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CO₂ emissions and their spatial patterns of Xinjiang cities in China

Can Cui^a, Yuli Shan^{b,*}, Jianghua Liu^c, Xiang Yu^d, Hongtao Wang^e, Zhen Wang^{a,*}

^a School of Resource and Environmental Sciences, Wuhan University, Wuhan 430079, China

^b Energy and Sustainability Research Institute Groningen, University of Groningen, Groningen 9747 AG, Netherlands

^c Institute of Finance and Economics Research, School of Urban and Regional Science, Shanghai University of Finance and Economics, Shanghai 200433, China

^d Institute for Urban and Environmental Studies, Chinese Academy of Social Sciences, Beijing 100028, China

^e State Key Laboratory of Pollution Control and Resource Reuse, Key Laboratory of Yangtze River Water Environment, Ministry of Education, College of Environmental Science and Engineering, Tongji University, Shanghai 200092, China

HIGHLIGHTS

- CO₂ emissions of Xinjiang cities in China and their uncertainty are reported.
- CO₂ emissions of Xinjiang cities are spatial autocorrelated.
- Population, urbanization, energy structure and industry structure influence emissions.
- Petroleum and power sectors contribute the largest CO₂ emissions in Xinjiang cities.
- CO₂ emissions in Urumqi rises during 2005–2015, mainly driven by the power sector.

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ABSTRACT

City-level CO₂ emission accounting is necessary to identify the different energy circumstances among all cities. However, due to a lack of data, energy consumption and emission statistics are not well documented. Focusing on the industrial production using fossil fuels, our work provides the first detailed city-level estimation of production-based sectoral CO₂ emissions in the Xinjiang Uygur Autonomous Region. In 2010, 15 cities in Xinjiang emitted a total of 304.06 million tonnes CO₂, and 97.7% of those emissions were related to fossil fuel combustion (i.e. energy-related emissions), with the remaining 2.3% from industrial processes associated with the production of cement (i.e. process-related emissions). The consumption of raw coal and crude oil were the main sources of Xinjiang's emissions (50.3% and 23.0%, respectively), whereas 'petroleum processing and coking' and 'power and heat production' were the two sectors that contributed the largest emissions at 32.6% and 27.9%, respectively. The cities in Xinjiang presented considerable variations in the total CO₂ emissions and emissions per capita. The emissions intensity and emissions per capita shared similar distributions, and the emissions are significantly spatial autocorrelated. Cities whose economies relied on emission-intensive pillar industries and/or energy mainly sourced from raw coal tended to have high emissions per capita and high emissions intensities. Those cities included Altay, Changji, Hami and Shihezi. We also examined the time-series emissions of Urumqi, the largest city, from 2005 to 2015. Urumqi presented a generally rising trend in CO₂ emissions over the decade, with emissions increasing by 324.2%. The major driving sector was 'power and heat', which showed increases in the total CO₂ emissions and percentage of Xinjiang's emissions. Based on the findings, policy recommendations for emission reductions and low-carbon development for the cities in Xinjiang are provided, including adjusting the energy structure and introducing multiple industries.

1. Introduction

Uneven energy resources and imbalanced energy consumption/CO₂ emissions occur across China from the coastal regions to inland areas [1]. Under increasing pressure to mitigate climate change, China must

allocate different emissions targets to its provinces, and specific attention should be focused on regions that play an important part in national, or even international, energy strategies. Given its vital location and nature, the Xinjiang Uygur Autonomous Region (hereafter referred to as Xinjiang) acts as an energy exporter in China and plays a vital role

* Corresponding authors.

E-mail addresses: y.shan@rug.nl (Y. Shan), sinoo@whu.edu.cn (Z. Wang).

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in the Belt and Road Initiative as “a window of westward opening-up to deepen communication and cooperation with Central, South and West Asian countries”, as well as a core area on the Silk Road Economic Belt [2]. Serving as a gatekeeper of international trade (as advocated by the initiative), Xinjiang and its CO₂ emission performance might influence the carbon emissions of other adjacent countries in Central Asia, for the potential energy consumption in the incremental construction of infrastructure [3], and the trade and investment patterns afterwards. Thus, the energy consumption and corresponding emissions in Xinjiang should receive close attention considering the background of global climate change [4].

Xinjiang is a provincial administrative unit located in north western China, with 8 adjacent countries. It has the largest land area (1.66 million square kilometres) of all administrative units and accounts for nearly one sixth of the entire country. Abundant natural resources are located in this region, including fossil fuels, such as coal, oil, natural gas, and mineral resources. In addition, based on its particular terrain and latitude, Xinjiang possesses rich renewable resources that include wind energy, solar energy, hybrid and hydrogen energy [5]. Considering its large land area, the population of Xinjiang is relatively small at approximately 21.85 million in 2010 and 23.60 million in 2016, less than 2% of the whole country. Xinjiang has presented a dramatically rising economy, with gross domestic production (GDP) increasing from 543.7 billion yuan in 2010 to 559.6 billion yuan (at constant prices) in 2015, less than 1.5% of the whole country, with potential to boost that in the future. The term “city” within this paper refers to city-level administrative units, whose area includes both urban and rural regions. Xinjiang includes 15 cities (briefly outlined in Table 1, with further details in Support Information-1): Urumqi, Karamay, Tacheng, Altay, Turpan, Hami, Aksu, Kashgar, Hotan, Chanji, Bortala, Bayangol, Kizilsu, Ili and Shihezi.

Xinjiang is home to productive agriculture and animal husbandry industries as well as large-scale industries based on mineral resources, with the region possessing huge reserves of coal, oil and natural gas and producing electric power and petroleum for local and outside consumption. Thus, its industries discharge large amounts of CO₂ emissions from the energy production and processing. A large area of desert (45.0% of the whole land area, in 2010) is found in this region, with forest coverage at 4.02% in 2010, which was relatively low compared with the national average level of 20.36% [6]. Therefore, the CO₂ sink capacity of Xinjiang’s natural environment is limited. Considering the importance of Xinjiang’s energy status, measures for energy saving and carbon reduction should be proposed and conducted.

To optimize energy consumption and reduce CO₂ emissions in Xinjiang, a concrete emissions inventory is urgently needed. Cities are

the direct executives that make policies for mitigating climate change and reducing CO₂ emissions by regulating and planning energy uses [7–9]. With the urbanization process, the urban population in the world grew from 220 million to 3530 million from 1900 to 2011, and with cities linked to more responsibility to cope with environmental challenges [10–12], a first complete dataset of CO₂ emissions is a necessity. Therefore, city-level CO₂ emission accounting is necessary to identify the different energy circumstances among all cities. However, due to a lack of data, energy consumption and emission statistics are not well documented. Focusing on the industrial production using fossil fuels, our work provides the first detailed city-level estimation of production-based sectoral CO₂ emissions in Xinjiang. Further emission characteristics of the cities are also discussed in the study.

2. Literature review

Studies of nationwide CO₂ emissions in China have produced regional estimates, and the CO₂ emissions of Xinjiang are usually calculated according to the Intergovernmental Panel on Climate Change [13]. Except for studies on consumption-based CO₂ emissions in Xinjiang using input-output analysis [14,15], research on production-based emissions is mainly conducted by aggregating emissions of various energy types and industry sectors [8,16]. The Extended Energy Accounting method was used to calculate the inclusion of energy and raw material supplies and other external factors [17]. Currently, researchers are also focusing on the CO₂ emissions (often divided into several sectors) of Xinjiang using similar methods and providing the energy-related emissions [18] or total emissions for the whole region [8,16,19]. Land-use-related CO₂ emissions of agriculture [20] and other different types [21] are also studied. In addition, several studies have focused on the energy consumption and carbon emissions of certain industrial sectors in Xinjiang. Sigmund et al. used the Publicly Available Specifications-2050 (PAS, 2050) to quantify the carbon footprint of cotton production in Xinjiang [22]. The spatial-temporal differences and driving factors of agricultural carbon emissions in Xinjiang have been analysed as well [20,21,23]. As an industry with high energy consumption, the thermal power industry in Xinjiang is under scrutiny, and the carbon emissions from that industry for the whole region have been calculated [24–26]. Household carbon emissions in Northwest China were estimated using residential electricity usage [27] by undertaking surveys in certain cities in north western China, including Xinjiang. To date, studies on energy consumption and carbon emissions in Xinjiang have covered the regional level and several sectors but are insufficient for more detailed estimations.

Recent studies on city-level CO₂ emissions have provided feasible

Table 1
Brief background and data availability for Xinjiang cities (2010).

