Provincial SO_2 emissions

Historically, total SO_2 emissions in China decreased by 43.9%, from 19.7 Mt in 2000 to 11.0 Mt in 2016. SO_2 emission intensities experienced a large decline, from 9.6 kg/tce to 1.9 kg/tce. There were significant differences in SO_2 emissions and intensities among provinces (see Fig. 3 and Fig. 4). Provinces with heavy industries or large populations were large SO_2 emitters, e.g., Shandong, Hebei, and Inner Mongolia (Fig. 3). In 2016, Shandong, Hebei, Shanxi, Guizhou, and

[1] Based on historical data, we calculated that the proportion of coal-fired power to the total thermal power is about 96%. Therefore, we adopted this percentage to estimate the coal-fired power generation.

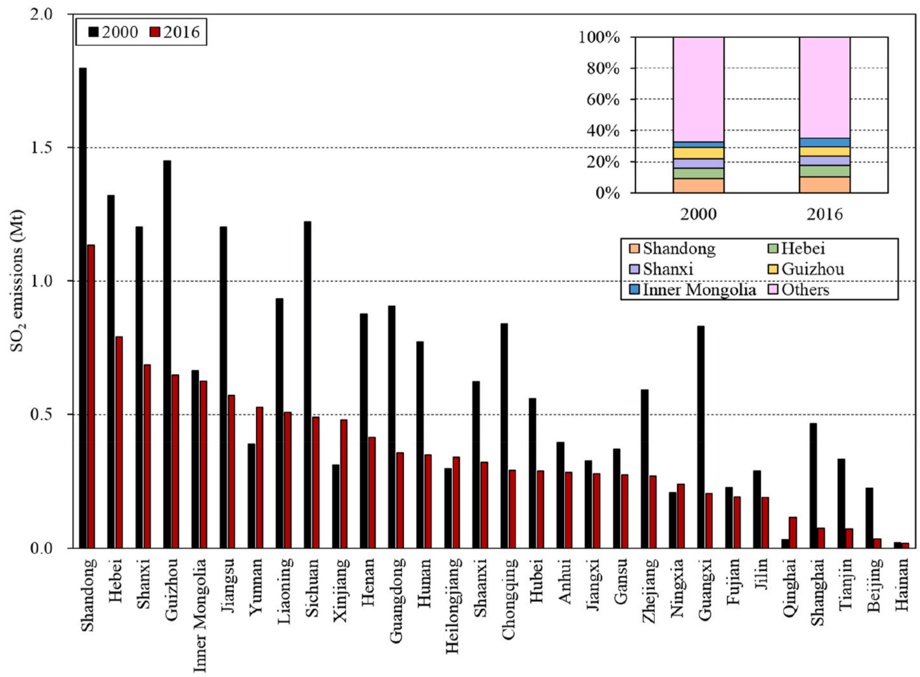

Fig. 3. SO_2 emissions of 30 provinces in 2000 and 2016. Inset shows the emission share of the five largest emitters in this study in 2000 and 2016.

Inner Mongolia were the largest emitters, accounting for 35.2% of the Chinese total. Shandong was the largest SO_2 emitter due to its heavy industry and large population, while Hainan was the lowest SO_2 emitter due to low levels of industry and population, consistent with Guo et al. (2016). In addition, SO_2 emissions in most provinces declined over time, with emissions in developed provinces reducing fastest. For example, during 2000–2016, SO_2 emissions in Beijing and Shanghai reduced by 85% and 84%, respectively. However, SO_2 emissions in some provinces increased, especially in the underdeveloped northwestern provinces. For example, emissions in Qinghai increased by 255% during 2000–2016 and ranked the highest in the growth of emissions, followed by Xinjiang (55%).

In terms of the SO_2 emission intensity of coal consumption, Fig. 4 shows that some underdeveloped southern provinces with heavy industries had a larger SO_2 emission intensity, e.g., Guangxi, Guizhou, Sichuan, and Hunan. In northeastern provinces, the sulfur content of coal is low, resulting in lower emissions (consistent with Zhao et al. (2008)). Some developed provinces also saw low emission intensities, e.g., Beijing, Shanghai, Fujian, and Zhejiang. Among the 30 provinces, the highest SO_2 emission intensity in 2016 was 5.0 kg/tce for Yunnan, followed by 4.1 kg/tce for Qinghai and 3.9 kg/tce for Sichuan. Emission intensities in most provinces declined where Shaanxi, Guangxi, Tianjin, Hunan, and Shandong showed the largest rates of reduction, with 92.8%, 91.7%, 87.5%, 86.9%, and 86.6%, respectively between 2000 and 2016. Most provinces with a high SO_2 emission intensity in the initial year (2000) showed a faster decline, e.g., Guangxi, Hunan, Shaanxi, Shandong, and Ningxia.

