Refined Estimate of China's CO_2 Emissions in Spatiotemporal Distributions

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Abstract: Being the largest contributor to the global source of fossil-fuel CO_2 emissions, China's emissions need to be accurately quantified and well understood. Previous studies have usually focused on the amount of national emissions and rarely discussed their spatiotemporal distributions, which are also crucial for both carbon flux and carbon management. In this study, we calculated China's CO_2 emissions from fossil fuel use and industrial process using provincial statistics and then mapped those emissions at 0.25^{o} resolution on a monthly basis. Several key steps have been implemented to gain a better understanding of the spatiotemporal distributions, including (1) development and application of China's CO_2 emission inventories using provincial statistics; (2) separate calculations of emissions from large point sources and accurate identification of their geographical locations; (3) development of 1km×1km gridded population and GDP data for China from 2000 to 2009 and application of them as dynamic spatial proxies to allocate emissions; and (4) monthly variation curves of CO_2 emissions from various sectors were developed for each province and applied to our inventory. China's total CO_2 emission from fossil fuel and industrial process have increased from 3.6 billion tons in 2000 to 8.6 billion tons in 2009, which may be off by 14-18% and are enough to skew global totals. The resulting spatiotemporal distributions of our inventories also differed greatly in several ways from those derived using national statistics and population-based approach for the various economic development levels, industrial and energy structures, and even large point emission sources within China and each province.

Keywords: CO_2 emissions, spatial resolution, monthly series, uncertainty analysis, China

1 Introduction

CO_2 emissions, which come from combustion of fossil fuel and industrial processes, are a major input to the global carbon cycle (Gregg et al., 2008). Existing emission estimates are usually made at national and regional level on annual basis (Boden et al., 2011; EIA, 2010; IEA, 2012; Olivier et al., 2011). However, previous studies have argued that existing anthropogenic CO_2 emission inventories may have potential biases (Gurney et al, 2005; Marland, 2012). Especially for China, a recent study revealed that an 18% gap of Chinese CO_2 emissions corresponded to approximately 1.4 billion tons, which was greater than total emissions from Japan (Guan et al., 2012). Actually, there has long been a concern about the accuracy and reliability of China's energy statistics (Sinton, 2001). Akimotoa et al. (2006) suggested that there were substantial differences in energy consumption data for China between official statistics, and verified province-by-province statistics data were in better agreement with satellite observations. However, few data on CO_2 emissions estimated on a sub-national spatial scale (e.g., province and city) exist in China (Guan et al., 2012; Wang et al., 2012a; Zhao et al., 2012).

Given that it is the largest emitting country, China's total emissions have already raised great concerns worldwide. However, the uncertainties of spatiotemporal distributions of these emissions, which are crucial for both carbon management and potential future climate models (Gregg and Andres, 2008), are rarely discussed. Previous studies usually applied population density as a proxy to distribute national emissions (Andres et al., 1996; Brenkert, 2003; Olivier et al., 2005). This methodology often works fairly well, but is not appropriate for explaining China's emission distribution because of the extremely uneven development and per capita emissions within the country (Wang et al., 2012a). Most existing studies quantified seasonal or monthly variations of CO_2 emissions based on monthly energy sales or consumption data (Blasing et al., 2005; Gregg and Andres, 2008; Losey et al., 2006; Rotty, 1987), which is impractical in China because the provincial governments do not report monthly fuel use by sector. Therefore, monthly variation curves were usually established by weighting the monthly fractions of national thermal electricity generation or values of industrial outputs (Gregg et al., 2008; Streets, 2003). However, results for monthly variations of CO_2 emissions over years in China are still scarce, especially at the sub-national level.

In this study, we calculated China's CO_2 emissions from fossil fuel consumption and industrial process using provincial statistical data and mapped emissions at 0.25^o and monthly resolutions. The methodology used in this work are presented in sect. 2, where we give a general overview of methods, data, and data sources for our emissions inventories and highlight the major improvements comparing with existing studies. In sect. 3, we present our results from total CO_2 emissions, and their spatial and temporal variations between 2000 and 2009. The differences between our results and other datasets are also discussed. Finally, in sect. 4, we summarize our major findings and highlight future improvements for present inventories.

2 Methodology and data

2.1 Provincial CO_2 emissions and uncertainties

We adopt IPCC sectoral approach (IPCC, 2006) to develop CO_2 emission inventories of fossil fuel consumption and industrial process for 31 provinces from 2000 to 2009 in China (excluding Hong Kong, Macao and Taiwan). To avoid double counting, total fossil fuel consumption data were calculated from production perspective based on final energy consumption (excluding transmission losses), plus energy used for transformation (primary energy used for power generation and heating) minus non-energy use. Emissions from fossil fuel consumption were further divided into three subsectors of industrial energy consumption (IEC), transportation energy consumption (TEC) and other energy consumption (OEC). Emissions from fossil fuel use for international bunker were not calculated here. Emissions from industrial process (INP) here referred to direct CO_2 emissions from chemical or physical transformation of materials during non-combustion industrial production (e.g. cement, steel, etc) processes (Wang et al., 2012a).

Data on energy consumption for the whole of society and for each sector in various provinces were derived from provincial energy balance tables in the China Energy Statistical Yearbook (NBSC, 2001-2010a), with exception of transportation fuel consumption. For Tibet, CO_2 emissions from IEC and OEC have not been calculated in this study because there are not any statistical data on energy consumption for the whole society and industrial sectors. As Chinese official statistics report only road transport fuel consumption caused by commercial activity, this study calculated fuel use by road transportation as the product of vehicle mileage traveled and the relevant fuel economy. Data on vehicle populations were taken from the Statistical Yearbooks (NBSC, 2001-2010b) for each province. For Tibet, only total vehicle populations but not vehicle populations by type are given in 2000-2001. So we have to estimate it by multiplying total population in these two years by the proportion of different vehicle type in 2002. Vehicle mileage travelled (VMT) and fuel economy (FE) data were taken from previous studies (Wang et al., 2010, 2011). Industrial products were taken from the statistical yearbooks for each province and the China Cement Yearbook. In contrast to previous studies, this study substituted cement production with clinker production (cement production will be used if no clinker production data in a few provinces like Tibet) in order to calculate CO_2 emissions from the cement industrial process.

Using Crystal Ball, the Monte Carlo stochastic simulation approach was employed to model probability distributions of key input parameters, and uncertainties estimated. Activity data (AD), such as energy consumption and industrial production, are primarily from two sources: China's provincial statistics and national statistics, which don't match well. A triangular distribution function is assumed for AD data for limited samples (Brinkman et al., 2005; Wu et al., 2010). The national data point was set as the minimum value, and then the maximum value was calculated by adding up the provincial AD data and absolute difference between provincial and national statistics. Table S1 summarized the key characteristics of distribution function curves for emission factors (EFs). Monte Carlo sampling number was set as 10,000.

2.2 Temporal variation

IEC and INP are the largest two contributors, accounting respectively 74% and 11% of China's total anthropogenic CO_2 emissions. Temporal variations of emissions from these two sectors are also significant, especially for IEC. Previous studies have shown that emissions from the combustion of liquid fuels, which are mainly consumed by transportation, are relatively constant throughout the year (Gregg and Andres, 2008). Thus, monthly variations of total CO_2 emissions are dominated by those of IEC and INP. As CO_2 emission factors changed little for specific energy type throughout the year, monthly variation of emission is consistent with that of AD, such as energy consumption and industrial productions.