City	Agricultural area (%)	Construction area (%)	GDP (10 ⁸ CNY)	Population (10 ⁴)	GDP Primary (%)	GDP Secondary (%)	GDP Tertiary (%)	EBT	ECIS
Aksu	41.3	1.0	396.1	237.1	34.8	30.9	34.3	No	Yes
Altay	90.9	0.4	134.9	60.3	21.9	43.4	34.7	No	No
Urumqi	79.7	3.9	1338.5	311.0	1.5	44.9	53.6	No	Yes
Bayangol	20.6	0.2	640.1	127.9	16.9	64.5	18.6	No	No
Bortala	77.2	0.9	131.5	44.4	37.6	19.6	42.8	No	No
Changji	77.7	1.5	558.0	142.9	29.8	42	28.2	No	Yes
Hami	31.2	1.3	167.4	57.2	14.4	44.8	40.8	No	No
Ili	84.5	1.6	408.3	248.3	24.2	35.8	40	No	No
Karamay	41.6	7.5	711.4	39.1	0.5	89.7	9.8	No	No
Kash	21.7	1.3	360.0	397.9	42.2	18.1	39.7	No	No
Khotan	16.2	0.4	103.5	201.4	35.1	16.9	48	No	No
Kizilsu	44.8	0.2	38.9	52.6	20.1	23.4	56.5	No	No
Shihezi	74.8	13.5	135.0	63.5	6.8	50.8	42.4	No	No
Tacheng	80.8	1.0	341.9	121.9	37	34.5	28.5	No	No
Turpan	12.5	0.4	182.8	62.3	13.4	63.5	23.1	No	Yes

The percentage of agricultural and construction land use area, and the components of GDP (i.e. the percentage of GDP of the primary, secondary and tertiary industry) in each city are listed. GDP, population and cement production data are available, while the energy balance tables (EBTs) and the final Energy Consumption by Industrial Sector (ECIS) are deficient.

estimation methods. Wang et al. used energy consumption data and DMSP/OLS (Defence Meteorological Satellite Program's Operational Linescan System) night-time light imagery models to estimate the CO₂ emissions at a city level during 1992 to 2013 [28]. Shan et al. proposed a methodology for calculating production-based CO₂ emission inventories in a number of cities in China [29], and Mi et al. developed a method using an input-output model to determine the consumption-based emissions in 13 cities [30]. Regression and inductive analyses have also been used to provide statistical estimates of city-level CO₂ emissions [31]. Apart from studies on nationwide cities' emissions, research has primarily focused on several mega cities in China, including Beijing [9], Shanghai [32,33], Tianjin [34], and Chongqing [8,35], and more developed regions, such as the urban agglomeration in the Yangtze River Delta [36]. Despite their importance, city-level CO₂ emissions in Xinjiang have rarely been accounted for.

As reviewed above, past and current studies of energy consumption in Xinjiang have mainly focused on the total emissions of the entire autonomous region and its influencing factors and estimations of emissions from a single, or several, sectors. However, detailed distributions of energy consumption or CO₂ emissions in Xinjiang are seldom mentioned, primarily because the energy consumption data in Xinjiang provided by the yearbooks lack city-level statistics [37]. In addition, the statistical yearbooks of most cities in Xinjiang do not offer energy balance tables, and certain yearbooks do not even have sectoral energy consumption statistics. Thus, there remains a vacant space for an in-depth accounting of emissions from Xinjiang's cities. This paper supplies a calculation of CO₂ emissions to fill that research gap and provide more detailed sectoral estimates.

3. Emission calculations, spatial econometric model and data collection

3.1. CO₂ emission estimation

In this study, we focused on the CO₂ emissions from the combustion of fossil fuels and calculated the administrative territorial-based CO₂ emissions, i.e. city-level CO₂ emissions. Based on production, we included both the energy-related emissions from the combustion of fossil fuels and the process-related emissions from cement production that discharge CO₂ through chemical reactions. Those two parts account for more than 99.9% of the overall human-induced CO₂ emissions [38].

3.1.1. Energy-related emissions

According to the Intergovernmental Panel on Climate Change (IPCC) guidelines, energy-related CO₂ emissions (CE_{energy}) can be calculated as the energy consumption multiplied by the emission factors (Eq. (1)).

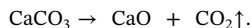
$$CE_{energy} = \sum_j \sum_i CE_{ij} = \sum_j \sum_i AD_{ij} \times NCV_i \times CC_i \times O_i \quad (1)$$

where CE_{ij} presents the CO₂ emissions from the combustion of fossil fuel i in sector j , and AD_{ij} refers to the intensity of human activity, which is herein measured by the amount of fossil fuel i combusted in sector j . In this study, 46 sectors and 17 fossil energy types were considered (see Support Information 2-3). NCV_i , CC_i , and O_i are the net calorific value, carbon content, and oxygenation efficiency of fossil fuel i , respectively. The parameters in use are from a previous survey of China's fossil fuel quality [35], which are supposed to be more accurate than former reports, including IPCC values.

3.1.2. Process-related emissions from the cement industry

Manufactures, mainly cement producers, also discharge CO₂ in chemical reactions (in addition to the requirement of heat for reactions), namely process-related emissions. In this paper we only investigated the cement production that accounts for 72.4% of the total process-related CO₂ emissions in China [38]. Cement is produced from

calcium carbonate by calcination at high temperatures, and this process discharges CO₂. The process can be expressed as follows:



CO₂ emissions from the process of cement production can be calculated by the product of a manufacturing activity and its emission factor as in Eq. (2).

$$CE_{cement} = AD_{cement} \times EF_{cement} \quad (2)$$

where AD_{cement} refers to cement production and EF_{cement} is the emission factor of the chemical process of cement production. The emission factor was obtained from [35] and is approximately 0.2906 tonnes CO₂ per tonne of cement production.

3.2. Activity data collection

The activity data in physical units for industrial sectors were collected from statistical yearbooks (see Support Information-4). Therein, the energy balance tables (EBTs) provide the amounts and compositions of energy consumption and the changes or transformations of all energy types. The final Energy Consumption by Industrial Sector (ECIS) contains detailed energy consumptions and types in each industrial sector. EBTs were used to calculate the total CO₂ emissions, and the ECIS was needed to allocate emissions into various sectors. Due to its complex administrative divisions and the disparate developments among them, Xinjiang has relatively incomplete statistics for city energy consumption. For example, Bortala's statistical yearbooks provided EBTs for the years 2011–2013 but not for 2010, which was also the case for other cities. Urumqi and Bayangol have a time series of energy consumption statistics, whereas comprehensive data for other cities are rare. For those cities in Xinjiang with missing energy data, GDP and population were used to estimate their shares of energy usage. More than 80 cement plants were in operation in Xinjiang in 2010 [39]. The production of cement can be found in the cities' statistical yearbooks and the Xinjiang Statistical Yearbook. The data used are briefly described in Table 1.

The Xinjiang Statistical Yearbook can provide a general allocation of different types of energy to each sector. For cities with incomplete energy data, sectoral energy consumption was estimated based on the average level of the autonomous region. The EBT was then estimated using energy production, transformation and consumption. Finally, the energy-related CO₂ emissions were measured using the table [40]. All the emission inventories can be found in the support information or freely downloaded from the China Emission Accounts and Datasets (www.ceads.net) after registration.

3.3. Uncertainty and Monte Carlo simulation

The collected data contain possible uncertainty caused by various reasons, e.g. the statistical calibre or human errors, therefore the estimation of the uncertainty of an emission inventory is important for its improvement [41]. As a method recommended by the IPCC [13], Monte Carlo simulations are widely used in the analysis of uncertainty [42], which is also employed in this study. As the CO₂ emissions were calculated using the activity data and emission factors, we evaluated the uncertainty of the emission inventories considering the two uncertainty sources. Assuming the activity data and emission factors are both distributed normally, the coefficients of variation (CV, i.e. the standard deviation divided by the mean) of them are collected from previous literature [29,43–45].

After repeating the simulation procedure for 20,000 times in Monte Carlo analysis, the average uncertainty of total CO₂ emissions was calculated with 95% Confidence Interval. This is –8.0% to 4.2% for the total emissions of the inventories used in this paper, falling in the range of 10–20% for non-OECD (Organisation for Economic Cooperation and Development) countries [46], and illustrates the estimations are

Table 2
Uncertainties of the cities' emissions.

City/sector	Lower limit	Upper limit
Ili2010	-6.4%	6.6%
Urumqi2010	-5.8%	5.9%
Turpan2010	-5.7%	5.8%
Tacheng2010	-6.6%	6.8%
Shihezi2010	-7.6%	7.8%
Kizilsu2010	-8.7%	8.9%
Karamay2010	-2.0%	2.0%
Kashgar2010	-6.9%	7.1%
Khotan2010	-9.4%	9.7%
Hami2010	-6.9%	7.3%
Changji2010	-10.1%	10.6%
Bortala2010	-5.6%	5.8%
Bayangol2010	-4.8%	4.9%
Altay2010	-7.0%	7.3%
Aksu2010	-4.6%	4.6%
Urumqi2005	-3.9%	4.0%
Urumqi2006	-5.1%	5.2%
Urumqi2007	-6.0%	6.0%
Urumqi2008	-5.1%	5.3%
Urumqi2009	-5.5%	5.6%
Urumqi2011	-22.9%	-13.5%
Urumqi2012	-18.4%	-8.2%
Urumqi2013	-17.1%	-6.8%
Urumqi2014	-10.7%	0.8%
Urumqi2015	-6.6%	6.8%
Total	-8.0%	4.2%
Primary and residence	-16.6%	13.6%
Coal mining and dressing	-14.5%	15.6%
Smelting and pressing of ferrous metals	-15.0%	13.2%
Nonmetal minerals mining and dressing	-13.9%	25.9%
Electricity generation	-13.2%	8.3%
Other industry	-8.2%	5.0%
Construction	-8.2%	7.2%
Service	-4.3%	0.7%

The deeper green colours show more negative uncertainties of the lower limits, and the deeper red show more positive uncertainties of the upper limits.

relatively accurate (city-level emissions inventories are probably more uncertain than national emissions inventories, for the differences among cities' source data). For 15 cities' emissions in 2010 and the emissions of Urumqi in 2005–2015, the uncertainties are shown in Table 2. The emission of Karamay has the smallest uncertainty of -2.0% to 2.0% , while the largest uncertainty appears in the emission of Changji as -10.1% to 10.6% , which are mainly from the uncertainty in the 'coal mining and dressing' sector. Among all sectors of Xinjiang's cities, the non-metal minerals mining and dressing sector contains the largest uncertainty (-13.9% to 25.9%), while the uncertainty of the service sector is the lowest, which is -4.3% to 0.7% . Detailed

uncertainties by sectors can be found in Support Information-5.