3.2. Adoption coefficient analysis

Fig. 4 shows large differences in SO_2 emission intensities among the 30 provinces, indicating large variations in factors that support desulfurization. The results of the adoption curve model are shown in Table 4. As shown in Table 4, the value of adjusted R^2 is 0.84, indicating a reasonable fit of Eq. (7). The F-statistic is 45 and the p-value is < 0.01, suggesting that this model shows statistically significant results.

Adoption coefficients (the parameter -b) of cumulative coal consumption for most provinces (except Qinghai) were <0, indicating that as cumulative coal consumption increased, SO_2 mitigation efforts increased (see Table 4 for further details). However, coefficients varied across provinces. There were 24 provinces with adoption coefficients lower than the national average (-0.25) where Guangxi saw the lowest (-0.63, meaning a 1% increase in cumulative coal consumption drives a -0.6% change in SO_2 intensity). Among the remaining provinces, Qinghai's adoption coefficient was the highest (0.09) and the only province with a negative adoption effect. This may be due to low environmental investments in Qinghai since it is one of the poorer provinces.

Provinces with high SO_2 emission intensities in 2000 also had high adoption rates. This is consistent with Pacini and Silveira (2014) who found that carbon intensities over time depended on the level at the start of the period (see Fig. 5). Provinces with high SO_2 emission intensities in the year 2000, e.g., Guangxi, Chongqing, and Guizhou, saw faster emission declines than provinces with lower SO_2 intensities, e.g., Heilongjiang, Qinghai, and Jilin. However, there were several exceptions where provinces displayed high initial SO_2 emission intensities but low adoption rates (e.g., Gansu) or low initial SO_2 emission intensities but high adoption rates (e.g., Shanghai, Zhejiang, and Inner Mongolia). For Gansu, although the emission intensity in 2000 was high, the rate of reduction (71.3%) was lower than the national rate (80.6%), resulting in a higher intensity by 2016. Analogously, although the emission intensities of Shanghai, Zhejiang, and Inner Mongolia in 2000 were low, the rates of decline were faster than the national average, reaching up to 84.5%, 82.5%, and 84.8%, respectively.

3.3. Outlook for the impact of renewable energy on SO_2 emissions

3.3.1. Reduction potential of SO_2 emissions at the national level

Based on the four scenarios introduced in Section 2.4 and the adoption curves derived in Section 3.2, the future reduction potential of SO_2 emissions can be calculated. As shown in Fig. 6, overall SO_2 emissions could be reduced to 4.1 Mt and 3.9 Mt under NPS and the other three scenarios in 2050, with an increased level of renewable power generation from 25% to ~80%. Compared to 2016, emissions would reduce by ~62–64% under the four scenarios by 2050. The provincial SO_2 emission intensity and SO_2 emissions in 2050 are shown in Table S4