Monthly variations of IEC's emissions in various provinces were estimated on the following assumptions: (1) monthly variations of emissions from electricity generation and combustion during steel production are consistent with the variation of respective productions. Monthly thermal power generation and steel production are available in provincial statistics (NBSC, 2001-2010b); (2) because the data on monthly heat production are not available in China, we assumed heat consumption is equal to the production. Monthly variations of residential and industrial heat consumption are respectively indicated by the variations of residential energy use (Streets, 2003) and industrial added values (NBSC, 2001-2010b); and (3) monthly industrial added values (NBSC, 2001-2010b) were used as proxy to reflect variations of emissions from other industries. Similarly, monthly variation curves of emissions from INP sector were established using monthly industrial production (e.g. cement and steel production).

2.3 Spatial distribution

As power plants accounted for nearly 30% of China's total emissions (Zhao et al., 2012) and cement production accounted for 60% of emissions from INP, we mapped those emissions as large point sources (LPS) and identify their locations exactly by latitude and longitude. Power plants ranking in the top 80% in terms of electricity production (CEC, 2000-2009) and cement plants with capacity above 1Mtyr^{-1} (ACC, 2003, 2006; CCTEN, 2009) were selected as LPS in this study. We derived the geographical coordinate of LPS by checking their addresses with Google Earth. Some LPS that could not be identified for lack of information were included in area emissions. For example, 861 LPS, which emitted 2304 million tons CO_2, have been separately calculated in 2009. However, geographical coordinates of 40 LPS accounting for 3.78% of the total LPS emissions were not available and were treated as area sources.

The emissions from other sources (except LPS) were treated as area emission and allocated to each grid at 0.25^{o} resolution via the proxies of population and/or GDP (Table S2). The 1km×1km gridded data of China's population and GDP densities (Yang et al., 2009; Liu et al., 2005) from 2000 to 2009 were developed and applied in this study. Figure 1 shows schematic methodology for the development of spatial distributions of our inventory.

Fig. 1. Schematic methodology for the development of spatial distributions

3 Results and discussion

3.1 China's CO_2 emissions trends 2000-2009

China's CO_2 emissions due to fossil fuel consumption and industrial processes both grew between 2000 and 2009, and total emissions increased from 3.6 to 8.6 billion tons, with an annual average growth rate (AAGR) of 10% (Fig. 2). The uncertainties of total emissions are quantified using Monte-Carlo simulation, producing a 90% confidence interval (CI) from -7.6%~6.9% in 2005 to -9.8%~8.5% in 2009. The uncertainty ranges of total emissions have become wider from since 2005 because the gaps between provincial and national energy consumption statistics become more significant from this year, especially for coal consumption (Table S3).

Fig. 2. Total CO_2 emissions of fossil fuel consumption and industrial process in China from 2000 to 2009

All Chinese provinces also showed increased CO_2 emissions during the past decade, although there were fluctuations for several provinces in individual years (Fig. 3a). As shown in Fig. 3b, per capita emissions for all the provinces also show growth trends, which will put huge pressure on the local governments as they seek to realize their carbon mitigation ambitions. The AAGR for CO_2 emissions varied from 3.4% (Beijing) to 17.0% (Inner Mongolia) for individual provinces and over half the provinces had an AAGR of over 10%. However, the provincial AAGR between 2007 and 2009 slowed down to 6%, which was 45% less than that during the period 2000–2007. As well as the general improvement in energy use efficiency (Zhang et al., 2009), it may be also related to the global recession of 2008–2009 (Peters et al., 2011). Furthermore, some important events, e.g. 2008 Olympic Games (Wang et al., 2012a), have also impacted on individual provincial CO_2 emissions. For example, CO_2 emissions from Beijing, China's capital, showed a relative decline over recent years due to measures associated with 2008 Olympic Games. Tianjin, Hebei, Shaanxi and Shandong are the surrounding provinces or municipalities of Beijing that were required to take measures to ensure good air quality during the games. Thus, many temporary measures for controlling or shutting down energy intensive and heavy polluting industries, such as cement, coke, iron and steel enterprises, during the games period also slowed down the CO_2 emission growth rate in 2008. As China's government has been developing Inner Mongolia to be strategic state energy base and will build it into China's largest power base (Clark and Isherwood, 2010a, b; Xinhua News Agency, 2008), its thermal power generation reached over 200 million kWh by the end of 2009, which is five times the level in 2000. These made CO_2 emissions of Inner Mongolia increase with the highest AAGR at 17% during the past decade.

Fig. 3. CO_2 emissions of 31 provinces and municipalities in China: (a) Total emissions, million tons; (b) Per capita emissions, ton/person. Shandong, Hebei, Jiangsu, Henan, Guangdong, Liaoning, Shanxi, Inner Mongolia, Zhejiang and Anhui were the ten provinces that contributed most to accumulated CO_2 emissions from 2000 to 2009. They emitted 36.5 billion tons of CO_2, which accounted for 61.5% of total Chinese emissions during that period. As the largest CO_2 emitting province, Shandong itself contributed 8.7% of China's total emissions from 2000 to 2009, with an AAGR of 14% (second only to Inner Mongolia). Inner Mongolia was the seventh

largest contributor to accumulated CO_2 emissions, but had the highest AAGR at 17% during the past decade. Geographical locations and abbreviations for the 31 provinces in China's mainland were shown in Figure S1.

Our emission inventory was compared with various exiting datasets of CDIAC, IEA, EIA, PBL, Zhao et al. (2012) and Guan et al. (2012). Overall, most of the existing results are statistically similar. However, there are still some minor differences between our results and the previous studies resulting from the differences in methodology and included sources. For example, fossil fuel CO_2 emissions of various studies were comparable before 2004, but our results are apparently greater than CDIAC, IEA, EIA and PBL since 2005 (Fig. 4a), which using the national statistics of energy consumptions and industrial productions. The gap between our results and CDIAC reached 0.84 gigatonnes CO_2 in 2008, which is larger than Germany's annual emissions. Discrepancies mainly arise from inconsistencies in energy consumption, especially coal consumption, among various statistics (Table S3). As some researchers (Akimotoa et al., 2006; Guan et al., 2012; Zhao et al., 2012) have already discussed possible reasons for this difference and raised the problems of China's energy statistics between national and provincial levels, we did not repeat the discussions here. Another example is that although we applied the same provincial statistical data as Guan et al. (2012) and Zhao et al. (2012), there are still minor differences among these three results, which is mainly due to different calorific values (CVs) and oxidation rates (ORs) (Table S4) applied in calculating local specific emission factors. Our application of IPCC recommended CVs and ORs for various fossil fuels may slightly overestimate (by 2%~4%) the CO_2 emitted to atmosphere. Furthermore, this study's calculations (sect. 2) of emissions from transportation energy consumptions (TEC) could reflect some smuggling oil consumption (not recorded in the statistics) in China, which could also contribute to the final emissions.

Fig. 4. Comparison of China's CO_2 emissions among various datasets: (a) Emissions of fossil fuel; (b) Emissions from cement productions. It should be noted that different datasets include different components in total emissions, e.g. CDIAC, IEA and PBL data omit emissions from fossil fuel use for international bunker (EFFIB), but EIA country-level data include EFFIB by incorporating the country of purchase). We excluded EFFIB and gas flaring emissions from the national total emissions in various data sets to ensure the results to be comparable.

CO_2 emissions from cement production process recorded in this study were close to Zhao et al. (2012) and PBL results, but much lower than CDIAC and Guan et al. (2012) results (Fig. 4b). As CO_2 emissions happen during the clinker production process, we calculated emissions by using clinker production rather than cement production. Nearly 10% of the cement clinker comes from industrial solid waste (e.g. carbide slag) (ACC, 2011) in China, therefore emissions tend to be overestimated when using cement production data.