3.4. Spatial econometric model with carbon emissions

3.4.1. Testing for spatial effects

The global Moran's I spatial autocorrelation was used to assess the correlation among neighbouring observations and to identify patterns and levels of spatial clustering in neighbouring cities. The global Moran's I can be calculated as follows.

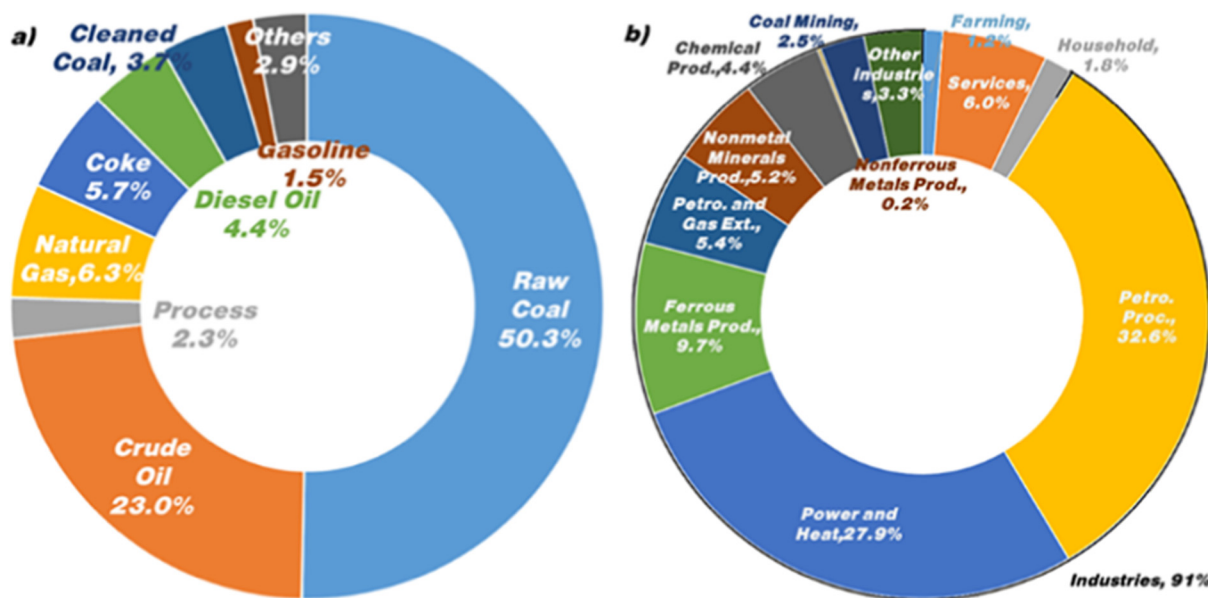


Fig. 1. Emission composition for Xinjiang in 2010. (a) Shows the energy mix in emissions, whereas (b) shows the sector mix.

$$\text{Moran's } I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^n \sum_{j=1}^n W_{ij}) \sum_{j=1}^n (y_j - \bar{y})^2} \quad (3)$$

In this equation, y_i and y_j represent the attributes of provinces or municipalities i and j , respectively, n is the number of provinces or municipalities, and W_{ij} represents the spatial weighting matrix describing the spatial relations between regions, ranging from 0 (for nonadjacent provinces or municipalities) to 1 (for adjacent provinces or municipalities). The Moran's I value range is $[-1, 1]$. The closer it is to 1, the greater is the clustering trend, and the closer it is to -1 , the greater is the dispersion effect. A value of 0 represents no spatial dependence.

In addition, Local Indicators of Spatial Association (LISA) statistic provides information related to the location of spatial clusters and outliers and the type of correlation. Both the global and local autocorrelation for the total emissions, the emission per capita and emission intensity (defined as CO₂ emissions per GDP) have been considered. In this study, a geographic spatial weights matrix via the inverse distance method is used.

3.4.2. The extended STIRPAT model

IPAT model which is an identity simply stating that environmental impact (I) is the product of population (P), affluence (A), and technology (T) was first used to explain dynamics of environmental impact, population and human wellbeing [47]. However, the IPAT equation is not best-suited to test hypotheses because it constrains a priori the effects of each driver to be proportional. STIRPAT (The Stochastic Impacts by Regression on Population, Affluence and Technology) model was an interdisciplinary innovation inspired by the variables of IPAT, an environmental accounting equation familiar to natural scientists, and linked to social science theory and methods by [48–50].

The standard STIRPAT model is:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (4)$$

where I represents total environmental impact, including carbon emission, which is determined by a multiple combination of three factors: population size (P), GDP per capita (A), and technology or the impact per unit of economic activity (T), which can be disaggregated into multiple variables other than A and P that influence I [50,51]. T can be chosen according to types of environmental impact being investigated, such as the share of industry and service in GDP [52] and

urbanization [51,53,54], etc. [55,56].

After taking logarithms, the model becomes:

$$\ln I_{it} = a + b(\ln P_{it}) + c(\ln A_{it}) + d(\ln T_{it}) + \ln e_i \quad (5)$$

where the subscript i denotes the observational units; t denotes year; b , c , and d are respectively the coefficients of P , A , and T ; e is the error term, and a is the constant.

Thus, as literature suggests [52,54], this paper uses urbanization rate to express T . Variables P , A , U , PP and TT respectively represent the total population of the cities, the per capita GDP, the urbanization rate, the share of service in GDP and the share of carbon emissions from coal intensive industries in total carbon emission. Using v to represent the virtual variables in the cities, representing some of the characteristics of cities that do not change with time – such as geographical location, weather conditions, historical culture and other factors that may influence carbon emissions – and using μ to represent the virtual variables of the year, which is the same for all cities, but change over time, such as the policy of national unification, the changes in these factors may have an impact on carbon emission. The advantage of adding v and μ is that, it can eliminate the problem of cross-section correlation. Using i represents the city, t represents the year, and the STIRPAT static panel data model is as follows:

$$\begin{aligned} \ln I_{it} &= \alpha_0 + \alpha_1 \ln P_{it} + \alpha_2 \ln A_{it} + \alpha_3 \ln U_{it} + \alpha_4 \ln PP_{it} + \alpha_5 \\ &\quad \ln TT_{it} + v_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (6)$$

$$\begin{aligned} \ln E_{it} &= \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln A_{it} + \beta_3 \ln U_{it} + \beta_4 \ln PP_{it} + \beta_5 \\ &\quad \ln TT_{it} + v_i + \mu_t + \varepsilon_{it} \end{aligned} \quad (7)$$

Starting from the improved STIRPAT, we built a spatial econometric model by taking into account the fact that carbon emissions are heterogeneous and spatially correlated among regions.

4. Results for emission calculation and spatial econometric model

4.1. Emissions in Xinjiang

In 2010, Xinjiang emitted a total of 304.06 million tonnes of CO₂ from energy combustion and the process of cement production (for

emission inventory, see Support Information-6). The emissions represented 3.8% of China's total emissions [12]. Energy and industrial structures have also affected the CO₂ emissions [57]. Fig. 1a shows the energy mix of Xinjiang's emissions. Raw coal (50.3%) and crude oil (23.0%) were the main energy resources that were the source of most CO₂ emissions, followed by natural gas (6.3%) and coke (5.7%). Cement production process accounted for 2.3% of the total emissions. The energy mix of Xinjiang partially differed from that of the nation, for which the composition included raw coal (55.8%), coke (13.6%), natural gas (2.3%), and industrial processes (6.9%) [57]. In comparison, the energy mix of Xinjiang included crude oil and natural gas. Xinjiang is rich in natural gas; thus, it can potentially reduce emissions by using more natural gas in place of traditional fossil fuels.

From a sectoral view (as shown in Fig. 1b), petroleum processing and coking (Petro. Proc.), electricity production (Power and Heat), and ferrous metal smelting (Ferrous Metals Prod.) were the largest emission contributors, with 32.6%, 27.9%, and 9.7%, respectively, and by comparison, their corresponding shares were 1.6%, 40.4% and 18.5% of the emissions of the whole nation, respectively [58]. As mentioned, with affluent energy resources, Xinjiang is a great exporter of energy for eastern China, including energy produced by oil, coal, natural gas and electricity. In addition, the petroleum processing and coking industry accounted for 72.1% of the industrial output in Xinjiang and supplied 12.6% of the country's crude oil production (2010) [59]. The petroleum processing and coking sector combusted a large amount of coal to generate heat for production. Therefore, this sector had an enormous influence on both the economy and emissions in Xinjiang. The thermal power industry sector is another energy sector that relied on coal combustion, thus becoming the second largest contributor of CO₂ emissions. By contrast, the smelting of ferrous metal is the largest consumer of coke, which is used to produce iron. Primary and tertiary industries and households emitted 1.2%, 6.0% and 1.8% of the total CO₂, respectively, and these emissions were much smaller than those of secondary industries. However, primary and tertiary industries and households shared 19.8%, 10.4% and 22.1% of Xinjiang's GDP, which were higher than the national averages at 11.0%, 7.6% and 14.3%, indicating a large potential for optimizing industry in Xinjiang.