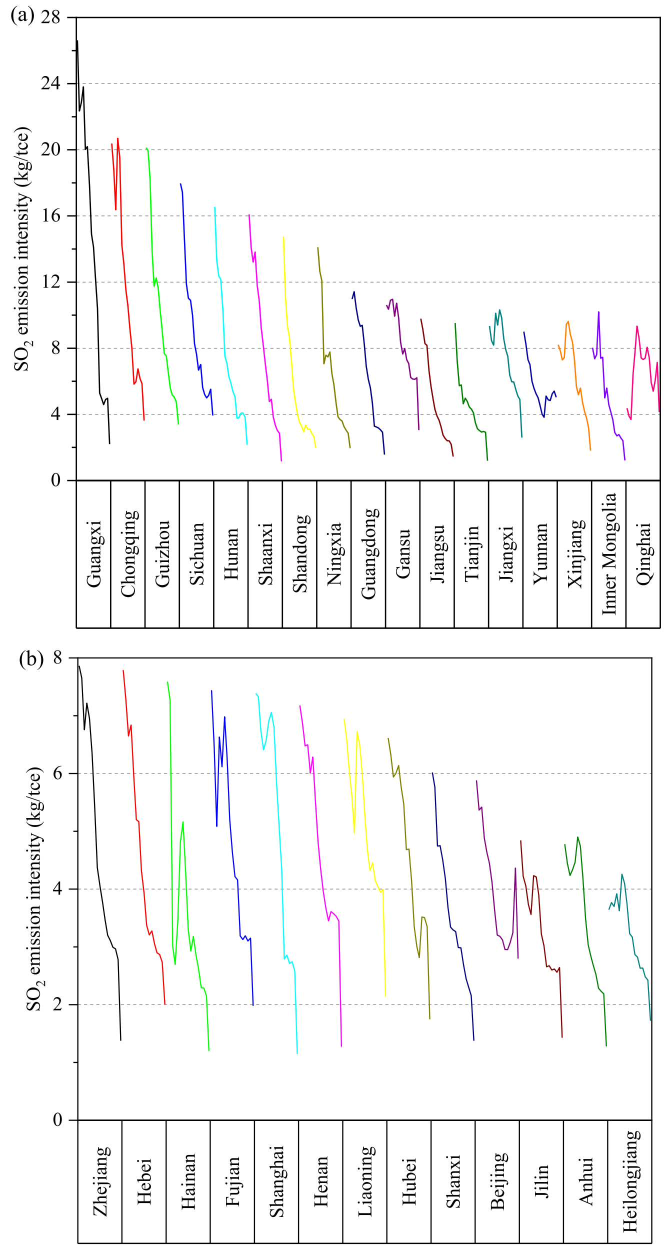

Fig. 4. The SO_2 emission intensity of 30 provinces in China during 2000–2016: (a) shows 17 provinces with initial SO_2 emission intensities higher than 8 kg/tce; (b) shows 13 provinces with initial SO_2 emission intensity lower than 8 kg/tce.

and Table S5, respectively. For ease of presentation, the 30 provinces were aggregated into eight regions (Feng et al., 2013; Qian et al., 2019; Wang et al., 2017) (see Table S3 for details).

Fig. 6 shows that the total SO_2 emissions continue to decrease under all four scenarios and the reduction potential under NPS was the lowest, which is due to the larger coal consumption under NPS than the other scenarios (Fig. 2). However, the differences in reduction potentials under the four scenarios were minor, especially compared to the potential improvement of SO_2 abatement technologies. Therefore, although renewable energy in the electric sector was helpful to the mitigation of SO_2 emissions, the main method appeared to be desulfurization technologies. With the adoption of desulfurization technologies, under the NPS, total SO_2 emissions would reduce by 1.9 Mt, 4.5 Mt, 5.9 Mt, and 6.9 Mt in 2020, 2030, 2040, and 2050, respectively. Furthermore, as shown in Fig. 6, the rate of emission abatement declined

Table 4
Results of the adoption curve model for 30 provinces between 2000-2016.

Province	$\ln(SI_0)$	-b	Province	$\ln(SI_0)$	-b
Beijing	−1.044	−0.277***	Henan	−0.196	−0.311***
Tianjin	−0.087	−0.423***	Hubei	−0.403	−0.311***
Hebei	0.313	−0.378***	Hunan	0.951	−0.475***
Shanxi	−0.106	−0.343***	Guangdong	1.200	−0.504***
Inner Mongolia	0.373	−0.399***	Guangxi	2.073	−0.627***
Liaoning	−0.677	−0.234***	Hainan	−1.532	−0.332***
Jilin	−1.233	−0.243***	Chongqing	1.333	−0.499***
Heilongjiang	−1.614	−0.178***	Sichuan	1.020	−0.434***
Shanghai	0.504	−0.474***	Guizhou	1.546	−0.501***
Jiangsu	1.148	−0.508***	Yunnan	−1.094	−0.182***
Zhejiang	0.198	−0.399***	Shaanxi	1.334	−0.544***
Anhui	−0.710	−0.306***	Gansu	−0.370	−0.258***
Fujian	−0.774	−0.280***	Qinghai	−2.525	0.095*
Jiangxi	−0.552	−0.243***	Ningxia	0.077	−0.418***
Shandong	1.153	−0.475***	Xinjiang	−0.307	−0.308***
Constant		3.939***	Obs.		510
R-squared		0.855	Mean dependent var		1.628
Adjusted R-squared		0.836	S.D. dependent var		0.569
S.E. of regression		0.230	Sum squared resid		23.825
F-statistic		45.072	Durbin-Watson stat		0.738
Prob(F-statistic)		0.000			

***/**/* Denote significance at the 1%, 5%, and 10% level, respectively.

over NPS, CPS, RES, and B2S, indicating that as desulfurization techniques improve there are fewer opportunities for further reduction. Additionally, as desulfurization technologies are implemented and improved, further SO_2 abatement sees higher marginal costs. With the increasing cost, it is expected to see more abatement potential through electrification of current industrial and residential energy use which allows for a further renewable energy transition. Therefore, future emission reductions to zero require the conversion of all energy production to non-fossil fuel generation.