3.2 Spatial distribution

Fig. 5. Spatial distributions (0.25^o resolution) and changes (2000-2009) of CO_2 emissions from energy consumption and industrial process in China.

China's CO_2 emission inventories (2000-2009) were developed at 0.25^o

resolution in this work. As shown in Fig. 5, CO_2 emissions of most geographical grids increased and spatial distributions changed greatly in the past decade. In 2000, emissions were concentrated in the most developed regions, like Beijing, Shanghai and Guangdong (Fig. S2). In 2009, high-emission centers expanded and new centers appeared in Shandong, Inner Mongolia, Hebei and some new city clusters in southwest China (Fig. 5a). Grids with higher emission intensities and more rapidly increasing emissions are mostly located in the eastern area, where there have already existed higher emissions (Fig. 5b). As Inner Mongolia is becoming China's strategic state energy base and largest power base, grids with higher emissions have also obviously appeared during the past decade. Significant decreases of emissions are usually due to the elimination or reduction of LPS with outdated technologies in the past decade in some cells (Zhang et al., 2009; Zhao et al., 2013).

Fig. 6. Distribution of emission ratios between our results and CDIAC's at 1^o resolution for year 2005. A ratio of 1 indicates that our results are equal to CDIAC, ratios larger than 1 indicate that our analysis are higher in certain grids, and ratios less than 1 indicate our analysis are lower. The ratios of cells having zero emissions in CDIAC and larger than zero emissions in our results are defined to be 100.

Spatial distribution characteristics of our refined CO_2 emission inventories were found to be obviously different with CDIAC (Fig. 6). The differences between the maps are clearly explained by the differences in the methodology and available information, which could be summarized into the following three major points.

First, our basic emission inventory was developed using provincial statistics and then aggregated to get national emissions. Therefore, on one hand, China's total CO_2 emissions are different among various studies as illustrated in Fig. 4; on the other hand, comparing with previous studies, e.g. CDIAC (Andres et al., 2011a), ODIAC (Oda and Maksyutov, 2011) and FFDAS (Rayner et al., 2010), using the national total as the basic emissions inventory to allocate into various provinces and locations, our inventories are directly calculated at provincial levels, thus definitely different with them at the provincial resolution.

Second, except for various absolute emissions, another important reason for the spatial differences between our results and CDIAC's is the process of LPS. As shown in Figs. 6 and 7b, most cells with a ratio greater than 1.5 contained LPS, but emissions from LPS are included in area sources and allocated to all cells using the proxy of population in CDIAC. However, the emissions from LPS are usually intense and poorly correlated with population (Oda and Maksyutov, 2011). Most LPS are situated in eastern China (Fig. 7), and CO_2 emissions from large coal-fired power plants accelerated from 2000 to 2009, especially in the province of NM (Inner Mongolia) as we illustrated above. Our selected LPS contributed over 25% of national total emissions and the fractions exceeded 35% for some individual provinces like Anhui, Guizhou, Ningxia, Zhejiang (Table S5). It means that 25-35% of total emissions have been accurately allocated in the geographical locations, which greatly improves the spatial resolution of our inventory.

Fig. 7. Geographical locations and CO_2 emissions of the large point sources. Red circles are

emissions from power plants and blue triangles are emissions from the non-combustion processes of cement plants. The bigger the size is, the more annual CO_2 emissions are. The number of LPS has increased from 240 in 2000 to 821 in 2009 (Table S5) and their emissions in each province also increased.

Third, the application of population density as a spatial proxy to distribute China's CO_2 emissions will inevitably introduce uncertainties in CDIAC and our distributions (where population is used as the spatial proxy, see Figure 1). As per capita emissions vary greatly across different provinces (Fig. 3b), due to unbalanced regional development, it is not surprising that large errors are introduced when population is used as a proxy to allocate emissions in various areas. Special policy and development characteristics in some provinces (such as Beijing and Inner Mongolia) of China also make their emission trends very different from others (Fig. 3), which further influence the spatial distributions of emissions. Furthermore, CDIAC assumed little change in spatial density of population and used population density data of 1984 (Andres et al., 1996, 2011a) to distribute CO_2 emissions for all other years. This means that fractions of each grid emissions to the total emissions remain the same in different years, which are equal to the fraction of each grid population to the total population in 1984. This assumption is proper for the developed countries with little change in the spatial distribution of population. However, it will lead to serious problems where there is rapid urbanization as in China (Yusuf, 2008; Zhang and Song, 2003), which has had great changes in the population and thus emissions distribution in recent years (Fig. S3).

3.3 Temporal distribution

China's total CO_2 emissions show strong seasonal variations with a peak in December and a significant valley from January to February for all years (except 2008) (Fig. 8a). There are three explanations for the emission peak in December: (1) Compared to the average, 12-43% more electricity and 76% more heat are generated in this month to meet the demand of air conditioning and heating (NBSC, 2001-2010b); (2) It could be found that the cement production in December was 9-21% higher than the average, while it was 27-42% lower from January to February (NBSC, 2001-2010b). The cement plants have to produce more in this month to balance the supply and demand after the Spring Festival. (3) It could also be a result of data manipulation to meet annual quotas by the end of the year to meet annual energy conservation targets or to match economic development (Gregg et al., 2008; Guan et al., 2012). Industrial activities usually stop for several days during the period January-February for traditional Chinese holidays of Spring Festival, which lead to the reduction of CO_2 emissions. It should be noted that fractions of heating-related emissions in northern provinces of China were very high during January to February, such as Heilongjiang and Beijing. However, the heating effect on the variation of national total emissions is very small because it contributes only about 1% to total CO_2 emissions in China.

Moreover, it could be found that our monthly variations curve of China's total CO_2 emissions is similar to that of CDIAC before 2008. But obvious differences were found for the year of 2008, which could be explained by the fact that monthly fuel consumption data in 2008 was estimated via Monte Carlo methods in CDIAC due to lack of data(Andres et al., 2011b). There is no doubt that the CDIAC's monthly curve estimated by Monte Carlo methods in 2008 will be similar to the previous years. However, monthly variations of national emissions in 2008 were very different as compared with other years for the following reasons: (1) Significant reduction in industrial activities and hence CO_2 emissions in China in second half of the year could have been caused by global financial crisis that started since September of 2008 (Fig. S4); and (2) measures for controlling or shutting down energy intensive and heavy polluting industries in Beijing and the surrounding areas during 2008 Olympic Games (sect. 3.1) also reduced CO_2 emissions in the summer of this year. In our study, we took advantage of the updated data for the year of 2008 to calculate the emissions, which will reflect the reality more accurately and also lead to the great differences comparing to CDIAC since the beginning of 2008.

Fig. 8. Monthly variations of emissions: (a) is the average monthly curves for China from 2000-2009; (b) is for some important provinces in 2009 (the results of other provinces are not shown here).

We developed monthly emission curves at China's provincial levels (Fig. 8b only showed some of them), and found each province has its own characteristics in monthly variations of CO_2 emissions which can differ greatly with the national average. For example, the impact of reducing industrial activities during the Spring Festival is smaller on Beijing, Shanghai and Heilongjiang than on other provinces. As heating contributed nearly 8% to Heilongjiang's total CO_2 emissions, which is well above national average level of 1%, growing heating consumptions in these two months have offset the impact of reducing industrial activity. For Beijing and Shanghai, tertiary industries, which respectively accounted for nearly 75% and 60% of their GDP, become more prosperous during the Spring Festival, and increased emissions from tertiary industry offset the impact of industrial activity reductions. Another example is the different power generation structures among various provinces. Hydropower is second in importance to thermal power, accounted for 16.6% (NBSC, 2001-2010b) of total electricity generation in 2009. However, it is significantly limited by the precipitation, which is influenced by the monsoonal climate and varies greatly from province to province and season to season. Therefore, thermal power will be adapted to the variation of hydropower to meet electricity demand. As shown in Fig. 9, summer contributed over 25% of annual CO_2 emissions from electricity generation for most provinces in China. However, the situations differed in some provinces with a larger proportion of hydropower (Lindner et al., 2013), such as Yunnan, Guangxi, Sichuan, Qinghai, Hubei and Fujian. As high rainfall in summer brings abundant hydropower resources, thermal electricity production and thus CO_2 emissions from thermal power plants are reduced. Therefore, application of national average temporal variation curves would cover the differences among various provinces in China which may have an impact on atmospheric carbon concentration simulation (Gurney et al., 2005).

