UNIVERSITY OF EAST ANGLIA

Energy-Pollution-Socioeconomic Assessment from Production- and Consumption-based Accounting Approach

JIAMIN OU

Submitted in accordance with the requirements for the degree of Doctor of Philosophy

The University of East Anglia

School of International Development

May 2020

Abstract

Rapid urbanization and industrialization in developing countries have stimulated energy consumption and resulted in environmental degradation. One of the global challenges today is to sustain socioeconomic development under the constraints of limited resources and without compromise in environmental wellness, climate resilience or function. Sustainable production and consumption is a promising way out of this grand challenge. A fundamental shift towards sustainable production and consumption patterns relies on a detailed characterization of material and emission flows between producers, consumers and environmental receptors. Such information, however, is greatly lacking in developing countries for both national and subnational levels.

This study presents an integrated assessment of the interlinkages between energy, pollution and socioeconomic demands in China and its provinces with the thread of production- and consumption-based emissions. The double-digit growth of China's economy before 2011 and its slow-down in the "new normal" period since then, rapid urbanization and rise of middle income class, and recession in export growth have resulted in dramatic changes in socioeconomic dimensions. It is important to understand how the socioeconomic drivers have evolved and fuelled the energy consumption and air pollution formation.

Production- and consumption-based accounting approaches provide two distinct yet complementary angles to understand the nexus of socioeconomic demands, energy and pollution. This study develops an integrated assessment framework to depict material and emission flows between producers, consumers and environmental receptors. A four-stage research framework is proposed. It starts from the compilation of a primary energy consumption matrix, followed by the establishment of production-based inventories of greenhouse gases and air pollutants. Energy and emission accounts are then connected to socioeconomic accounts through environmentally-extended input-output (EEIO) analysis and decomposition techniques. Socioeconomic drivers that are responsible for energy consumption or emissions can be revealed, including entities such as intermediate sectors and final consumers and macroeconomic factors such as population growth, economic growth, industrial structure, energy intensity and energy mix. Meanwhile, production-based emissions marked by different socioeconomic drivers are fed into environmental modelling tools such as an air quality model. Through environmental models, a vast variety of environmental end-points can be evaluated, including but not limited to the ambient air pollutant concentration, air quality attainment rate, pollution formation regimes and death toll. With the corresponding relationship between production- and consumption-based emissions, socioeconomic demands and environmental consequences can be connected in an explicit and quantitative way.

The proposed framework has been demonstrated at the provincial and national levels in China to advance the understanding of causes and effects of environmental issues in a socioeconomic context. Recognizing the central role of energy consumption in climate and air pollution problems, the production-based patterns of energy consumption in 30 provinces in China and their socioeconomic drivers are first investigated. Energy elasticity (the percentage change in energy consumption to achieve a 1% change in national GDP) in China have decreased continuously from 2003 to 2016. Starting at a level of 1.11 from 2003 to 2007, the energy elasticity dropped to 0.58 from 2007 to 2011, followed by an even lower value of 0.42 from 2011 to 2016. The reduction in the growth of energy consumption is even more prominent at the provincial level. Eight of the provinces saw declines in their total primary consumption from 2011 to 2016. They differed from their counterparts since 2011, when the decreasing effect of energy intensity was enhanced and, for the first time, surpassed or approximated the increasing effect of economic growth. The catching-up was more associated with the significant reduction of energy intensity rather than the slowdown of economic growth. New decreasing factors such as the share of coal and industrial structure change were also emerging to curb the growth. In addition, six provinces have levelled off their total primary consumption and decreased the combined consumption of coal and petroleum. Their driver mechanisms were similar but the share of cleaner fuels, e.g., natural gas and non-fossil fuels, increased significantly. Nevertheless, such declines were demonstrated to be initial rather than structural changes. To secure the trend or fasten transition, one path is to sustain the strong decreasing effect mainly from energy intensity, which is applicable to Hebei, Liaoning, Jilin, Henan, Hubei and Yunnan, whose energy intensities are still high (3.0~5.8 tce/10^4 $USD in 2016). The other path is to complement energy intensity with new decreasing drivers, which better suits the other provinces which have reached relatively low levels of energy intensity and have less potential for further reduction.

Another two case studies at province levels are conducted. One is to investigate the demands behind air pollutant emissions in a fast developing region in China. Guangdong is a typical fast-developing region with annual GDP growth around 11% and China's export industry hub. It is beset with air pollution problems featured by fine particulate matter ($PM_{2.5}$) and ground-level ozone (O_3). This study reveals that the varying trends of air pollutants from 2007 to 2012 were associated with production-based control measures and changes in economic structure and trading patterns. From the consumption perspective, due to the stringent control of SO_2 in power plants and key industries, SO_2 emissions saw substantial declines, while the less controlled PM_{10}, $PM_{2.5}$, non-methane volatile organic compounds (NMVOCs) and CO emissions continued to grow. The contributions of the cleaner service sectors to all seven pollutants increased. This increase could be a consequence of the expansion of the service sector, which grew by 41% in terms of its contributions to Guangdong's GDP in 5 years. Meanwhile, exports accounted for more than 50% of the emissions, but their share had started to decrease for most pollutants except NMVOCs and CO. It suggests that Guangdong is moving towards a cleaner production and consumption pathway. The transformation of the industrial structure and increase in urban demand should help to further reduce emissions while maintaining economic development.