4.2. Emission socioeconomics of Xinjiang's cities

The total CO₂ emissions for the year 2010 from each city in Xinjiang were highly disparate. As Fig. 2a shows that Urumqi had the largest CO₂ emissions at 108.44 Mt, which represented 35.7% of the CO₂ emissions for the whole autonomous region and was over 200 times higher than that of Kizilsu. Karamay and Changji also contributed over 10% of the CO₂ emissions in Xinjiang and were followed by Aksu, Bayangol, Shihezi, Turpan, Ili and Hami, which were each responsible for 2–7% of Xinjiang's CO₂ emissions. The other cities accounted for a total percentage of 6.1%. The geographical distribution is shown in Fig. 2a. The mid-northern part of Xinjiang had a higher CO₂ emission volume than the southern part. The mid-north cities, including Urumqi, Changji, Karamay, Bayangol and Aksu, had most of the energy resources, more developed economies and larger populations. The disparity was possibly caused by energy utilization and industrial development based on their geographical conditions, which will be discussed in Section 4.4.

Considering the different socioeconomic stages of the cities, the CO₂ emissions per capita and emission intensity were used as indicators to measure the cities' CO₂ emission performances. Similar to the total CO₂ emissions, the 15 Xinjiang cities had a large range of CO₂ emissions per capita, which ranged from 156.4 tonnes (in Karamay) to 0.8 tonnes (in Khotan). The distribution of CO₂ emissions per capita in Xinjiang was similar to that of the total emissions. The cities of Karamay, Urumqi, Shihezi and Changji, which are located in mid-northern Xinjiang, had the highest CO₂ emissions per capita (higher than 20 tonnes), located in mid-northern Xinjiang. The western city of Aksu had lower emissions

per capita (7.8 tonnes), whereas the total emissions were respectable (18.53 Mt). Hami emitted 7.27 Mt CO₂ but had high emissions per capita at 12.7 tonnes. Urumqi and Karamay had both high total emissions and high per capita emissions, which should receive special attention. However, Kizilsu and Khotan had the best performance on both indicators.

The CO₂ emission intensity and emissions per capita shared similar distributions, which are shown in Fig. 2b as the deeper blue regions accompanied by larger yellow circles. The highest emission intensity at 1.21 tonnes/thousand yuan was observed in Shihezi, which presented high energy consumption with low efficiency. Karamay and Urumqi followed with 0.86 tonnes/thousand yuan and 0.81 tonnes/thousand yuan, respectively. However, Bayangol possessed relatively high emissions of 17.95 Mt but a low emission intensity of 0.28 tonnes/thousand yuan. Tacheng and Kizilsu had the best performances of 0.13 tonnes/thousand yuan and 0.12 tonnes/thousand yuan, respectively.

Generally, developed areas have large total emissions and large populations. Economic growth and population scale are two factors that contribute to CO₂ emissions [15,19]. As industries are intensified, energy use tends to become more efficient, which helps cut the emissions per capita. Developed economies and large populations often co-exist and are correlated with each other. Consequently, CO₂ emissions per capita and emission intensities share similar distributions. Mega cities such as Urumqi, Karamay and Changji had more developed industries and large populations, thus accounting for the advanced labour forces and technology, and they shared relatively large emissions per capita and intensity.

4.3. Spatial relationships of emissions from Xinjiang cities

4.3.1. Testing for spatial effects

The emission maps give a hint that a possible spatial relationship is supposed to be investigated. Global Moran's I's scatter plots of total emissions, CO₂ emissions per capita and emission intensity are demonstrated in Fig. 3. It can be observed that the X-axis shows the CO₂ emission (CO₂ emissions per capita or emission intensity) and the Y-axis shows the lag- CO₂ emission (CO₂ emissions per capita or emission intensity) defined by the weights matrix. All the values and associated p-values of global Moran's I mean that there is spatial autocorrelation between geographic areas in terms of CO₂ emission (CO₂ emissions per capita or emission intensity) at a city-level in Xinjiang province.

In order to further investigate the spatial distribution of the above three variables, LISA maps are drawn. The LISA cluster maps, shown in Fig. 4, confirm the significance of local spatial autocorrelation according to the above three variables at city-level in Xinjiang province. Generally, Karamay and Changji are the clustering centres of high emissions while Kashgar is the clustering centre of low emissions. Karamay, envired by Aksu, Bayangol, Changji, Shihezi and Urumqi, of which the total emissions are of relatively high volume, thus the city is of significant high-high type (with high emissions envired by areas with high emissions). While for the emission per capita, which Karamay performs poorly as well, but comparing with the total emissions, the clustering centres of the emission per capita turned to Changji and Urumqi (high-high type, surrounded by high-emission cities i.e. Bayangol, Karamay, Hami, Shihezi and Turpan), whereas Karamay is recognized as the high-emission area surrounded by lower-emission area (high-low type). Changji is also the clustering centre of high emission intensity, envired by Turpan, Bayangol, Shihezi and Karamay. Kashgar, however, remains the clustering centre of low-low type of all the three kinds of emissions, meaning that areas with relatively low emissions cluster towards Kashgar. Thus, we take spatial autocorrelation into account as we do regression analysis.

4.3.2. The extended STIRPAT model

This paper utilizes a spatial cross-sectional data econometric model, which integrates spatial econometrics (spatial effects) and cross-section

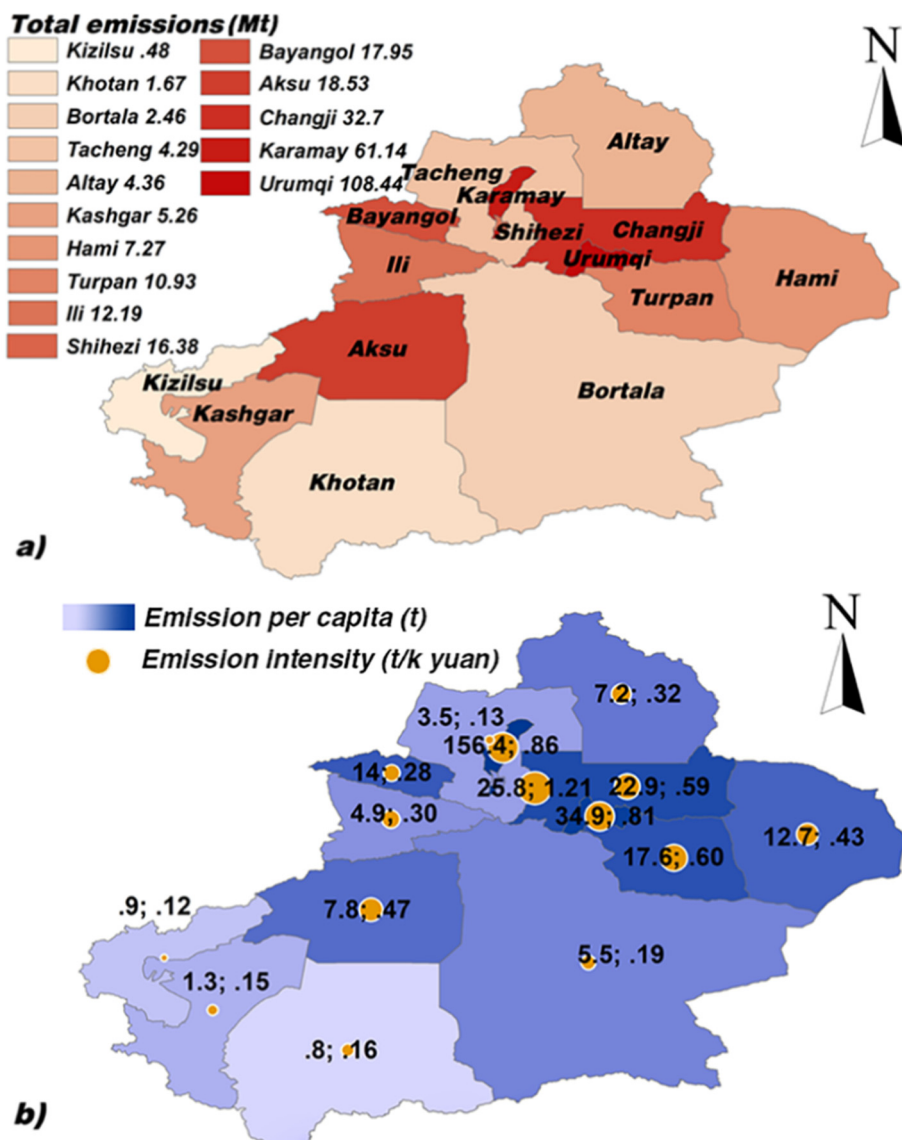


Fig. 2. Emissions of Xinjiang cities in 2010.

effects. This makes spatial econometric analysis more efficient. Two basic spatial econometric models – Spatial Lag Panel Data Model (SLPDM) and Spatial Error Panel Data Model (SEPDm) – are employed and compared with the traditional OLS regression model to choose the best-fit model.