Fig. 9. Contribution of CO_2 emissions from electricity generation for 31 provinces in the summer (June, July and August) of 2009. The y-axis represents the difference between the fractions of CO_2 emissions from electricity generation in summer of each 31 provinces and 25%. We calculate it based on the fractions of CO_2 emissions from electricity generation in summer of each 31 provinces, minus 25%.

3.4 Uncertainties in spatial distributions

The most important step (except the calculation of provincial and sectoral CO_2 emissions, which has already been discussed in sect. 3.1 and 3.2) to reduce uncertainty in spatial distributions of our emission inventory is the separate calculation of emissions from LPS. We comprehensively checked the address of each LPS on various materials, which include internet and other available materials (ACC, 2003, 2006; CCTEN, 2009; CEC, 2000-2009). However, if the information about LPS is not accurate enough, errors will be introduced to the spatial distribution of emission, although the regional total is unaffected.

Comparing with CARMA dataset (www.carma.org), which has already been applied (Oda and Maksyutov, 2011; Wang et al., 2012b) in calculating emissions from global power plants, the following points should be stressed: (1) CARMA only provides data for 2000, 2004, 2007 and 2009, which introduces significant uncertainty when extend emissions to other years for rapid development of new power plants with advanced technologies and elimination of old ones with outdated technologies in China; (2) CO_2 emissions from power plants are 3.12 billion tons in 2007 using

CARMA dataset, accounting for over 40% of China's total emissions, which is much higher than our and other published results (25-35%) (Zhao et al., 2012). Estimates of emissions from China's individual plants in CARMA (Table S6) also show great differences with our localized results (Table S7); and (3) CARMA dataset provides city center as the location of a reported power plant and could introduce big spatial errors (Table S7) comparing to our LPS database, which mapped emissions to the big chimneys of 80% of the power plants (Fig. S5). Therefore, it should be cautious when CARMA dataset were applied to estimate emissions of power plants in China.

As county is China's basic statistical administrative unit and is comparable to the spatial resolution (0.25^o) in our work, it seems more reasonable to develop the inventory at 0.25^o resolution based on current existing datasets. Cautions should be paid if a higher resolution inventory, like ODIAC (1km resolution), is developed, because every tiny error for an individual LPS and even small point sources will impact emissions in such small grids. And only evaluation of LPS (assumed no errors or omissions) is not enough to produce such high resolution inventories for China. Furthermore, original national emissions inventory, or even our provincial inventory, with some proxies may also introduce greater uncertainties when higher resolution inventories are developed.

4 Conclusions

New inventories of China's CO_2 emissions of fossil fuel consumption and industrial process from 2000 to 2009 at 0.25^o resolution are developed using provincial statistical data and our large point sources dataset. We estimate China's total CO_2 emission from fossil fuel consumption and industrial process reach 8.6 billion tons in 2009, which is 2.4 times that in 2000. And several keys steps have been implemented to gain a better understanding of the spatiotemporal distributions of China's emissions, including (1) development and application of China's CO_2 emission inventories, which are based on provincial statistics; (2) separate calculations of emissions from large point sources and accurate identification their geographical locations; (3) development of 1km×1km gridded population and GDP data for China from 2000 to 2009 and application of them as dynamic spatial proxies to distribute the emissions; and (4) monthly variation curves of CO_2 emissions from various sectors were developed for each province and applied to our inventory. Except the absolute emissions, great uncertainties in the spatiotemporal distributions of China's CO_2 emissions were also found in this study.

Although we thought China's CO_2 emissions and their spatiotemporal distributions were refined comparing with previous studies, there could still be large uncertainties remaining in individual locations. This is because emissions are estimated at the provincial level, while emission patterns may vary within a province due to local differences in economic and industrial structures and large point sources. To develop higher resolution inventories, therefore, the emissions from more point sources should be determined and estimated individually, and original emissions inventories at finer regional scales, such as the city level (Wang et al., 2012a), using more region-specific activity data/emission factors are also required. Furthermore, the applications of various data sources (e.g. satellite NO_2 data) to verify and improve the accuracy of time series in our inventory should be further processed in future study.

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Fig. 1. Schematic methodology for the development of spatial distributions