The other case study focuses on CO_2 emission in a less developed region in China. The production- and consumption-based characteristics of Tibet's CO_2 emissions and its linkages with other regions in China are studied. Results show that the consumption-based CO_2 emissions in Tibet (18.8 Mt, similar to Guinea's emissions in 2015) were three times as high as the production-based estimate (6.2 Mt). Tibet displays unique emission patterns with the highest ratio of consumption- to production-based emissions in China, which are more similar with the east developed provinces rather than its counterparts in west China. More than half of Tibet's consumption-based emissions are supported by Qinghai, Hebei, Sichuan, and others, enabled by the Qinghai-Tibet railway that connected Tibet to China's national railway system. High carbon footprint but low life expectancy is found in Tibet, suggesting the emerging need of a more sustainable consumption pathway under the intensifying interregional connections by Belt and Road Initiative.

This study also presents a national study on the nexus of demand-emission-pollution-health. While China has made enormous progress in combatting $PM_{2.5}$ pollution, its O_3 exposure metrics increased by more than 50% from 2013 to 2017. This study investigates the socioeconomic drivers behind the O_3 precursor emissions (NMVOCs, NOx and CO) and their effects on O_3 formation chemistry, ambient O_3 level and mortality. As the world's factory, goods produced in China for foreign markets lead to an increase of domestic non-methane volatile organic compounds (NMVOCs) emissions by 3.5 million tons in 2013; about 13% of the national total or, equivalent to half of emissions from European Union (EU). Export demand driven emissions have mixed impacts on China's ozone (O_3) formation, but they generally contribute about 6~15% of peak O_3 levels (6~10 μg/m^3) caused by human activities in the coastal area resulting in an estimated 4615 (1514 ~ 7600) premature deaths. By benchmarking emission intensity in China to EU, the export footprint and NMVOCs emissions from the whole production capacity can be reduced by nearly 60% at moderate costs (at an annualized cost equivalent to 0.05% to 0.30% of industrial output). Such efforts will slow down the upward trend of O_3 with notable health benefits. For a substantial attenuation of O_3 pollution in China, however, concerted actions addressing domestic demands from urban and rural household are in great need.

This PhD study presents an integrated assessment framework and captures how socioeconomic demands in China evolved and acted as driving forces of national and regional energy consumption, air pollutant emissions and pollution formation. In addition to end-of-pipe treatments, the roots of environmental problems need to be understood in socioeconomic context. The booming socioeconomic demands are responsible for the rise of energy consumption and poor air quality, but China as a whole and some of its more developed regions have been under a crucial transition towards sustainable production and consumption while maintaining the prosperity of individual and society. Experiences in China can be mirrored to other developing countries to foster sustainable production and consumption patterns.

Contents

List of Tables

List of Figures

List of Appendix Tables

Abbreviations

Abbreviations	Descriptions
AVERT	AVoided Emissions and geneRation Tool
BenMAP	Benefits Mapping and Analysis Program
CAMx	Comprehensive Air Quality Model with Extensions
CDM	Clean Development Mechanism
CESM	Community Earth System Model
CMAQ	Community Multiscale Air Quality
CO	Carbon monoxide
CO_2	Carbon dioxide
CUSUM	Cumulative sum
DA	Decomposition Analysis
EAD	Expected annual damage
EBT	Energy Balance Table
EEIO	Environmentally-extended input-output
ESMs	Energy system models
EU	European Union
EU28	28 European countries
FCEVs	Fuel cell electric hydrogen vehicles
HPLC	High-pressure liquid chromatography
GAINS	Greenhouse Gas - Air Pollution Interactions and Synergies
GC	Gas chromatography
GCM	General circulation model
GDP	Gross domestic product
GEOS	Goddard Earth Observing System
GHG	Greenhouse gas
GMAO	Global Modelling Assimilation Office
GTAP	Global trade analysis project
IAMs	Integrated assessment models
IDA	Index decomposition analysis
IIASA	International Institute for Applied System Analysis
IO	Input Output
IOTs	Input Output Tables
LMDI	Logarithmic mean Divisia index
LPG	Liquefied Petroleum Gas
LRTAP	Convention on Long-range Transboundary Air Pollution
MESSAGE	MESSAGE Integrated Assessment Model

MRIO	Multi-region Input-Output
Mtce	Million tonnes of coal equivalent
NDCs	Nationally determined contributions
NH_3	Ammonia
NMVOCs	Non-methane volatile organic compounds
NO_2	Nitrogen dioxide
NOx	Nitrogen oxides
O_3	Ozone
OECD	Organisation for Economic Co-operation and Development
OSPM	Operational Street Pollution Model
OVOCs	Oxygenated VOCs
PM	Particulate Matter
PM_{10}	Particulate matter with an aerodynamic diameter of less than 10 μm
$PM_{2.5}$	Particulate matter with an aerodynamic diameter of less than 2.5 μm
PMF	Positive matrix factorization
RM	Receptor model
SDA	Structural Decomposition Analysis
SDGs	Sustainable development goals
SMOKE	SparseMatrix Operator Kernel Emissions
SO_2	Sulphur dioxide
TIAM	TIMES Integrated Assessment Model
UNFCCC	United National Framework Convention of Climate Change
US	United State
WRF	Weather Research and Forecast

Acknowledgements

This PhD study is only possible with the enormous help from my dedicated supervisors, examiners, groupmates and other researchers contributing to the knowledge and debates. Firstly, I would like to express my sincere gratitude to my supervisors Prof. Dabo Guan and Prof. Konstantinos Chalvatzis for the continuous support of my PhD study and related research, for their patience, motivations and immense knowledge. I am especially indebted to Prof. Guan for his support and advice in not only research but also life and career. I would like to acknowledge the financial support from Joint Leverhulme Trust and Social Sciences Faculty Postgraduate Studentship, by Economic and Social Research Council of UK.

Beside my supervisors, I would like to thank my thesis examiners: Prof. Claire Reeves and Prof. Maria Rosa Duarte Pac. I really appreciate their time and efforts in examining this work and their insightful comments, corrections and encouragement. I also owe thanks to Dr Emma Gilberthorpe, who has acted as an independent chair of my viva and coordinated the whole process.