It has to be noted that the reductions in SO_2 emissions can be attributed to two drivers: (1) extrapolation of reduction rates to the future and (2) a shift to renewables in the electric sector. However, the assumption of the first driver can be questioned, especially for the electricity sector. Between 2000 and 2016, the vast majority of coal-fired power plants were equipped with scrubbers, implying further reductions of the SO_2-emission intensity in this sub-sector may be too optimistic (even though the level of these reductions declines over time due to the adoption curve relationship). There are also limits to other factors in the first driver above, e.g., the use of coal with low sulfur content and efficiency improvements of scrubbers and within the energy system. As such, the projection in this study may represent an upper estimate, and reductions may be lower than this. Assuming no further reduction in the SO_2-emission intensity of coal use is possible, only the reductions due to a shift to renewables in the electricity sector can still be expected, i.e. the difference in Fig. 6 between the NPS scenario (fully relying on reduced emission factors for coal) and the other scenarios. For example, compared to NPS, a further reduction of 220 kt could be achieved under CPS in 2050. At the same time, assuming no reductions in sulfur emission factors for coal is too pessimistic. After all, some 50% of the coal is used outside the electricity sector where further reductions can be expected. Overall, similar reductions to Fig. 6 may be observed if the historical reduction rates persist into the future, much smaller reductions may be observed if the expansion of renewable electricity generation is the only factor driving reductions, and somewhere in between if there is a mix of factors.

3.3.2. Future reduction potentials at the provincial level

Fig. 7 shows that all provinces see decreasing emissions for all four scenarios, with the exception of Qinghai (more details can be seen in Table S6). As an economically underdeveloped western province in China, Qinghai's economic growth mainly depends on energy-intensive industries, resulting in a variety of environmental problems (Guo et al.,