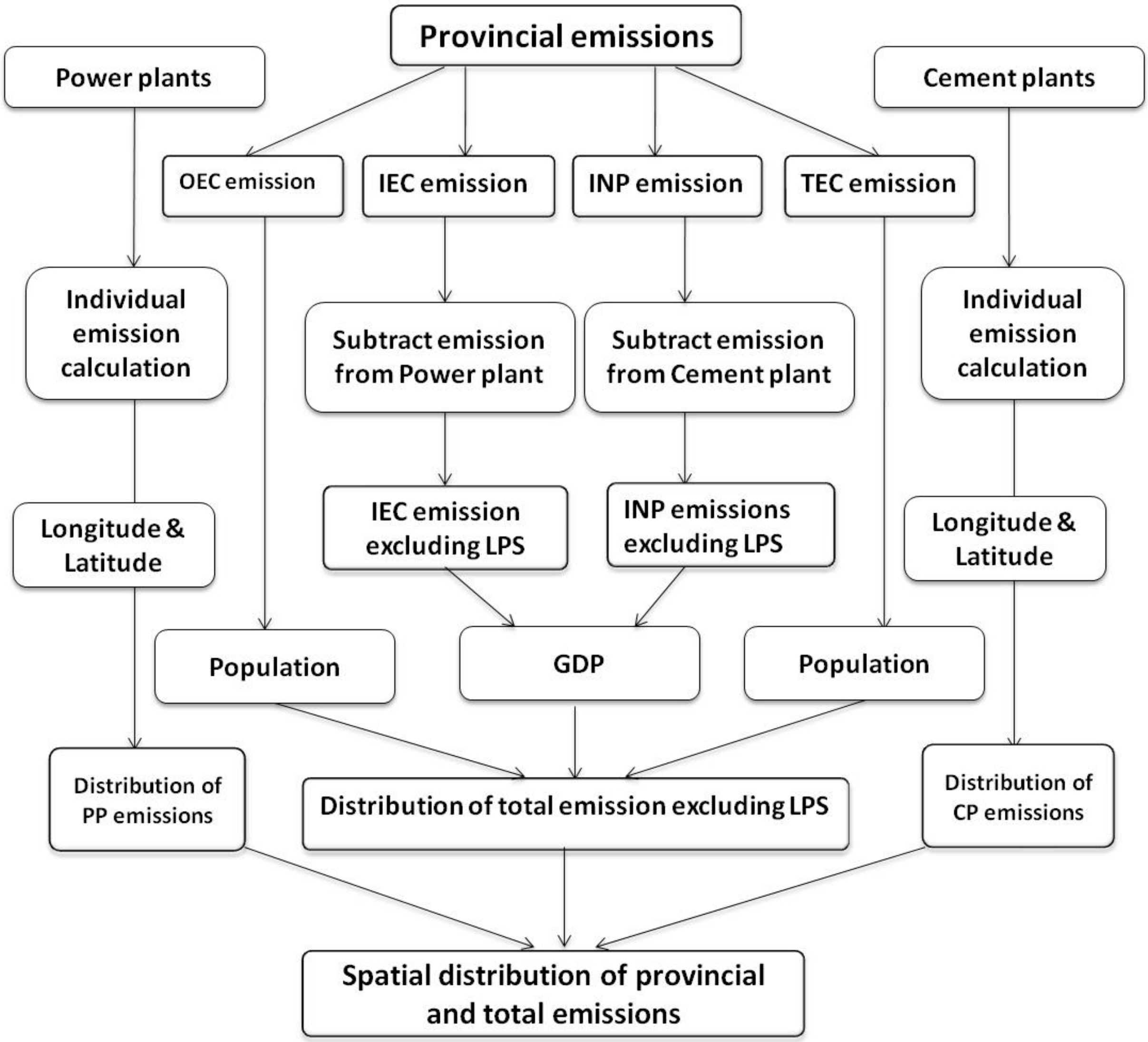


Fig. 2. Total CO_2 emissions of fossil fuel consumption and industrial process in China from 2000 to 2009

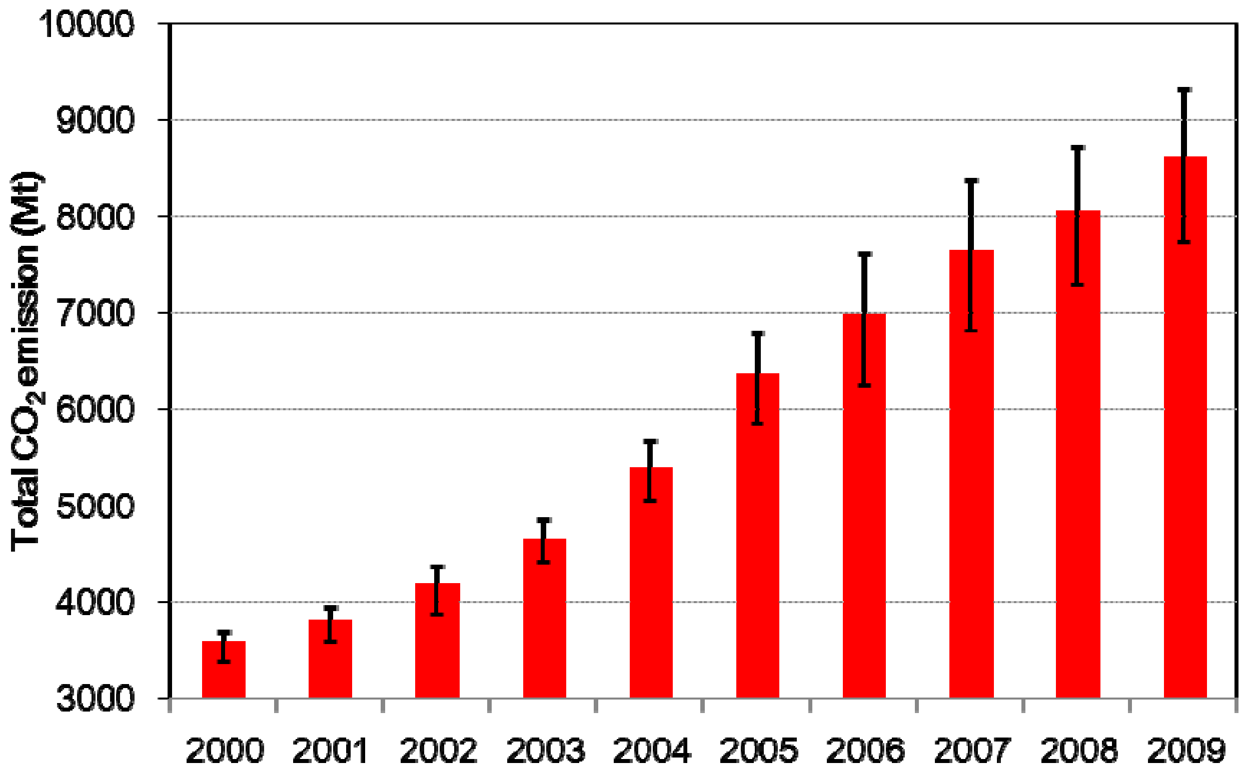
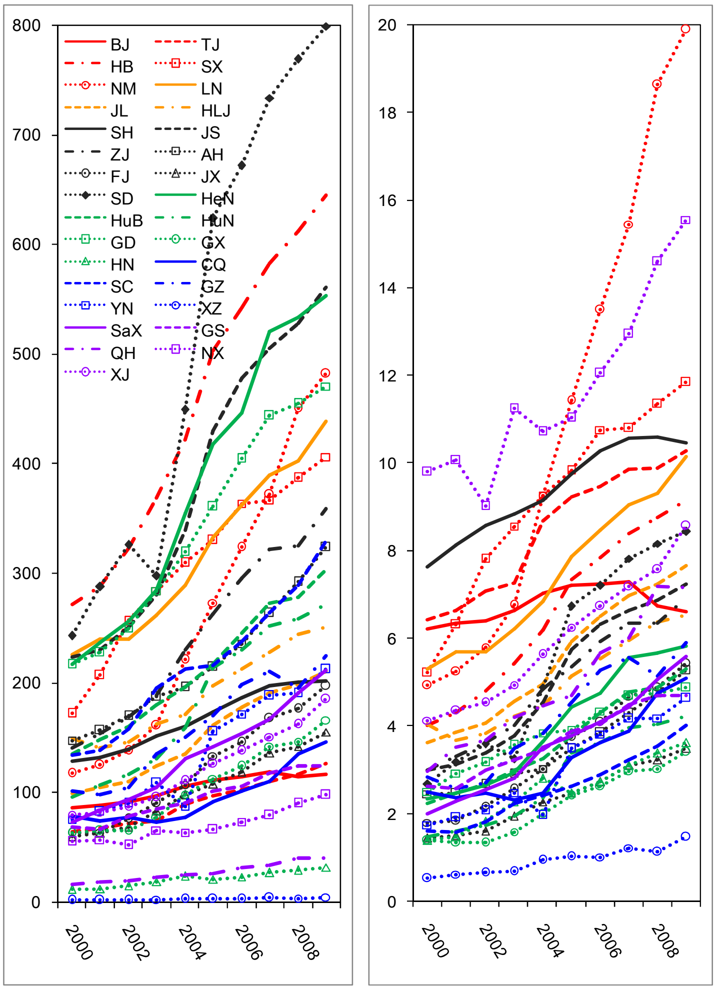
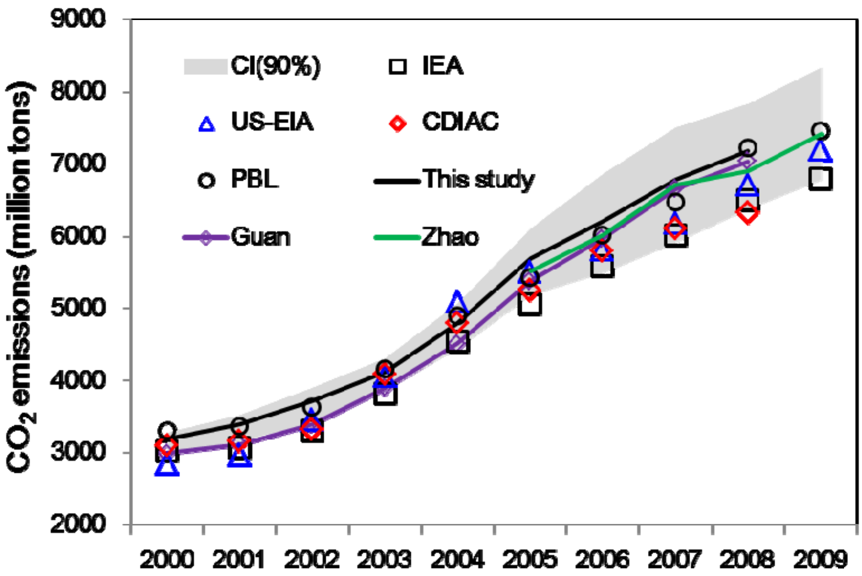