Apart from the great supervisions I have received in UEA, this study has been greatly benefited from my stay in International Institute for Applied System Analysis (IIASA). I have been lucky enough to work with Dr Zbigniew Klimont, Dr Shaohui Zhang and other researchers in IIASA. Their fantastic supervision, time and input have shaped this work into a direction of more policy-relevant, and informative for wider audience. My stay in IIASA is supported by Natural Environment Research Council, UK.

I am also deeply grateful to Prof. Junyu (Allen) Zheng, Dr. Zhijiong Huang, Dr Guanglin Jia in Jinan University, P.R. China, who have provided vital technical support of this study.

I appreciate all the great support I have received from the Gilly Potter, Emma Gilberthorpe and the other supporting staff in the PGR office and the school of international development.

Special thanks are reserved for my groupmates and friends who have seen me through the journey. Many thanks to Dr Jing Meng, Dr Yuli Shan, Dr Zhifu Mi, Dr Zhao Zeng, Dr Yang Xia, Heran Zheng, Yixin Hu, Huiqing Wang, Yixi Zheng, Xian Li, Acknowledgements

Yue Wu, Sarah, Jason, Mamata, Lucas, Tau-cefe and all the lovely fellows in Room 2.83 and 1.83. I would also like to thank all the participants in Young Scientists Summer Programme of IIASA in 2018 and 2019, who have provided me joy and inspiration in two great summers.

I would like to thank my family for their understanding, support and tolerance. They have supported me spiritually throughout this PhD journey and my life in general.

Jiamin Ou

09/05/2020

PhD Achievements

Peer-reviewed papers

J.M. Ou, Z. J. Huang, Z. Klimont*, G. Jia, *et al.*, 2019. Role of export industries on China's ground-level ozone pollution. Under review by ***Science Advance***.

J.M. Ou, J. Meng, Y. Shan, H. Zheng, Z. Mi, D. Guan*, 2019. Initial Declines in China's Provincial Energy Consumption and Their Drivers. ***Joule***, 3, 5, 1163-1168.

J.M. Ou, J. Meng, J.Y. Zheng*, Z.F. Mi, Y.H. Bian, X. Yu, J.R., Liu, D.B., Guan*, 2017. Demand-driven air pollutant emissions for a fast-developing region in China. ***Applied Energy*** *(IF=7.900)*, 204: 131-124.

J.M. Ou, J. Meng, H. Zheng, Z. Mi, Y. Shan, D. Guan*, 2019. Frequent Interactions of Tibet's CO_2 emissions with those of other regions in China. ***Earth's Future*** *(IF=4.594)*, 7, 491-502.

J.M. Ou, J. Zheng*, Z. Yuan, D. Guan, Z. Huang, F. Yu, M. Shao, PKK Louie, 2018. Reconciling discrepancies in the source characterization of VOCs between emission inventories and receptor modeling. ***Science of the Total Environment*** *(IF=4.900)*, 628, 697-706.

Z. Mi, Jing Meng, J. Zheng, **J.M. Ou,** D. Guan, Klaus Hubacek, Z. Liu, D'Maris Coffman, Nicholas Stern, Bi-Ying Yu, Yi-Ming Wei, 2019. Converging household carbon footprints in China. ***Nature Sustainability***, accepted.

Y. Bian, Z. Huang, **J.M. Ou**, Z., Zhong, Z., Xu, Y., Zhang, Z., Xiao, X., Ye, X., Wu, Y., Yin, X., Chen, L., Shao, M., and Zheng, J.,2019. Evolution of Anthropogenic Air Pollutant Emissions in Guangdong Province, China, from 2006 to 2015, ***Atmos. Chem. Phys***. 19, 11701–11719.

Z. Huang, J. Zheng*, **J.M. Ou**, Z. Zhong, Y. Wu, M. Shao, 2019. A Feasible Methodological Framework for Uncertainty Analysis and Diagnosis of Atmospheric Chemical Transport Models. ***Environmental Science & Technology*** *(IF=6.198)*, 53, 6, 3110-3118.

H. Zheng, Z. Zhang, Z Zhang, X Li, Y. Shan, M. Song, Z Mi, J Meng, **J.M. Ou**, D. Guan*, 2019. Mapping Carbon and Water Networks in the North China Urban Agglomeration. ***One Earth***, 1(1): 126-137.

H. Zheng, J. Meng*, Z. Mi, M. Song, Y. Shan, **J.M. Ou**, D. Guan, 2019. Linking city-level input-output table to urban energy footprint: Construction framework and application. ***Journal of Industrial Ecology*** *(IF=6.198)*, 2019, 1-5.

Z Mi, J Zheng, J Meng, Y Shan, H Zheng, **J.M. Ou**, D Guan, YM Wei, 2019. China's energy consumption in the new normal. ***Earth's Future*** *(IF=4.594)*, 6(7), 1007-1016.

J. Meng, J. Liu, K. Yi, H. Yang, D. Guan, Z. Liu, J .Zhang, **J.M. Ou**, S. Dorling, et al., 2019. Origin and radiative forcing of black carbon aerosol: production and consumption perspectives. ***Environmental Science & Technology*** *(IF=6.198)*, 52, 11, 6380-6389.

H. Zheng, Y. Shan, Z. Mi, J Meng, **J.M. Ou**, H. Schroeder, D. Guan*, 2018. How modifications of China's energy data affect carbon mitigation targets. ***Energy***

policy *(IF=4.039)*, 116, 337-343.

C. Li, B.K. Jens, J.Y. Zheng*, Z.B. Yuan, **J.M. Ou**, Y. Li, Y.L. Wang, *et al*., 2018. Decadal evolution of ship emissions in China from 2004 to 2013 by using an integrated AIS-based approach and projection to 2040. ***Atmospheric Chemistry and Physics*** *(IF=5.509)*, 18 (8), 6075-6093.