Compared with traditional OLS model, SLPDM and SEPDm fits the data better as more coefficients are significant in the latter two models. As Table 3 demonstrates, the coefficients on most of the independent

variables are significant and have the expected signs. The coefficients for the spatially lagged dependent variables are positive and significant, indicating that carbon emissions are spatially correlated. When comparing SLPDM and SEPDm models, we could look at the AICc value. A lower AICc value means the model is a better fit for the data. Regarding the log likelihood and Schwarz criterion, the higher the log likelihood, the better the fit and the lower the Schwarz criterion, the better the fit of the model. Thus, SEPDm best fits the data, indicating that an increase

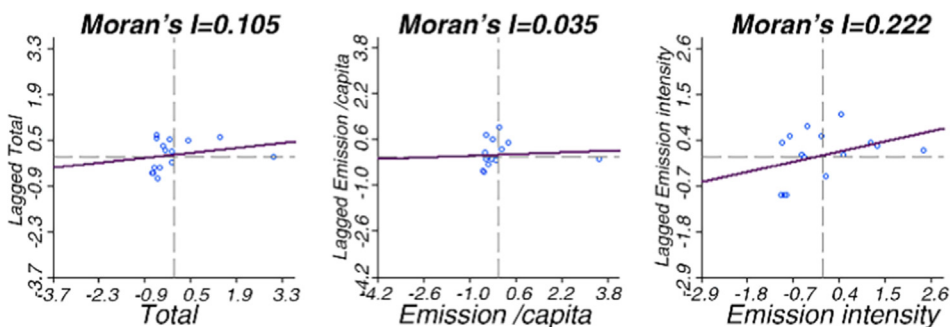


Fig. 3. Moran's I plots of the total CO₂ emissions (a), the emission per capita (b), and the emission intensity (c) in Xinjiang cities (2010).

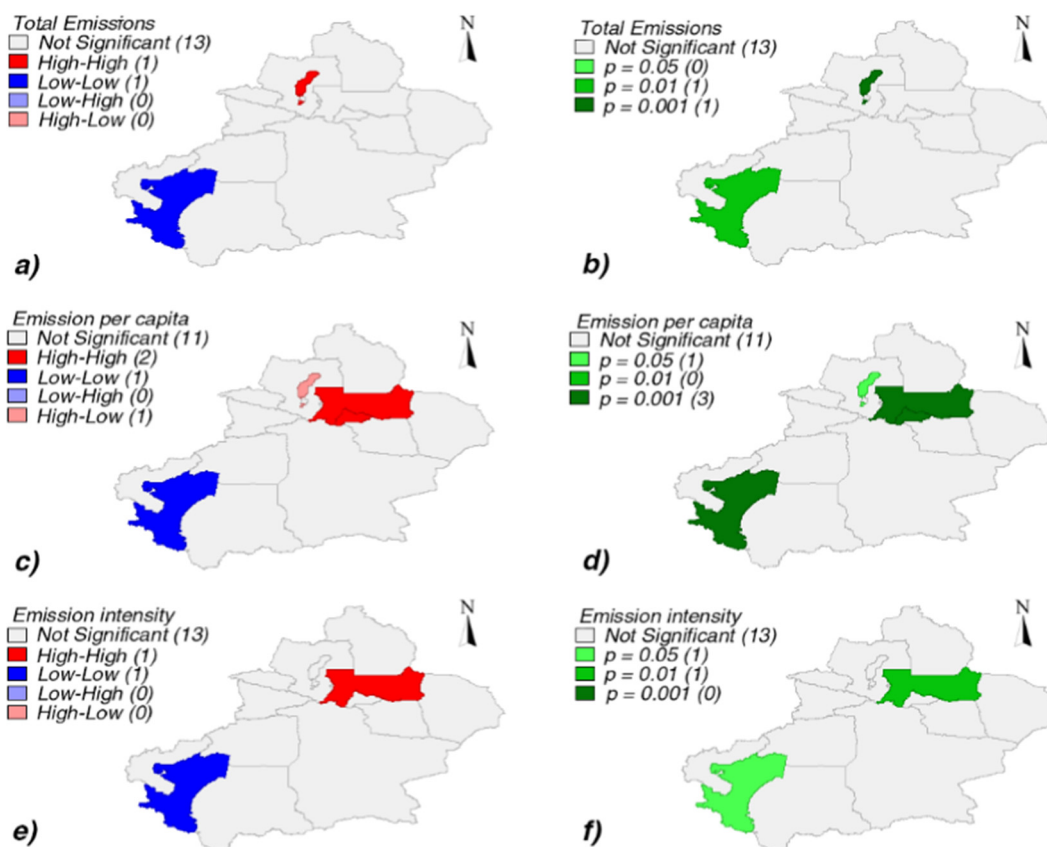


Fig. 4. LISA cluster map and the LISA significance of the total CO₂ emissions, the emission per capita and the emission intensity in Xinjiang cities (2010).

Table 3

Regression results for OLS, SLPDM and SEPDM.

Variables	OLS	SLPDM	SEPDM
Constant	-2.4536 (3.3568)	-4.2939 [†] (2.4879)	-3.8710 [†] (2.2015)
Log(P)	0.6887 (0.6456)	0.9156 [†] (0.4742)	1.0120 ^{**} (0.3861)
Log(A)	-0.0144 (0.1486)	-0.0448 (0.1110)	-0.0082 (0.0997)
U	3.4856 (1.9277)	3.4526 [†] (1.4161)	3.0813 [†] (1.2278)
W*Log(Total)		0.4783 [†] (0.2030)	-
LAMBDA		-	0.5685 ^{**} (0.1834)
R ²	0.2410	0.4423	0.5096
Adjusted R ²	0.0340	-	-
Log-likelihood	-23.6728	-22.0435	-21.4212
AICc value	55.3456	54.0870	50.8425
Schwarz criterion	58.1778	57.6272	53.6747

Note: St. Errors are in the parentheses. [†] represents significance at 10% and ^{**} 5% respectively.

of 1% of population would lead to about 1% increase of CO₂ emission, and an increase of 1% of urbanization rate would result in 3% increase of CO₂ emission.

4.4. Energy and sector mix in Xinjiang's emissions

Cities, however, have a variety of energy uses and industrial sectors and carbon reduction should focus on key energy types and major industrial sectors [60]. Therefore, more detailed investigations of the energy and sector mixes responsible for each city's emissions should be undertaken.

Fig. 5 demonstrates the proportions of CO₂ emissions from energy types and sectors in the 15 Xinjiang cities. Primary energy, such as coal and oil, and cement production process contributed most of the CO₂

emissions in all the cities. In Urumqi, 54.3% of the CO₂ was emitted from the combustion of raw coal, which was followed by crude oil combustion (15.3%). Karamay, which was ranked as the second largest CO₂ emitter, sourced energy mainly from crude oil (73.8%). Bortala, whose CO₂ emissions were relatively small, emitted CO₂ mainly from burning coke (39.6%). Nine other cities presented high percentages of raw coal-related CO₂ emissions (higher than 50%). The percentages for Altay, Changji, Hami and Shihezi exceeded 70%. Industrial processes (cement production) were responsible for a fair amount (more than 10%) of the emissions in industrial cities, such as Khotan, Kizilsu and Tacheng. The different energy types varied in their emission factors. For example, the emission factor for coke is 0.104 tonnes CO₂/tonne, which is larger than that for raw coal (0.087 tonnes CO₂/tonne) and crude oil (0.073 tonnes CO₂/tonne) [34]. Therefore, the energy mix affected total emissions. For example, in Karamay, which uses crude oil as the major energy type, the emissions intensity was relatively low compared with that of Urumqi, which depends more on raw coal. Natural gas has a low emission factor of 0.056 tonnes/10⁴m³ and is used more in Bayangol, Karamay, Kizilsu and Turpan (discharging over 10% of the CO₂ of each city). Compared to the regional average of 6.3% and national average of 2.3%, those cities had better emission performances and provide good examples for reducing emissions.