Fig. 3. CO_2 emissions of 31 provinces and municipalities in China: (a) Total emissions, million tons; (b) Per capita emissions, ton/person. Shandong, Hebei, Jiangsu, Henan, Guangdong, Liaoning, Shanxi, Inner Mongolia, Zhejiang and Anhui were the ten provinces that contributed most to accumulated CO_2 emissions from 2000 to 2009. They emitted 36.5 billion tons of CO_2, which accounted for 61.5% of total Chinese emissions during that period. As the largest CO_2 emitting province, Shandong itself contributed 8.7% of China's total emissions from 2000 to 2009, with an AAGR of 14% (second only to Inner Mongolia). Inner Mongolia was the seventh largest contributor to accumulated CO_2 emissions, but had the highest AAGR at 17% during the past decade. Geographical locations and abbreviations for the 31 provinces in China's mainland were shown in Figure S1.

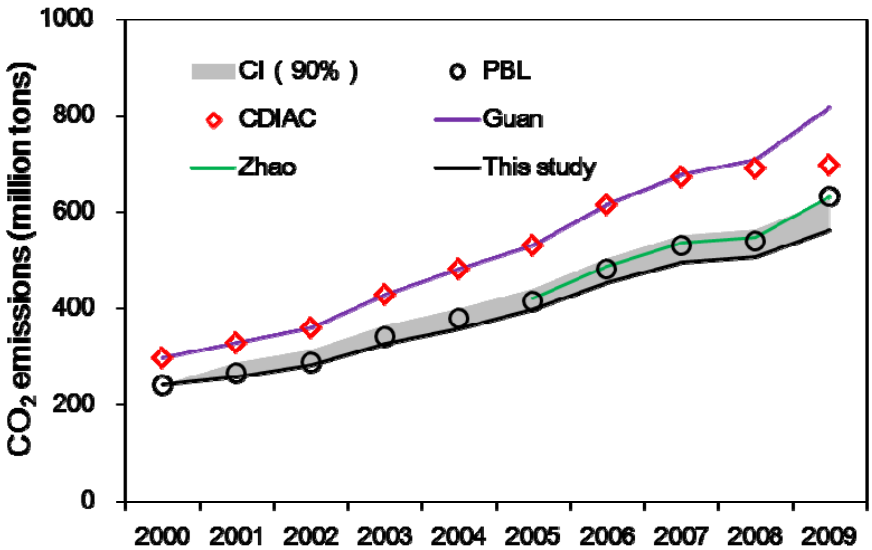


(a) **(b)**

Fig. 4. Comparison of China's CO_2 emissions among various datasets: (a) Emissions of fossil fuel; (b) Emissions from cement productions. It should be noted that different datasets include different components in total emissions, e.g. CDIAC, IEA and PBL data omit emissions from fossil fuel use for international bunker (EFFIB), but EIA country-level data include EFFIB by incorporating the country of purchase). We excluded EFFIB and gas flaring emissions from the national total emissions in various data sets to ensure the results to be comparable.

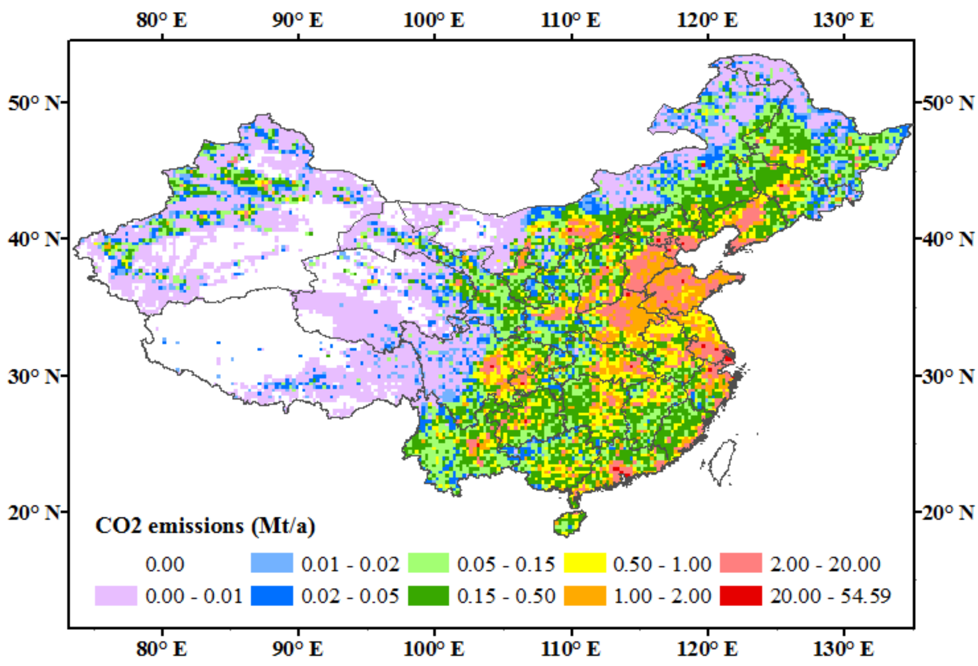


(a) Fossil fuel

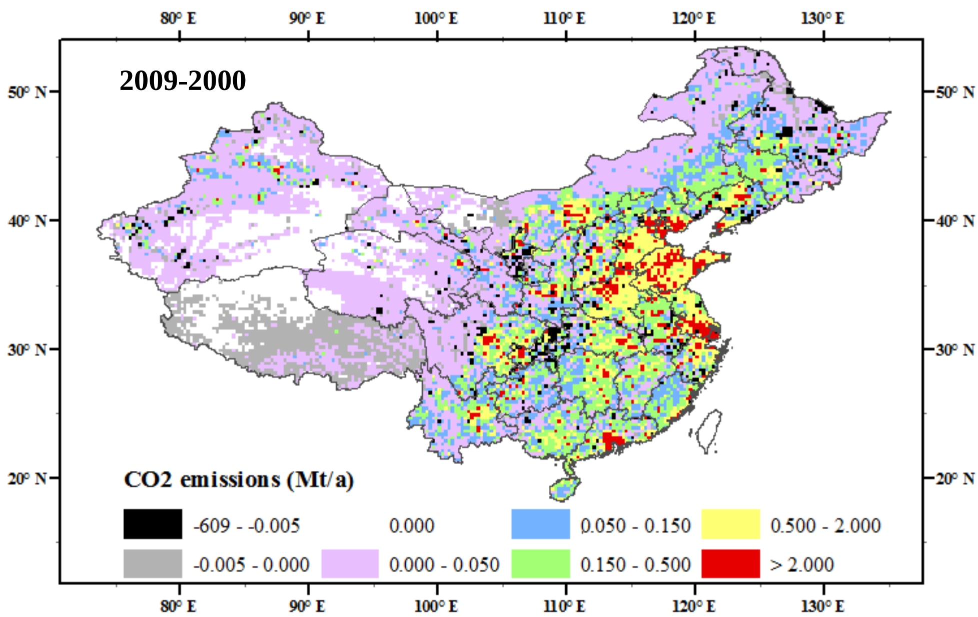


(b) Cement production process

Fig. 5. Spatial distributions (0.25^o resolution) and changes (2000-2009) of CO_2 emissions from energy consumption and industrial process in China.