Y.L. Shan, D.B. Guan, H.R. Zheng, **J.M. Ou**, Y. Li, J. Meng *et al*, 2017. China CO_2 emission accounts 1997-2015. ***Scientific Data*** *(IF=5.305), 6:190027*.

Z. Huang, Y. Hu, J. Zheng, Z. Yuan, A.G. Russell, **J.M. Ou**, Z. Zhong, 2017. A new combined stepwise-based high-order decoupled direct and reduced-form method to improve uncertainty analysis in PM2. 5 simulations. ***Environmental Science & Technology*** *(IF=6.198)*, 51 (7), 3852-3859.

Z. Huang, **J.M. Ou**, J.Y. Zheng, Z. Yuan, S. Yin, D. Chen, H.B. Tan, 2016. Process contributions to secondary inorganic aerosols during typical pollution episodes over the Pearl River Delta region, China. ***Aerosol & Air Quality Research*** *(IF=6=2.589)*, 16 (9), 2129-44.

C. Li, Z. Yuan, **J.M. Ou**, X. Fan, S. Ye, T. Xiao, Y. Shi, Z. Huang, SKW Ng, *et al*, 2016. An AIS-based high-resolution ship emission inventory and its uncertainty in Pearl River Delta region, China. ***Science of the Total Environment*** *(IF=4.900)*, 573:1-10.

Report

J.M. Ou. China's export industries and their contributions to ground-level ozone pollution (Mikhalevich Award of IIASA). September 2018. Available via http://www.iiasa.ac.at/web/home/education/yssp/YSSP_report_Jiamin_20180929.pdf

Grants, Awards, and Academic Services

Participant of Young Scientists Summer Program (YSSP) of International Institute for Applied Systems Analysis (IIASA), 2018, Stipend from Natural Environmental Research Council, UK

Recipient of 2018 Mikahlevich Award, aiming at mathematically and methodologically oriented research, given by International Institute for Applied Systems Analysis (IIASA)

Chinese Government Award for Outstanding Self-Financed Students Abroad, China Scholarship Council (2018)

Joint Leverhulme Trust and Social Sciences Faculty Postgraduate Studentships at the University of East Anglia, 2016-2019, £14,000 per annual plus tuition fee

Reviewer of Applied Energy (IF=7.182), Environmental Research Letters (IF=6.192), and Atmospheric Environment (IF=4.012)

Chapter 1 Introduction

Many developing countries have seen substantial socioeconomic improvements in the past decade, but in return they are confronting severe challenges to sustain fast growth in a resource- and emission-constrained world. However, not all forms of socioeconomic growth cause damage to the environment. Environmental sustainability can be integrated with economic growth and welfare through responsible consumption and production. To enable such a transition, nevertheless, lots of efforts are still needed in the developing countries from knowledge gap, capacity building to institutional setting.

Experiences in China serve as valuable real-world examples for the world to fathom the feasibility and progress of responsible consumption and production in developing economies. This chapter provides an introduction to socioeconomic development and transition, energy consumption patterns, and air pollution characteristics in China. Under such backdrops, research aims, objectives and framework of this study will be proposed.

1.1. China's socioeconomic status

The socioeconomic development of China can be reflected from its national gross domestic product (GDP), main sectors to the increase of GDP, per capita GDP, urbanization rate, rural poverty rate and household consumption expenditure. In general, China has made huge progress in its socioeconomic development by maintaining high GDP growth (>7% per annual), increasing per capita GDP by more than 4 times and lifting 384 million rural population out of poverty [1] from 2000 to 2017.

[1] Poverty is defined as annual income less than 1274 yuan (2010 constant price) per head.

China's economy saw high growth before global financial crisis in 2007 and is under crucial transitions in the "new normal" period which aims at "low but high-quality growth". As shown in Figure 1-1, its national GDP grew by 10.7% annually from 2000 to 2007, then slowed down to around 8.2% from 2008 to 2017. Since China's total population is generally stable over the years, per capita GDP grew at similar spaces as the national GDP. The share of GDP by sectors also changed significantly, as shown in Figure 1-2. Contribution from primary industries dropped from 19% in 2000 to 8% in 2017. The increase of GDP was mainly induced by the rapid growth of secondary and tertiary industries, both grew by more than 9% every year. By 2017, tertiary industries, including wholesale and retail trades, transport, storage and post, hotel and catering, finance, real estate and others, have made up 51% of national GDP.

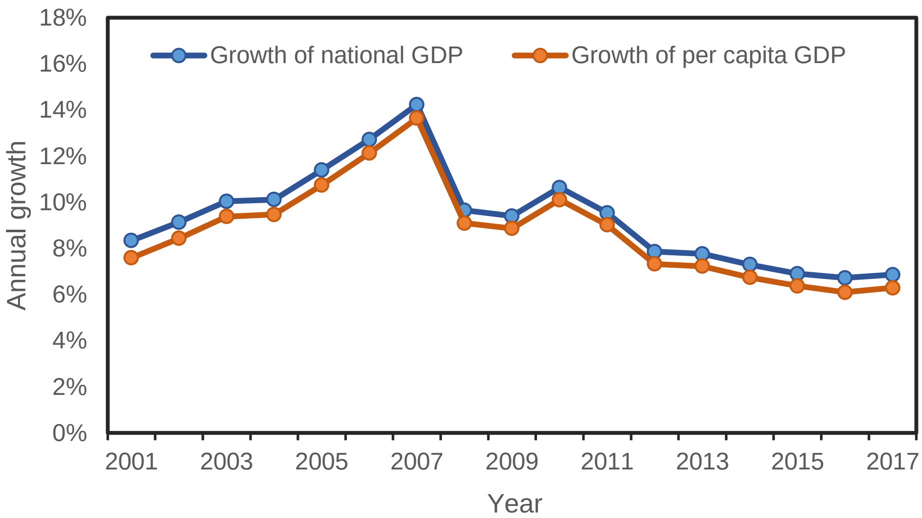

Figure 1-1 China's annual growth in national GDP and per capita GDP

Data source: National Bureau of Statistics, P.R.China, 2018a.