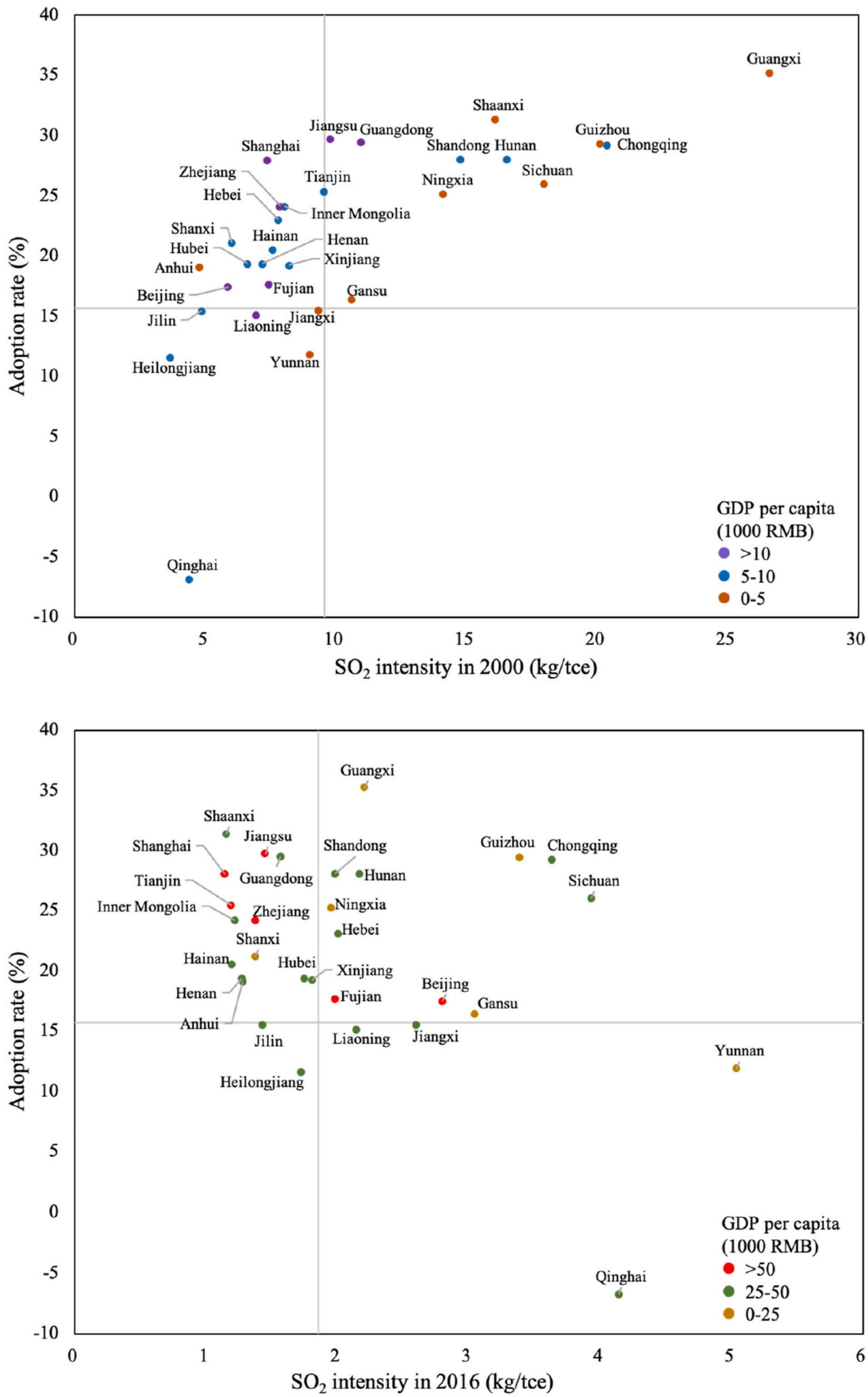

Fig. 5. Adoption rates and SO_2 emission intensities for 30 provinces between 2000 and 2016.

2016). The potential emission reduction across Beijing, Hainan, Shanghai, and Tianjin was minor under the four scenarios. One potential reason is that emissions in these provinces were already the lowest among the 30 provinces in 2016, indicating that further reduction potential is limited. In addition, the economic structure could also affect the SO_2 emissions. For Hainan, economic development depends predominantly on tourism and agriculture, while industrial development is slow, resulting in a low level of emissions. For Beijing, Shanghai, and Tianjin, as the most developed city-level provinces in China, the economic focus gradually moved from secondary to tertiary economic sectors. In 2016, the output in services in Beijing, Shanghai, and Tianjin accounted for about 80.2%, 69.8%, and 56.4% in the total, much higher than the national average (49.1%). Over 2000–2016, emissions in these provinces reduced by 85.2%, 84.0%, and 78.6%, respectively.

As shown in Fig. 7, some provinces see a large reduction potential in the future, e.g., Shandong, Inner Mongolia, Shaanxi, Xinjiang, Guizhou,