(a) Spatial distributions in 2009



(b) Variations of emissions from 2000 to 2009

Fig. 6. Distribution of emission ratios between our results and CDIAC's at 1^{o} resolution for year 2005. A ratio of 1 indicates that our results are equal to CDIAC, ratios larger than 1 indicate that our analysis are higher in certain grids, and ratios less than 1 indicate our analysis are lower. The ratios of cells having zero emissions in CDIAC and larger than zero emissions in our results are defined to be 100.

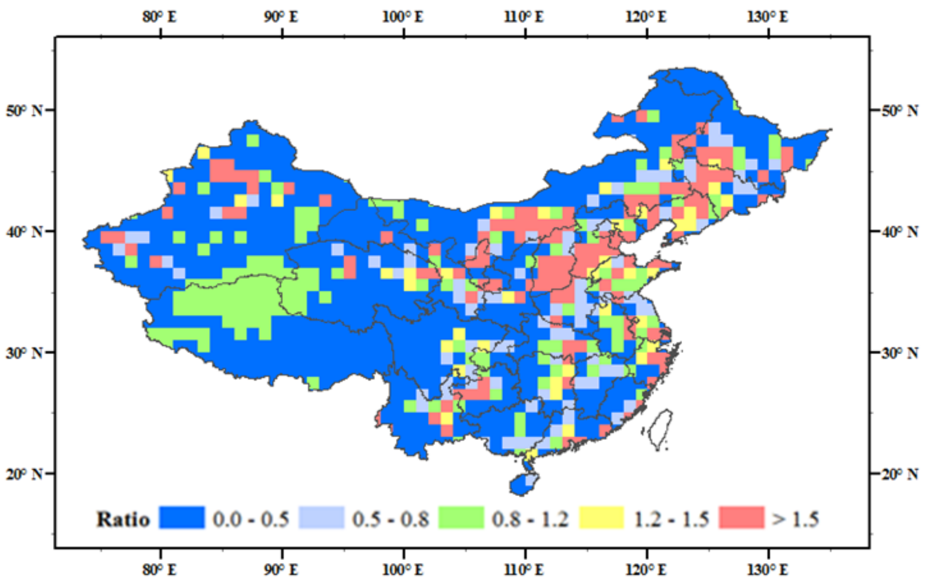
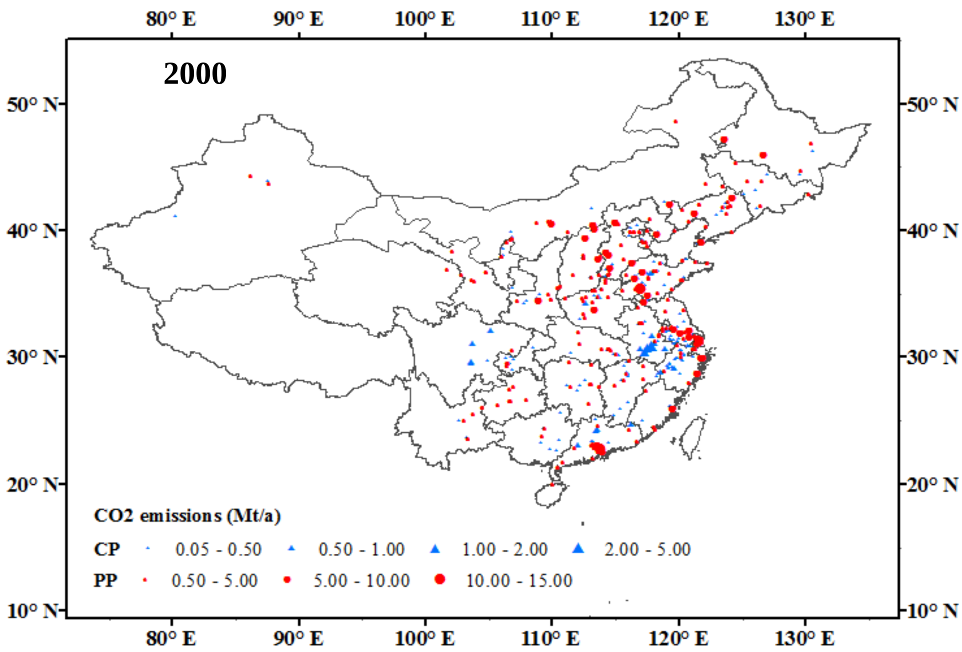
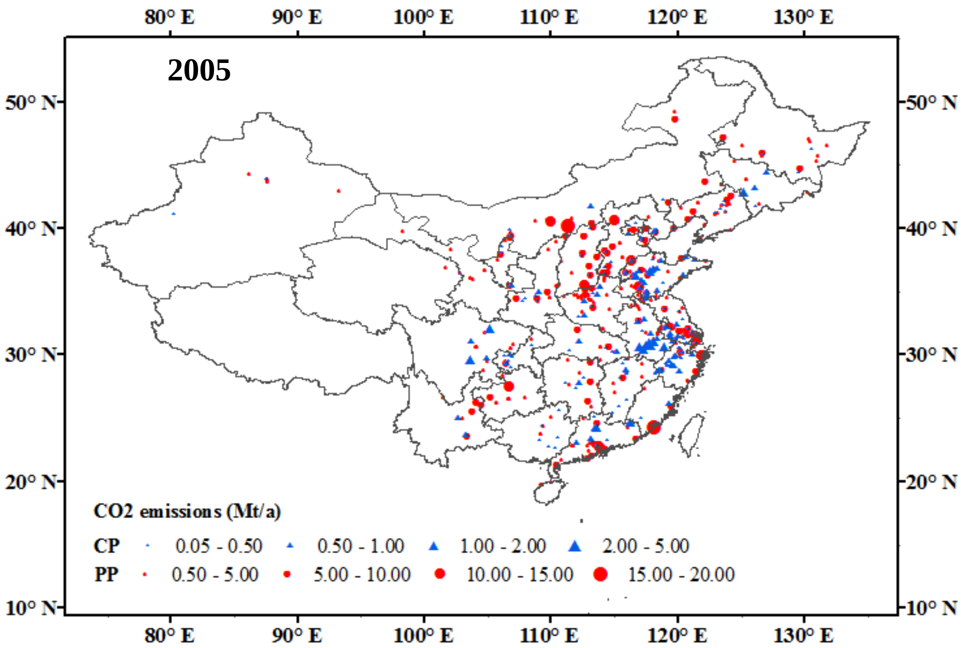