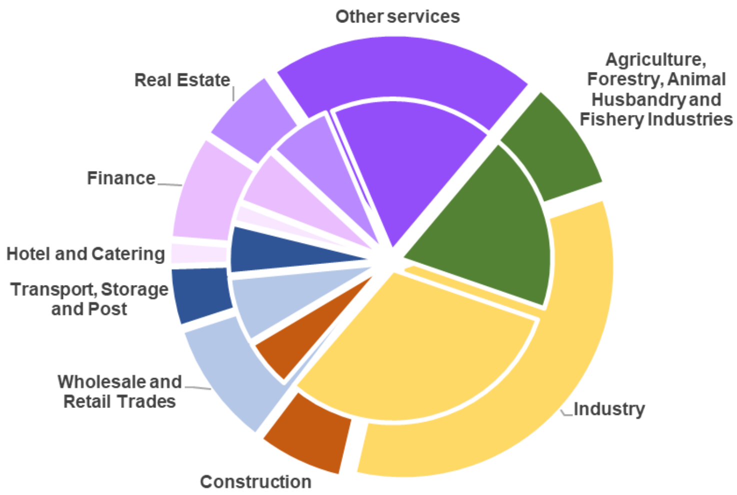

Figure 1-2 Share of national GDP by sectors in 2000 (inner pie) and 2017 (outer pie)
Data source: National Bureau of Statistics, P.R.China, 2018a.

Though China's total population remains relatively stable after 2000, the movement of people from rural to urban areas is enormous. In 2000, approximately 459 million people lived in the rural areas. By 2017, the number of city dwellers had reached 813 million, accounting for 58.53% of China's total population. Such a movement entails significant change of consumption patterns and final demands, which is partly revealed by recent studies using input-output analysis in China. In the wake of fast urbanization, the percentage of poor rural population had decreased from 49.8% in 2000 to 3.1% in 2017, equal to 384 million people.

Household consumption expenditure increased rapidly but the gap between rural and urban households is still huge. As Figure 1-3 showed, consumption expenditure in urban households tripled from 2000 to 2017, reaching 29914 yuan (in 2015 constant price). Growth in rural household was even higher, with expenditure 3.57 times that of 2000. The absolute differences between urban and rural household, however, remain large. Despite of rapid growth rate, rural household expenditure in 2017 was equivalent to the value of urban household in 2002, or only 37.9% that of urban household in 2017.

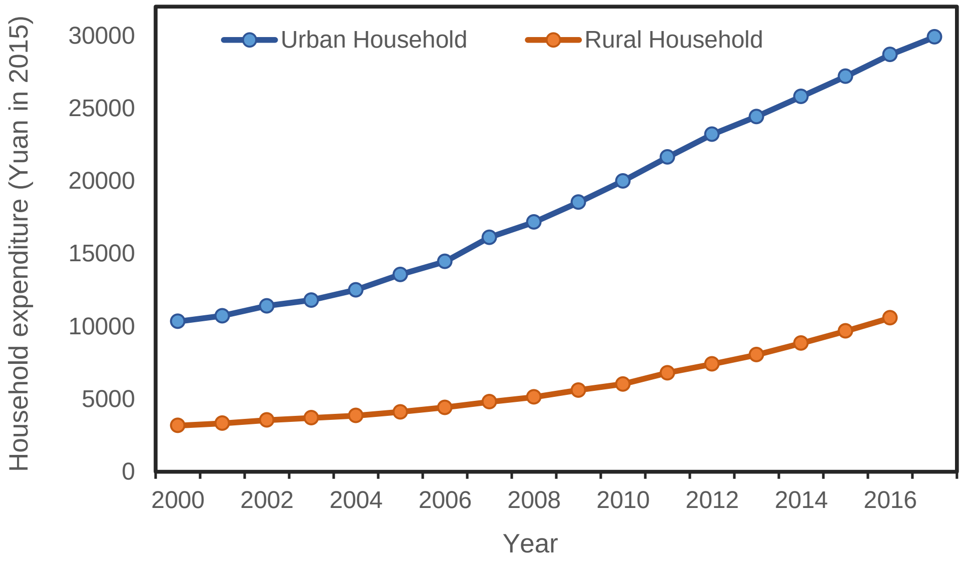

Figure 1-3 Consumption expenditure of urban and rural household (per head, constant price in 2015, yuan)

Data source: National Bureau of Statistics, P.R.China, 2018a.

In addition to the disparity in urban and rural households, provincial differences are also notable. China is a vast country that comprises more than 30 administrative regions widely divergent in their development statuses. If the per capita GDP of each province in China was compared to the national total of other countries in the globe, one would find that the gap between provinces in China is equal to the differences of more than 80 countries. Taking the data in 2017 as an example (as shown in Figure 1-4), Beijing had the highest per capita GDP among all the provinces and was comparable to the national average of Estonia in 2017. Estonia was ranked as 56^{th} highest among 264 countries in the globe in terms of per capita GDP (International Monetary Fund, 2018). On the contrary, Gansu had the lowest per capita GDP in China which was around the national average of Guyana. Per capita GDP of Guyana was ranked as 141^{st} in the world in 2017 (International Monetary Fund, 2018).