The industrial structures of the 15 cities' emissions are depicted in Fig. 5b. Industries provided the major contribution to CO₂ emissions in Xinjiang (91.21%), of which the power and heating sector, petroleum processing and coking, and ferrous metal production were the largest contributors. The regional disparity was large. Generally, however, the production and supply of electric power, smelting of ferrous metals, petroleum processing and coking, and non-metal mineral products were the four main sectors contributing to industrial emissions. In Urumqi, the first three aforementioned sectors were the largest sectors for CO₂ emissions, which were mainly from raw coal, consequently strengthening the role of raw coal in that city. The petroleum processing and

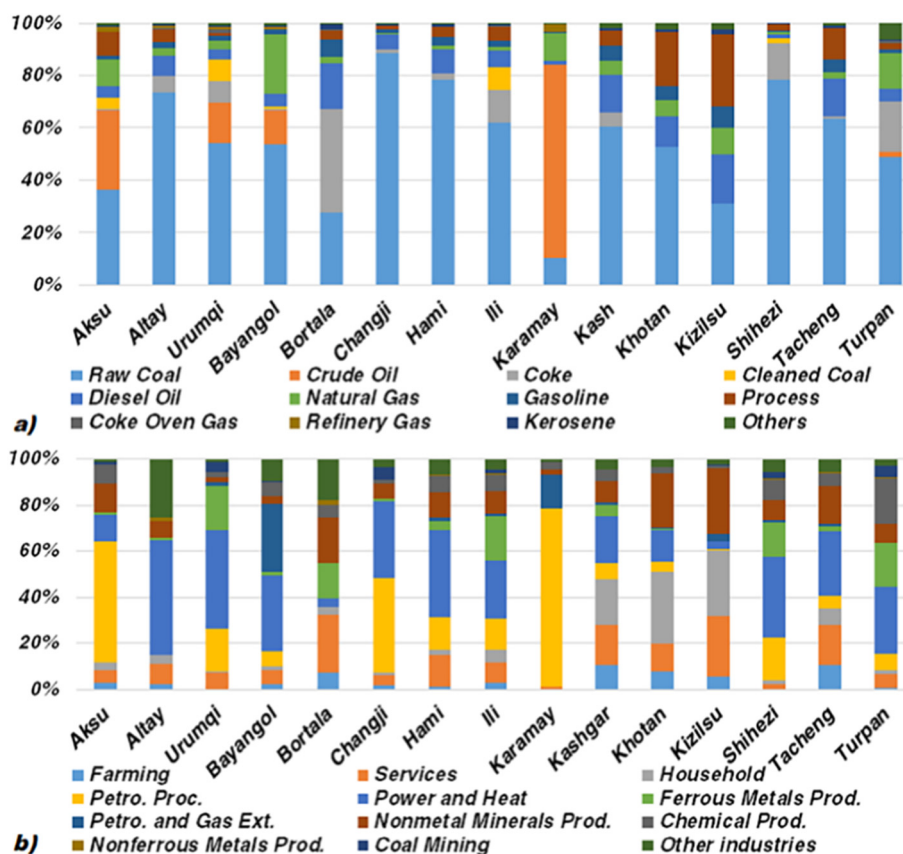


Fig. 5. Contributions of various energy types (a) and sectors (b) to the CO₂ emissions in Xinjiang cities (2010).

coking sector was the major consumer of crude oil at 92%, which contributed over 70% of the CO₂ emissions in Karamay. However, the petroleum processing and coking sector accounted for only 58.3% of the industrial output in Karamay and 62.3% of the output of Xinjiang's petroleum processing and coking sector [6]. The production of electricity played an important role in other cities. Altay, Bayangol and Hami emitted CO₂ mainly from the production of electricity, whereas Changji and Shihezi had large emissions from electricity production, petroleum processing and ferrous metal production. In Ili, Kashgar, Khotan and Tacheng, the major sectoral sources of CO₂ emissions were electric power production, petroleum processing and coking, non-metal mineral products, residential use and transportation. In contrast, Turpan presents a different industry structure consisting of the manufacture of chemical products and non-metal products with a low emissions intensity. Thus, energy-intensive sectors, e.g. electricity production, iron smelting and petroleum processing, led to high CO₂ emissions per capita and intensity (for detailed emission intensity of each sector, see Support Information-7). In addition, one city's economy relied on those sectors, significantly influencing its emission performance.

Primary industries, tertiary industries and households contributed small percentages of CO₂ emissions in Xinjiang at 1.2%, 6.0% and 1.8%, respectively. The service sector should be encouraged to expand against the background of the Belt and Road Initiative because of its high potential for improving energy efficiency. In Kizilsu, Bortala, Kashgar, Tacheng, Hami and Khotan, the CO₂ emissions from the service sector were only ~10% of the emissions and presented relatively low emission intensities. For example, the service sector (including transportation, storage, post and telecommunication services, wholesale, retail trade and catering services and other services) accounted 42.8% of Bortala's GDP, which was higher than the region's average of 32.5% and closely related to the performance of Bortala's emission intensity,

suggesting the importance of tertiary industries in energy savings and CO₂ reduction.

4.5. Time series of emissions in Urumqi, 2005–2015

Urumqi is the capital and the largest city in Xinjiang, and as such is the largest contributor to CO₂ emissions in Xinjiang with an emission performance that is a representative facet of the province. Thus, its historical emissions were inspected for the period 2005–2015. Generally, a rising trend was observed in the studied period except in 2006. An apparent decrease in crude oil consumption (Fig. 6a) and drop in the production from the petroleum processing and coking sector (Fig. 6b) in 2006 might have caused the lower emissions in that year. Special attention should be paid to the data showing that the crude oil consumption of the petroleum processing and coking sector was zero in 2006, which is significantly different from that in other years. However, CO₂ from other energy types rose in the decade from 2006 to 2015. The raw coal-related CO₂ emissions increased at a rate of 21.6% per year, and the percentage of total emissions increased from 38.4% in 2005 to 64.1% in 2015. However, crude oil presented a gently decreasing percentage of 19.9% in 2005 to 12.4% in 2015 (3.2% in 2006). Other sectors discharged increasing amounts of CO₂, with mild fluctuations from 2008 to 2010, which might be related to the economic crisis that affected all sectors. After 2010, a dramatic increase in total CO₂ emissions could be observed in Urumqi, where the power and heat sector served as the main driving factor. The growth rate of this sector was 28.0% per year, whereas the total emissions in Urumqi were approximately 15.6%. Consequently, the percentage of that sector's emissions rose from 20.3% in 2005 to 56.4% in 2015. The sectors smelting and processing of ferrous metals, petroleum processing, coking, and services presented mild increases and steady annual growth rates of 9.7%, 7.4% and 9.8% respectively, which is consistent with the growth of the

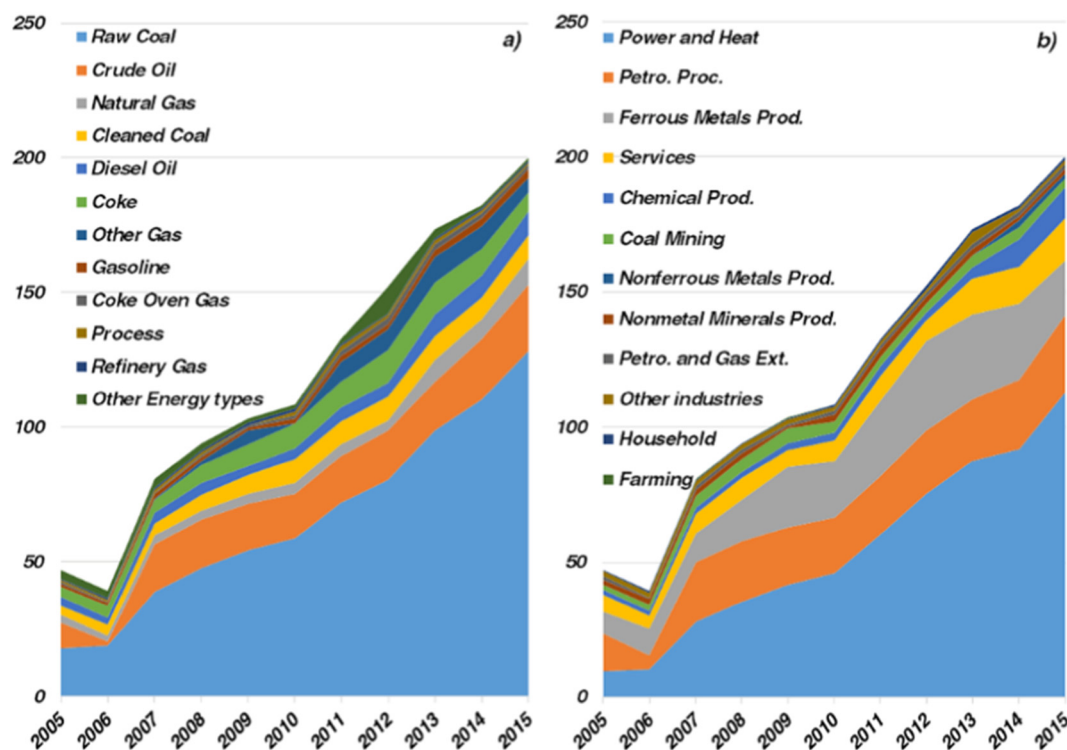


Fig. 6. CO₂ emissions from Urumqi in 2005–2015 (millions of tonnes).

economy. The other sectors had stable and smaller percentages.

The energy structure and industrial structure of Urumqi were representative of Xinjiang. Because of the abundant resources, the industries of Urumqi were mainly dependent on the mining, processing and exporting of various mineral or fossil energies to serve other regions of the country. A high reliance on industries related to resources leads to unbalanced industrial structures and limits the development of tertiary industries to some degree. As Fig. 6 shows, the CO₂ emissions of Urumqi are still climbing, and the key emission-producing industries appear to be more dominant. To better control energy consumption and achieve effective carbon reductions, the energy and industrial structures in this region should be adjusted. As the capital of Xinjiang and the largest CO₂ emitter, Urumqi should lead policy making and take action, which would also contribute to considerable carbon reductions throughout the region.

5. Conclusions and policy recommendations

Detailed city-level and sectoral level energy consumption statistics for Xinjiang are incomplete under the current statistical system. Previous studies on Xinjiang's energy consumption and CO₂ emissions have mainly focused on the total emissions of the autonomous region or emissions from a single sector or several sectors. For the first time, this study estimated the energy consumption of cities in Xinjiang and calculated the energy-related and process-related CO₂ emissions from 46 sectors. The following results were obtained over the course of this study.