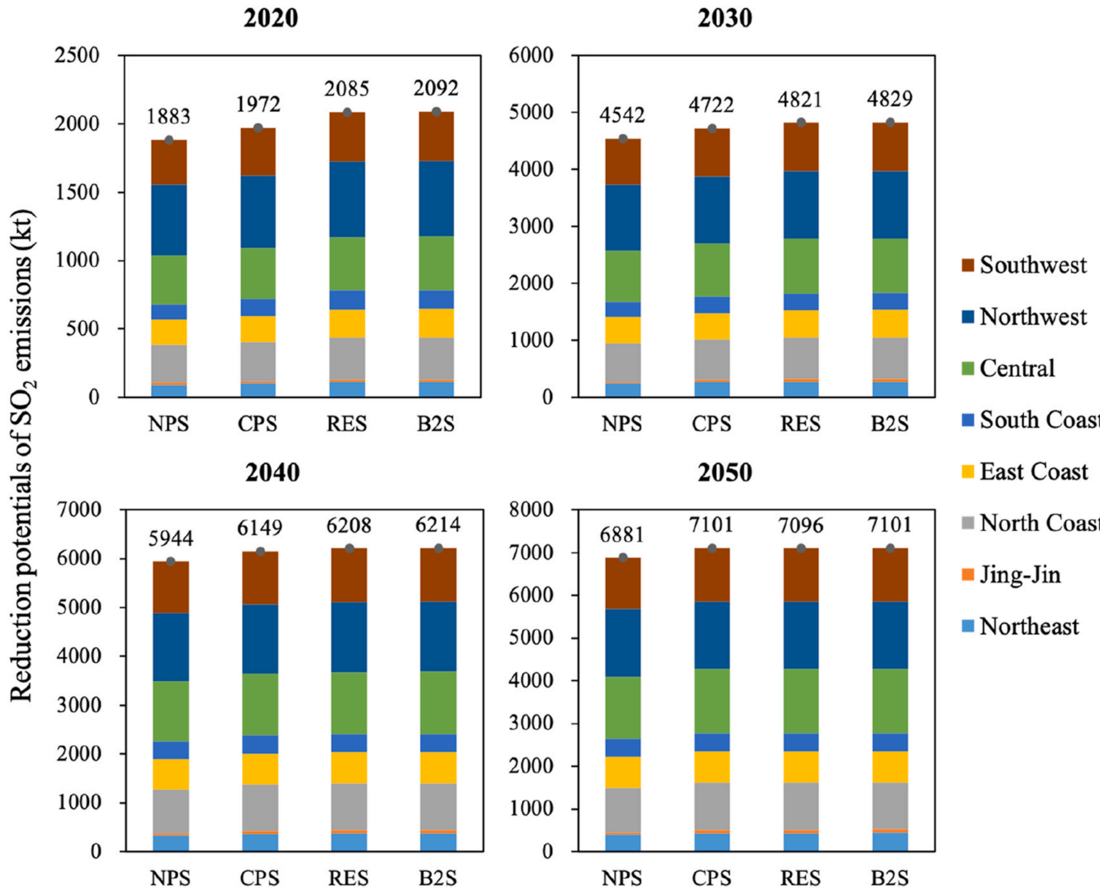

Fig. 6. Reduction potentials of SO_2 emissions for 8 regions in 2020, 2030, 2040, and 2050.

Jiangsu, Shanxi, Hebei, and Guangdong. One of the reasons is that the energy-intensive industries played an essential role in the economic development in these provinces. For example, in 2016, the thermal generation in Shandong, Jiangsu, and Inner Mongolia were largest, followed by Guangdong, Shanxi, Hebei, and Xinjiang. The thermal generation in these provinces accounted for about 27.6% of the total generation in 2016.

In addition, some provinces with a larger adoption effect also exhibited a higher reduction potential, e.g., Shaanxi and Guizhou. According to the results shown in Fig. 7, under the four scenarios, the abatement amount of SO_2 emissions in Shaanxi and Guizhou would account for ~11.2–15.1% to the total abatement amount in the future. However, there were also some exceptions. For example, in Anhui, both emissions and potential reductions in emission intensity are lower than those in Shanghai, even though the potential for the reduction was higher in Anhui. This can be explained by a slower rate of reduction in thermal generation in Anhui. By 2050, the estimated thermal generation of Anhui reduces by 4.9% compared to 2016 under the B2S; for Shanghai, it is 10.8%. Again, these conclusions assume historical reductions of the SO_2 emission intensities from coal use can be extrapolated towards the future.

3.4. Outlook for climatic effect of SO_2 emissions in the future

Naturally, the reduction in SO_2 emissions results in an increase in global average temperature between 2016 and 2050, estimated at ~0.6 °C, very similar for all four energy scenarios. In addition, MAGICC results indicated an increase of ~0.01 °C in the global average temperature from SO_2 mitigation by 2050 due to the adoption of renewables in the electric sector. Specifically, NPS saw an increase of 1.42 °C compared to the pre-industrial baseline, while the increase was 1.43 °C under B2S. However, although a reduction in SO_2 emissions could lead to increasing global temperatures, this effect can be offset by a change in other emissions, e.g., a reduction in carbon dioxide or black carbon (Carmichael et al., 2002). When renewable energy is deployed, the benefits of emission reductions in other gases and aerosols largely outweigh the costs of a reduced cooling effect from sulfate aerosols (de Gouw et al., 2014; Shahsavari and Akbari, 2018; van den Broek et al., 2009). It should also be noted that the sulfate aerosols are short-lived components, which would lead to radiative forcing and cause climatic change only during the period with SO_2 mitigation measures. For some other long-lived components (e.g., CO_2, N_2O, and CH_4), the climatic change caused by these gases is a long-term issue (Berntsen et al., 2006).