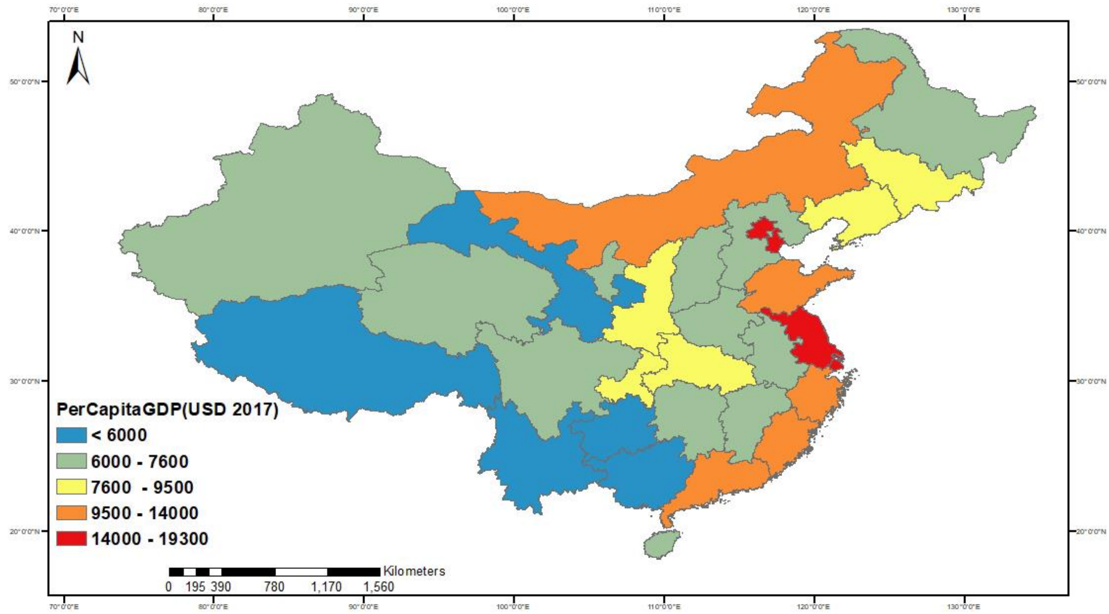

Figure 1-4 Per capita GDP by provinces in 2017

Data source: National Bureau of Statistics, P.R.China, 2018a.

1.2. China's energy consumption patterns

China is now the world's largest energy consumer, accounting for about 22% of the global budget in terms of the total primary energy supply in 2017 (International Energy Agency (IEA)., 2017). The growth of energy consumption does not strictly follow that of economic growth, as shown in Figure 1-5. To illustrate the efficiency of energy consumption, elasticity of energy consumption, which is the percentage change in energy consumption to achieve one per cent change in national GDP, is also introduced in Figure 1-5. Energy consumption in China increased steeply before 2004, at a rate that was much faster than GDP growth. Energy elasticity was highest in 2004 with the value of 1.67, indicating energy consumption around 2004 was relatively inefficient. Growth of GDP outpaced that of energy consumption after 2005, leading to energy elasticity that was less than 1. Energy elasticity reached an all-time low in 2015, with only 0.14% growth of energy consumption to achieve 1% GDP growth. Nevertheless, total energy consumption has rebounded since 2016.

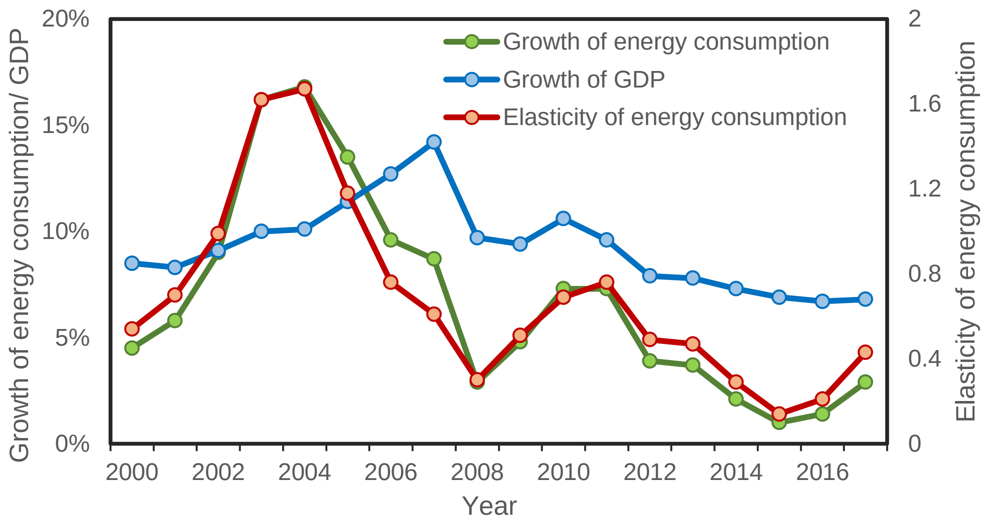

Figure 1-5 Growth of energy consumption and GDP, and elasticity of energy consumption from 2000 to 2017

Data source: National Bureau of Statistics, P.R.China, 2018b.

The rebound of energy consumption is mainly driven by the rapid growth of non-fossil fuels and natural gas in recent years. As shown in Figure 1-6, while coal is still the dominant fuel, its consumption has plateaued from 2011 to 2016. Before 2011, coal consumption grew by 11% per year, then slowed down to around 4% per year. Relative contributions by provinces are stable. Jiangsu, Shandong, Hebei, Inner Mongolia, Shanxi, Henan and Liaoning are the major consumers within China in terms of primary energy. The growth of petroleum consumption saw similar trends. From 2003 to 2011, four years in a row, annual growth of petroleum consumption was 13% and 8%, respectively. After 2011, petroleum consumption grew by 5% per year. Provinces in the east and south China are major drivers, including Jiangsu, Shandong, Shanghai, Zhejiang and Guangdong.