In 2010, 15 cities in Xinjiang emitted a total of 304.06 million tonnes of CO₂, 97.7% of which was related to fossil fuel combustion. Industry process emissions were mainly generated from the production of cement. Raw coal and crude oil are the main energy types for Xinjiang's emissions. Two sectors, petroleum processing and coking and electric power, steam and hot water production and supply, produce the largest emissions. LISA results show that Karamay and Changji are the clusters of high emissions, while Kashgar is the clusters of low emissions. The CO₂ emissions from cities in Xinjiang vary. Urumqi and

Karamay contribute more than half of the region's CO₂ emissions. The total CO₂ emissions and emissions per capita have similar distribution patterns among the cities. However, the emissions intensity and emissions per capita distributions are similar. Altay has the largest emissions per capita and the highest emissions intensity, whereas Turpan has the best performance on both indicators due to low-carbon industry structure.

The major energy types and key sectors determine the CO₂ emissions per capita and per GDP. Cities with energy-intensive sectors as pillar industries and cities that source raw coal as major fuel tend to have worse emissions performances. As an example, Urumqi had a general rising trend in CO₂ emissions from 2005 to 2015, which was driven in large part by the production and supply of power and heat.

Accordingly, the following policy recommendations are proposed:

- (1) To reduce CO₂ emissions, dirty fossil fuels – especially raw coal and crude oil – should be regulated. Alongside that, advanced energy conservation methods, such as encouraging the use of highly efficient combustion equipment, should be employed. In addition, over the long run, fossil fuels must be replaced with low-carbon energy types, such as renewable wind power and solar energy, to allow for greater control over the total CO₂ emissions of Xinjiang.
- (2) City-level policies that suit local conditions should be encouraged to improve energy and industry structures. Rather than depending on a single energy type or single industrial sector, diversified industrial and energy structures should be developed for Xinjiang cities and industrializing cities elsewhere. With the introduction of cleaner industries and low-emission energy types, carbon reductions could be gradually realized. For example, Karamay could promote less emission-intensive industries (e.g. by importing services) to balance the industrial structure, reduce the use of crude oil and encourage the development of renewable energy. For Altay, however, priority should be given to cleaner industries with high energy efficiencies and investment invitations and energy-intensive technologies should be reduced.
- (3) There are spatial clustering patterns among cities in Xinjiang, with

Karamay and Changji as the high-emission centres, and Kashgar as the low-emission centre. A better planning of industrial distribution is needed, by which the enterprises share infrastructure, reuse the materials and thus save costs and reduce excessive CO₂ emissions. Cross-city industrial parks may be beneficial for total emission reduction.

- (4) By introducing an environmental protection tax and carbon price, Xinjiang might obtain a better regulation of upstream and downstream industries [61] via mitigating the market demand for power and heat, for instance. Xinjiang could also consider how to influence the market for carbon emissions to control the major industries, e.g. the power and heat production sector, which should be encouraged to regulate excessive emissions from the enterprises.
- (5) For Urumqi, the electric power, steam and hot water production and supply sector should receive a large amount of attention because of its continuous increase. By adjusting the energy strategy, Urumqi can relieve the imbalance of energy supply and demand. In addition, a more diverse industrial structure must be established.

Our study has limitations due to data availability. The estimates of city-level CO₂ emissions were based on the statistical yearbooks of the cities and autonomous region. Regional averages were used for those cities lacking data, which could cause significant uncertainty. Using more detailed statistics to optimize the accuracies of the calculations could be a focus of future work. In addition, the time series of CO₂ emissions for other cities also needs closer attention and further work to provide more practical advice for policy making.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.apenergy.2019.113473>.

References

- Wang F, Shackman J, Liu X. Carbon emission flow in the power industry and provincial CO₂ emissions: evidence from cross-provincial secondary energy trading in China. *J Clean Prod* 2017;159:397–409. <https://doi.org/10.1016/j.jclepro.2017.05.007>.
- National Development and Reform Commission, Ministry of Foreign Affairs PR of C, Ministry of Commerce PR of C. Vision and Actions on Jointly Building Silk Road Economic Belt and 21st-Century Maritime Silk Road; 2015.
- Liu Z, Zhang N, Zheng X, Xue J. Carbon footprint of China's belt and road. *Science* (80-) 2017;357:1107. <https://doi.org/10.1126/science.aa06621>.
- Jun Xu L, Chao Fan X, Qing Wang W, Xu L, Lian Duan Y, Jing Shi R. Renewable and sustainable energy of Xinjiang and development strategy of node areas in the "Silk Road Economic Belt". *Renew Sustain Energy Rev* 2017;79:274–85. <https://doi.org/10.1016/j.rser.2017.05.031>.
- Fan X, Wang W, Shi R, Cheng Z. Hybrid pluripotent coupling system with wind and photovoltaic-hydrogen energy storage and the coal chemical industry in Hainan, Xinjiang. *Renew Sustain Energy Rev* 2017;72:950–60. <https://doi.org/10.1016/j.rser.2017.01.085>.
- National Bureau of Statistics of China (2011)[Chinese Document]. China Statistical Yearbook 2011. Beijing, China: China Statistics Press; 2011.
- Zhang R, Liang T, Guo J, Xie H, Feng Q, Aimaiti Y. Grassland dynamics in response to climate change and human activities in Xinjiang from 2000 to 2014. *Sci Rep* 2018;8:1–11. <https://doi.org/10.1038/s41598-018-21089-3>.
- Fang C, Wang S, Li G. Changing urban forms and carbon dioxide emissions in China: a case study of 30 provincial capital cities. *Appl Energy* 2015;158:519–31. <https://doi.org/10.1016/j.apenergy.2015.08.095>.
- Wei J, Huang K, Yang S, Li Y, Hu T, Zhang Y. Driving forces analysis of energy-related carbon dioxide (CO₂) emissions in Beijing: an input e output structural decomposition analysis. *J Clean Prod* 2017;163:58–68. <https://doi.org/10.1016/j.jclepro.2016.05.086>.
- Kennedy CA, Stewart I, Facchini A, Cersosimo I, Mele R, Chen B, et al. Energy and material flows of megacities. *Proc Natl Acad Sci* 2015;112:5985–90. <https://doi.org/10.1073/pnas.1504315112>.
- Xu X, Huo H, Liu J, Shan Y, Li Y, Zheng H, et al. Patterns of CO₂ emissions in 18 central Chinese cities from 2000 to 2014. *J Clean Prod* 2018;172:529–40. <https://doi.org/10.1016/j.jclepro.2017.10.136>.
- Shan Y, Zheng H, Guan D, Li C, Mi Z, Schroeder H, et al. Energy consumption and CO₂ emissions in Tibet and its cities in 2014. *Earth's Futur* 2017;854–64. <https://doi.org/10.1002/efdt.231>.
- Intergovernmental Panel on Climate Change (IPCC). IPCC Guidelines for national greenhouse gas inventories. Hayama, Japan: Institute for Global Environmental Strategies (IGES); 2006.
- Wang C, Liu Y, Kong X, Li J. Spatiotemporal decoupling between population and construction land in urban and rural Hubei province. *Sustain* 2017;9. <https://doi.org/10.3390/su9071258>.
- Wang C, Wang F, Kaya Zhang H. The process of energy-related carbon emissions and influencing mechanism(in Chinese). *Acta Ecol Sin* 2016;36:2151–63. <https://doi.org/10.5846/stxb201410152033>.
- Song M, Shi J. Estimation of carbon dioxide emission in Xinjiang(in Chinese). *Arid Zo Res* 2014;31:188–91. <https://doi.org/10.13866/j.azr.2014.01.021>.
- Chen F, Shen L, Liu L, Gao T. Spatial differences of exergy use of cement manufacturing industry in China based on extended exergy accounting method. *J Geogr Sci* 2015;25:13393–21407. <https://doi.org/10.1007/s11442-015-1241-4>.
- Guo B, Geng Y, Dong H, Liu Y. Energy-related greenhouse gas emission features in China's energy supply region: the case of Xinjiang. *Renew Sustain Energy Rev* 2016;54:15–24. <https://doi.org/10.1016/j.rser.2015.09.092>.
- Wang C, Wang F, Zhang X, Yang Y, Su Y, Ye Y. Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang. *Renew Sustain Energy Rev* 2017;67:51–61. <https://doi.org/10.1016/j.rser.2016.09.006>.
- Su Y, Ma H, Yan L. Spatial-temporal differences and driving mechanism of agricultural land use carbon emission in Xinjiang(in Chinese). *Arid L Geogr* 2013;36:1162–9. <https://doi.org/10.13826/j.cnki.cn65-1103/x.2013.06.015>.
- Tang H, Ma H, Su Y, Xin C, Wang J. Carbon emissions and carbon absorptions of different land use types in Xinjiang(in Chinese). *Arid Zo Res* 2016;33:486–92.
- Sigmund I, Günther J, Thevs N. Carbon and phosphorus footprint of the cotton production in Xinjiang, China, in comparison to an alternative fibre (Apocynum) from Central Asia. *J Clean Prod* 2017;148:490–7. <https://doi.org/10.1016/j.jclepro.2017.01.153>.
- Xiong C, Yang D, Huo J. Spatial-temporal characteristics and LMDI-based impact factor decomposition of agricultural carbon emissions in Hotan Prefecture, China. *Sustainability* 2016;8:1–14. <https://doi.org/10.3390/su8030262>.
- Zhou G, Chung W, Zhang Y. Carbon dioxide emissions and energy efficiency analysis of China's regional thermal electricity generation. *J Clean Prod* 2014;83:173–84. <https://doi.org/10.1016/j.jclepro.2014.06.047>.
- Yan D, Lei Y, Li L, Song W. Carbon emission efficiency and spatial clustering analyses in China's thermal power industry: evidence from the provincial level. *J Clean Prod* 2017;156:518–27. <https://doi.org/10.1016/j.jclepro.2017.04.063>.
- Zhang X, Zhao Y, Wang C. Sectorial difference on carbon emission of energy consumption in Xinjiang based on input/output principle(in Chinese). *Resour Ind* 2017;19:85–92. <https://doi.org/10.13776/j.cnki.resourcesindustries.2017.01.005>.
- Li J, Huang X, Yang H, Chuai X, Li Y, Qu J, et al. Situation and determinants of household carbon emissions in Northwest China. *Habitat Int* 2016;51:178–87. <https://doi.org/10.1016/j.habitatint.2015.10.024>.
- Wang S, Liu X. China's city-level energy-related CO₂ emissions: spatiotemporal patterns and driving forces. *Appl Energy* 2017;200:204–14. <https://doi.org/10.1016/j.apenergy.2017.05.085>.
- Shan Y, Guan D, Zheng H, Ou J, Li Y, Meng J, et al. Data Descriptor: China CO₂ emission accounts 1997–2015. *Sci Data* 2017;5:1–14. <https://doi.org/10.1038/sdata.2017.201>.
- Mi Z, Zhang Y, Guan D, Shan Y, Liu Z, Cong R, et al. Consumption-based emission accounting for Chinese cities. *Appl Energy* 2016;184:1073–81. <https://doi.org/10.1016/j.apenergy.2016.06.094>.
- Chen Q, Cai B, Dhakal S. CO₂ emission data for Chinese cities. *Resour Conserv Recycl* 2017;126:198–208. <https://doi.org/10.1016/j.resconrec.2017.07.011>.
- Liu Z, Geng Y, Xue B. Inventorying energy-related CO₂ for City: Shanghai study. *Energy Proc* 2011;5:2303–7. <https://doi.org/10.1016/j.egypro.2011.03.396>.
- Wang Q, Wu SD, Zeng YE, Wu BW. Exploring the relationship between urbanization, energy consumption, and CO₂ emissions in different provinces of China. *Renew Sustain Energy Rev* 2016;54:1563–79. <https://doi.org/10.1016/j.rser.2015.10.090>.
- Feng K, Hubacek K, Sun L, Liu Z. Consumption-based CO₂ accounting of China's megacities: the case of Beijing, Tianjin, Shanghai and Chongqing. *Ecol Indic* 2014;47:26–31. <https://doi.org/10.1016/j.ecolind.2014.04.045>.
- Liu Z, Guan D, Wei W, Davis SJ, Ciais P, Bai J, et al. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* 2015;524:335–8. <https://doi.org/10.1038/nature14677>.
- Wang L, Gong Z, Gao G, Wang C. Can energy policies affect the cycle of carbon emissions? Case study on the energy consumption of industrial terminals in