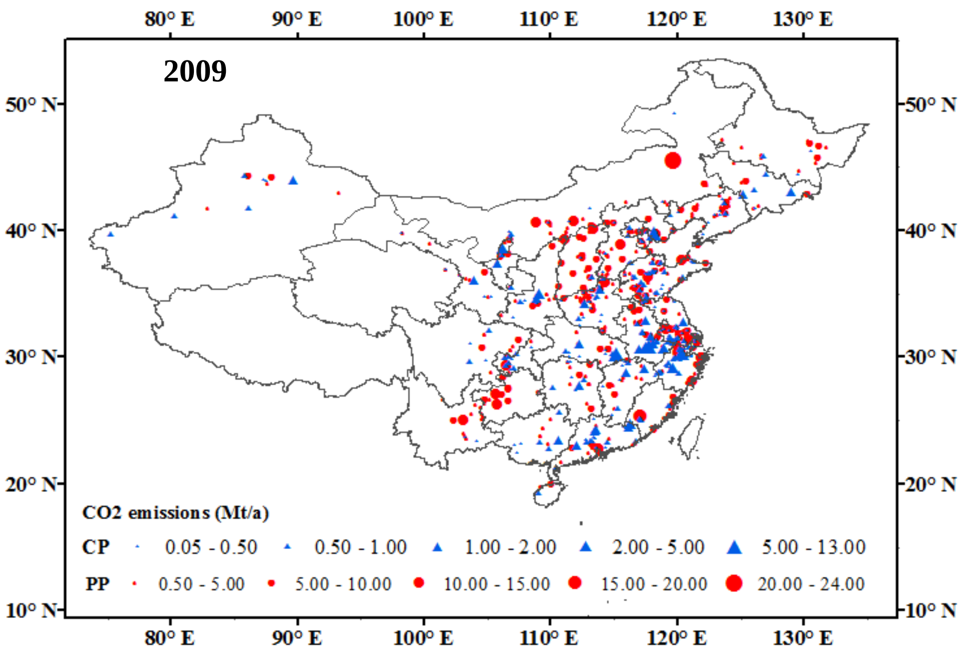
Fig. 7. Geographical locations and CO_2 emissions of the large point sources. Red circles are emissions from power plants and blue triangles are emissions from the non-combustion processes of cement plants. The bigger the size is, the more annual CO_2 emissions are. The number of LPS has increased from 240 in 2000 to 821 in 2009 (Table S5) and their emissions in each province also increased.



(a)

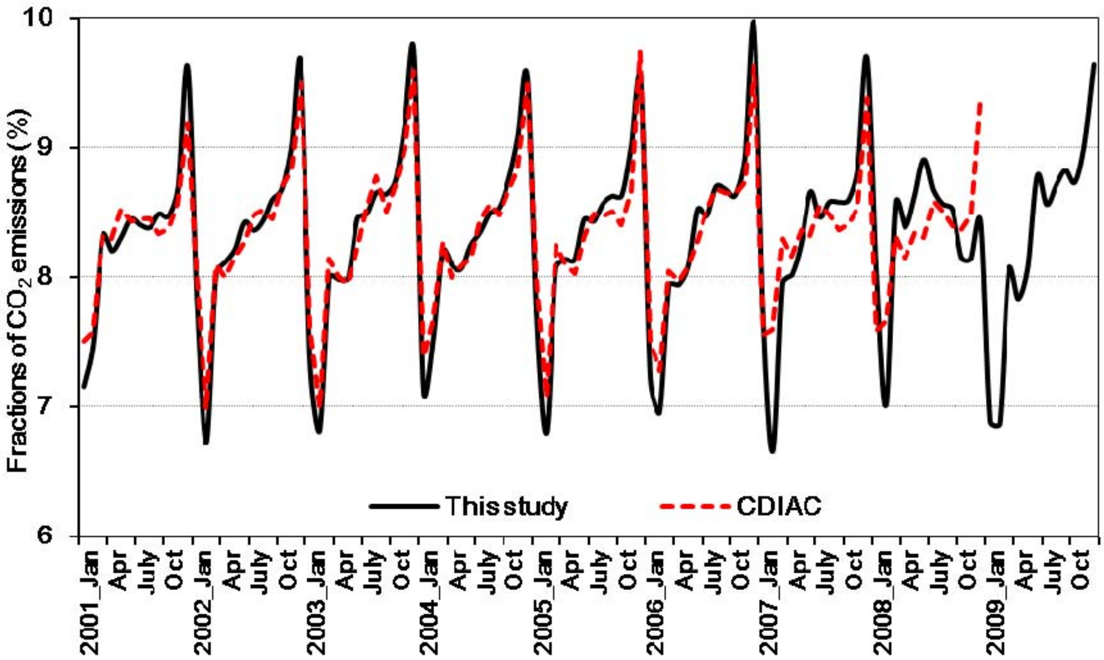

2005
80° E
90° E
100° E
110° E
120° E
130° E
50° N
40° N
30° N
20° N
10° N
CO2 emissions (Mt/a)
CP 0.05 - 0.50 0.50 - 1.00 1.00 - 2.00 2.00 - 5.00
PP 0.50 - 5.00 5.00 - 10.00 10.00 - 15.00 15.00 - 20.00

(b)

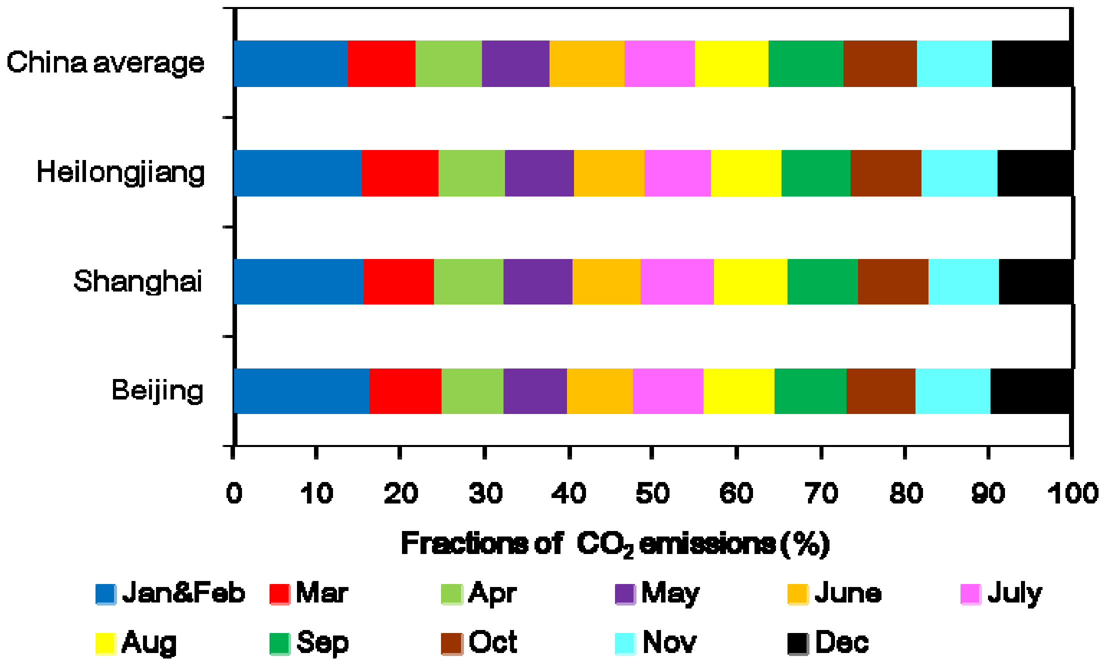

2009
80° E
90° E
100° E
110° E
120° E
130° E
50° N
40° N
30° N
20° N
10° N
CO2 emissions (Mt/a)
CP 0.05 - 0.50 0.50 - 1.00 1.00 - 2.00 2.00 - 5.00 5.00 - 13.00
PP 0.50 - 5.00 5.00 - 10.00 10.00 - 15.00 15.00 - 20.00 20.00 - 24.00

(c)

Fig. 8. Monthly variations of emissions: (a) is the average monthly curves for China from 2000-2009; (b) is for some important provinces in 2009 (the results of other provinces are not shown here).



(a) National level



(b) Provincial level

Fig. 9. Contribution of CO_2 emissions from electricity generation for 31 provinces in the summer (June, July and August) of 2009. The y-axis represents the difference between the fractions of CO_2 emissions from electricity generation in summer of each 31 provinces and 25%. We calculate it based on the fractions of CO_2 emissions from electricity generation in summer of each 31 provinces, minus 25%.