3.5. Limitations of this study

As stated above, part of the SO_2 mitigation was caused by the installation of end-of-pipe scrubbers after combustion which was extrapolated into the future based on the adoption curve, assuming that the current desulfurization technologies will continue to improve. However, since there is currently a large proportion of scrubbers installed in the electric sector, the additional SO_2 mitigation due to scrubbers from power plants in the future may be limited to technological or operational improvements of existing infrastructure. Furthermore, there are limits for improvement of these desulfurization technologies in the future (e.g., 100% removal efficiency of scrubbers is not practical due to thermodynamic considerations). Therefore, the reduction potential of SO_2 emissions will likely be less than the results shown in Fig. 6.

If the effect of scrubbers is to be distinguished from other approaches (such as using low-sulfur content coal), more detailed data are required, e.g., SO_2 emissions due to thermal generation and investment in

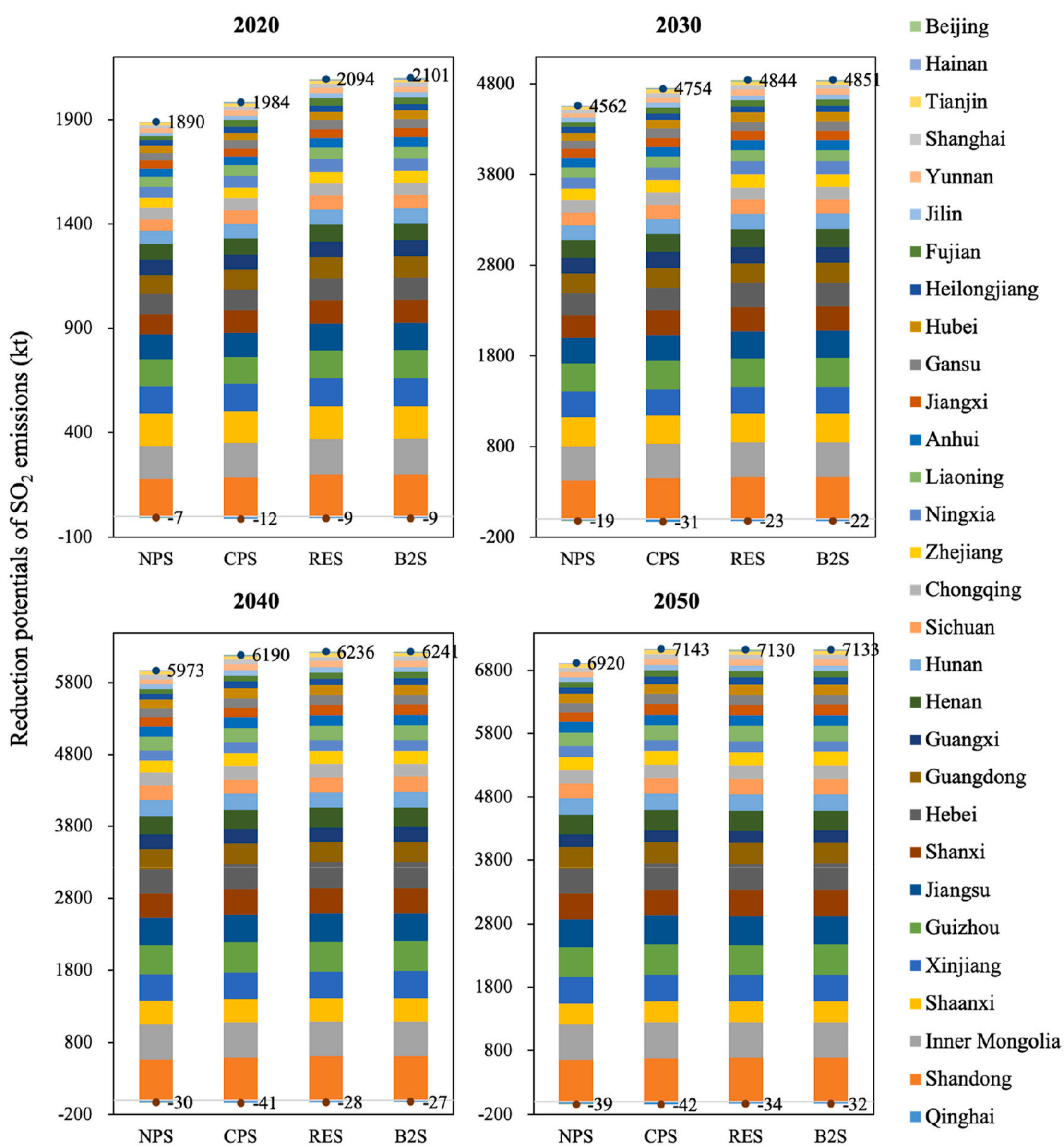

Fig. 7. Reduction potentials of SO_2 emissions for 30 provinces in 2020, 2030, 2040, and 2050 (The colors in the legend follow the same order as the stacked bars. The points below 0 show a total increase in SO_2 emissions under different scenarios, the points above the stacked bars denote the total reduction of SO_2 emissions under different scenarios.). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

desulfurization treatment in power plants at the provincial level. The *China Environment Yearbook* provides some data on the investments in desulfurization treatment for industrial SO_2 emissions over 2011–2015 and shows that some provinces with high levels of environmental investments also have a high adoption rate. For example, in Ningxia, environmental investment in desulfurization treatment accounts for ~17% of the regional GDP in 2015, and the adoption rate of Ningxia is also high (adoption coefficient of −0.418). However, provinces have different economic levels and environmental efforts can also differ. For example, some provinces may put more money in the desulfurization technologies before 2011 and others invest more after 2011. Since the temporal coverage of environmental investment data begins in 2011, using these data to explain the technological effect of scrubbers at the provincial level may be misleading. Therefore, the effect of end-of-pipe treatment was not separated from the overall effect in this study.

In addition, due to the lack of data, this study only covers 2000 to 2016, a period when China was rapidly expanding its power plant and industrial infrastructure. This implies that every year a significant number of new plants came into operation. Although other studies have also made similar analyses over such short time spans (Fukui et al., 2017; Pan and Köhler, 2007), it should be kept in mind that this is an anomalous period in China's development and that the lag time for electric power infrastructure is very long. If more relevant data are available, an analysis over a longer time period may provide further insights.