- Shanghai, Jiangsu and Zhejiang. *Ecol Indic* 2017;83:1–12. <https://doi.org/10.1016/j.ecolind.2017.07.036>.
- [37] Xu S, He Z, Long R, Chen H, Han H. Comparative analysis of the regional contributions to carbon emissions in China. *J Clean Prod* 2016;127:406–17. <https://doi.org/10.1016/j.jclepro.2016.03.149>.
- [38] National Development and Reform Commission. China 2nd National Communication on Climate Change[Chinese Document]; 2013. http://qhs.ndrc.gov.cn/zcfg/201404/t20140415_606980.html.
- [39] Liu C. Study on the cement industry sustainable development in the area of Xinjiang. Wuhan University of Technology; 2011.
- [40] Shan Y, Guan D, Liu J, Mi Z, Liu Z, Liu J, et al. Methodology and applications of city level CO₂ emission accounts in China. *J Clean Prod* 2017;161:1215–25. <https://doi.org/10.1016/j.jclepro.2017.06.075>.
- [41] Zheng H, Shan Y, Mi Z, Meng J, Ou J, Schroeder H, et al. How modifications of China's energy data affect carbon mitigation targets. *Energy Policy* 2018;116:337–43. <https://doi.org/10.1016/j.enpol.2018.02.031>.
- [42] Lang J, Cheng S, Zhou Y, Zhang Y, Wang G. Air pollutant emissions from on-road vehicles in China, 1999–2011. *Sci Total Environ* 2014;496:1–10. <https://doi.org/10.1016/j.scitotenv.2014.07.021>.
- [43] Zhang Q, Streets DG, He K, Wang Y, Richter A, Burrows JP, et al. NO < inf > x < / inf > emission trends for China, 1995–2004: the view from the ground and the view from space. *J Geophys Res Atmos* 2007;112:1995–2004. <https://doi.org/10.1029/2007JD008684>.
- [44] Zhao Y, Nielsen CP, Lei Y, McElroy MB, Hao J. Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China. *Atmos Chem Phys* 2011;11:2295–308. <https://doi.org/10.5194/acp-11-2295-2011>.
- [45] Zhao Y, Wang S, Duan L, Lei Y, Cao P, Hao J. Primary air pollutant emissions of coal-fired power plants in China: current status and future prediction. *Atmos Environ* 2008;42:8442–52. <https://doi.org/10.1016/j.atmosenv.2008.08.021>.
- [46] Marland G. Uncertainties in accounting for CO₂ from fossil fuels. *J Ind Ecol* 2008;12:136–9. <https://doi.org/10.1111/j.1530-9290.2008.00014.x>.
- [47] Ehrlich PR, Holdren JP. Impact of population growth. *Science* (80-) 1971;171:1212–7. <https://doi.org/10.1126/science.171.3977.1212>.
- [48] Dietz T, Rosa EA. Rethinking the environmental impacts of population, affluence and technology. *Hum Ecol Rev* 1994;1:277–300. <https://doi.org/10.2307/24706840>.
- [49] Dietz T, Rosa EA, Stern PC, Ruttan VW, Socolow RH, Sweeney JL. Environmental impacts of population and consumption. *Environ Signif Consum* 1997.
- [50] York R, Rosa EA, Dietz T. STIRPAT, IPAT and ImpACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecol Econ* 2003;46:351–65. [https://doi.org/10.1016/S0921-8009\(03\)00188-5](https://doi.org/10.1016/S0921-8009(03)00188-5).
- [51] Poumanyong P, Kaneko S, Dhakal S. Impacts of urbanization on national transport and road energy use: evidence from low, middle and high income countries. *Energy Policy* 2012;46:268–77. <https://doi.org/10.1016/j.enpol.2012.03.059>.
- [52] Shi A. The impact of population pressure on global carbon dioxide emissions, 1975–1996: evidence from pooled cross-country data. *Ecol Econ* 2003;44:29–42. [https://doi.org/10.1016/S0921-8009\(02\)00223-9](https://doi.org/10.1016/S0921-8009(02)00223-9).
- [53] York R. Structural influences on energy production in South and East Asia, 1971–2002. *Sociol Forum* 2007;22:532–54. <https://doi.org/10.1111/j.1573-7861.2007.00034.x>.
- [54] Poumanyong P, Kaneko S. Does urbanization lead to less energy use and lower CO₂ emissions? A cross-country analysis. *Ecol Econ* 2010;70:434–44. <https://doi.org/10.1016/j.ecolecon.2010.09.029>.
- [55] Jorgenson AK, Rice J, Clark B. Cities, slums, and energy consumption in less developed countries, 1990 to 2005. *Organ Environ* 2010;23:189–204. <https://doi.org/10.1177/1086026610368376>.
- [56] Liddle B, Lung S. Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Popul Environ* 2010;31:317–43. <https://doi.org/10.1007/s11111-010-0101-5>.
- [57] Ouyang X, Lin B. An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. *Renew Sustain Energy Rev* 2015;45:838–49. <https://doi.org/10.1016/j.rser.2015.02.030>.
- [58] Shan Y, Liu J, Liu Z, Xu X, Shao S, Wang P, et al. New provincial CO₂ emission inventories in China based on apparent energy consumption data and updated emission factors. *Appl Energy* 2016;184:742–50. <https://doi.org/10.1016/j.apenergy.2016.03.073>.
- [59] National Bureau of Statistics of China(2011). China Energy Statistical Yearbook 2011[Chinese Document]. Beijing, China: China Statistics Press; 2011.
- [60] Zhang L, Lei J, Zhang X. Variations and influential factors of carbon emissions of primary energy consumption in Xinjiang during the period 1952–2008 (in Chinese). *Resour Sci* 2012;34:42–9.
- [61] Skelton ACH, Allwood JM. The carbon price: a toothless tool for material efficiency? *Philos Trans R Soc A Math Phys Eng Sci* 2017;375:20160374. <https://doi.org/10.1098/rsta.2016.0374>.