On the other hand, consumption of natural gas and non-fossil fuels in China increased rapidly since 2011. The annual growth rate of natural gas and non-fossil fuels was 11% and 8% from 2011 to 2016. As a result, dependence of coal was decreasing and the energy mix was decarbonizing. Percentage of coal dropped from 76% in 2003 to 71% in 2016. Share of natural gas and non-fossil fuels, in turn, increased from 6% to 11% during the same period.

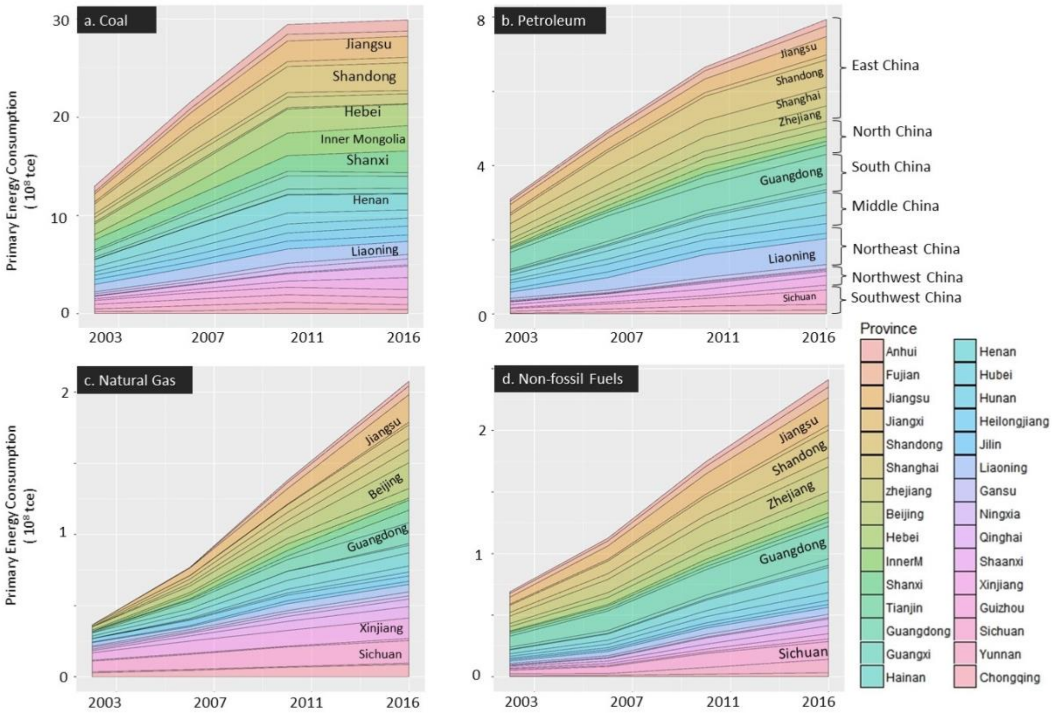

Figure 1-6 Energy consumption by fuel types and provinces from 2003 to 2015.
Data source: National Bureau of Statistics, P.R.China, 2018b.

1.3. Air pollutant emissions and control

Air pollution is one of the environmental problems of most concern in China. Emission from China contributes 18-35% of global air pollutant emission budget (Hoesly *et al.*, 2018). Major air pollutants in China include sulphur dioxide (SO_2), nitrogen oxides (NOx), carbon monoxide (CO), nonmethane volatile organic compounds (NMVOCs), ammonia (NH_3), and particulate matter (PM). Their emissions from human activities are responsible for reduced visibility and frequent haze events characterized by high concentrations of $PM_{2.5}$ (particulate matter with an aerodynamic diameter of less than 2.5 μm) and ground-level ozone (hereafter referred to as "O_3"). In particular, the O_3 here refers to the "bad" O_3 in the troposphere, which irritates the respiratory system when inhaled and significantly increases the risk of death from respiratory causes (Jerrett *et al.*, 2009).

For decades air pollutant emissions have paralleled economic growth, but a trend of decoupling is emerging, especially after China enacted the Clean Air Action and implemented the new air quality standard. China has strengthened its emission standards since 2010, covering all the major source sectors including thermal power plants, industrial boilers, residential sector, and vehicles (Zheng *et al.*, 2018a). Take coal-fired power plants as examples, emission limits were 400 mg/m^3 for SO_2, 450-1100 mg/m^3 for NOx and 50 mg/m^3 for TSP before 2012. Since 2012, emission limits have been tightened to 100 (new units) or 200 (existing units) mg/m^3 for SO_2, 100 (new and existing units) mg/m^3 for NOx and 30 (new and existing units) mg/m^3 for total suspended particulate (TSP). Though the emission standard proposed in 2012 was ambitious, its implementation turned out to be a success. In December 2015, China pledged to reduce emissions from coal power plants by 60% by 2020 with "Ultra-low" emission standard. Emission limits for SO_2, NOx and TSP are lower at 35, 50, and 10 mg/m^3, respectively.

Regarding industrial sectors, efforts were highlighted in improving efficiency and strengthen emission standards. On the one hand, outdated industrial capacities have been phased out. Small and inefficient workshops that failed to meet the energy efficiency, environmental or safety standards have been retired and replaced with efficient facilities. As a result, energy intensity (energy consumed per unit of industrial gross output) had decreased by 3.3%, 2.9%, 1%, 4.2% and 3.0% for steel, cement, aluminium, ethylene and synthetic ammonia, from 2013 to 2016 (National Bureau of Statistics, 2018b). On the other hand, new industrial emission standards have been put into effect since 2013. Emission-intensive industries have been targeted, such as iron and steel, cement, brick, coke, glass and chemical industries. Emission standard for cement industry, for example, has tightened from 800 mg/m^3 for NOx and 50 mg/m^3 for TSP before 2014 to 400 mg/m^3 (NOx) and 30 mg/m^3 (TSP) after 2014. For coal boilers in industrial sectors, SO_2 and TSP emission standard before 2014 was 900 mg/m^3 and 80-250 mg/m^3, respectively, and NOx emission was not regulated. New emission standard has set lower values for SO_2 (300 mg/m^3) and TSP (50 mg/m^3) and included NOx (300 mg/m^3).