4. Conclusions and policy implications

This study analyzed the overall effect of adopting desulfurization technologies (e.g., use of coal with less sulfur content, improvement of energy efficiency, and installation of scrubbers) and substitution with renewable energy in the electric sector on SO_2 emission intensity over 2000–2016. Using an adoption curve modelling approach, estimates of the reduction potential of SO_2 emissions in 2020, 2030, 2040, and 2050 were made. Based on this, a change in the global average temperature above the pre-industrial level was projected.

Different trends were found among the different provinces. All provinces showed a positive adoption effect, except for Qinghai, indicating a lower level of environmental deployment. The higher the SO_2 emission intensity in the starting year (2000), the higher is the adoption effect over the rest of the period. Provinces with energy-intensive industries and high SO_2 emissions show a large abatement potential.

The four scenarios also revealed that both desulfurization technologies in industry and renewable energy substitution in the electric sector help to reduce future emissions. In general, overall SO_2 emissions could be reduced from 11.0 Mt in 2016 to 4.1 Mt and 3.9 Mt under NPS and the other three scenarios in 2050. With regard to the SO_2 mitigation measures, the effect of adoption across the industry sector as a whole appears to contribute most to future emission reductions. While future projections suggest a shift from 25% renewables in 2016 to around 80% renewables in 2050, this is less effective, since electric sector emissions only represented 27% of the Chinese total in 2015. However, considering the reduced abatement opportunities from the further improvement of desulfurization technologies and climate change effects of coal combustion, renewable energy provides the most promising option for SO_2 mitigation.

A reduction in SO_2 emissions and thus sulfate aerosols in China leads to a notable global warming effect. Due to the adoption of renewables in the electric sector, the global average temperatures could increase ~0.01 °C by 2050. However, the adoption of renewables can also lead to a reduction in other emissions and global temperatures. Despite this trade-off, it is still necessary to mitigate SO_2 emissions due to its adverse effect on health and the environment. The findings in this study are highly relevant for other countries around the world whose electricity production still heavily relies on coal consumption, such as India, Poland, and South Africa.

CRediT authorship contribution statement

Yuan Qian: Formal analysis, Visualization, Writing - original draft. **Laura Scherer:** Conceptualization, Methodology, Writing - review & editing. **Arnold Tukker:** Conceptualization, Writing - review & editing. **Paul Behrens:** Conceptualization, Methodology, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2020.111856.

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