Emissions from transport sector are regulated by strengthening vehicle emission standards, retiring old vehicles, and improving fuel quality. Following the Euro III standard enacted in 2008, standards for newly-registered light duty gasoline vehicles and diesel vehicles have been upgraded to Euro V in 2017. For heavy duty gasoline vehicles, the current emission standard is in line with Euro IV. Fuel economy, meanwhile, has reduced from 8.0 L/100 km in 2010 to 6.9 L/100 km in 2015, for new cars. Efforts in the residential sector mainly target direct coal-burning activities with alternatives such as natural gas and electricity. Fuel switch has been promoted in millions of residences in north China.

Such measures turned out to be successful with decreased air pollutant emissions and improved air quality. SO_2 emission peaked at 2011 with 29.1 Tg then decreased sharply to 10.5 Tg in 2017, as shown in Figure 1-7a. Similarly, NOx emission has peaked at 29.2 Tg in 2012 and dropped to 22.0 Tg in 2017. Primary $PM_{2.5}$ emission is also under control and decreases steadily by 7% per year from 2012 to 2017.

Air pollution control efforts had been devoted to SO_2, NOx and PM before 2017, with strict end-of-pipe treatments from fossil fuels combustion. They fell short in NMVOCs and NH_3, which are mainly emitted by non-combustion sources. For example, emissions of NMVOCs increase persistently from 2000 to 2017, as shown in Figure 1-7b. While SO_2 and NOx each decreased by 62% and 17% after China's Clean Air Actions, NMVOCs emissions grew by 13%, from 2010 to 2017 (Figure 1-7b). Emissions of CO_2 seem to peak around 2013, partly thanks to the switch from coal to other fuels and the improvement of fuel quality driven by air quality concerns. Nevertheless, since most end-of-pipe treatments for air pollutants are not effective for CO_2 (or even increase its emissions due to the extra energy burden to run the air pollutant emission treatment devices), the decrease of CO_2 emissions after the plateau in 2013 should be much slower than other air pollutants such as SO_2 and NOx. Some studies also argue that CO_2 emission rose in 2018 (Figueres *et al.*, 2018).

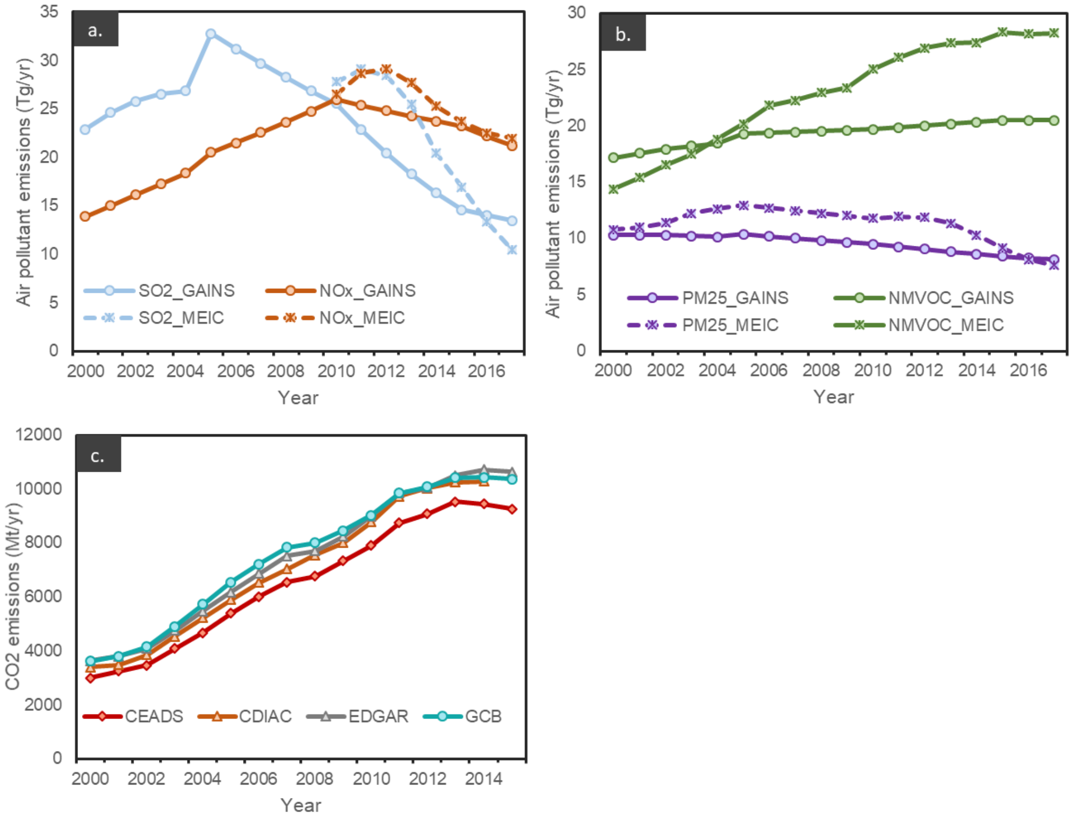

Figure 1-7 Emissions of (a) SO_2 and NOx, (b) $PM_{2.5}$ and NMVOC, and (c) CO_2 in China

Data source: SO_2, NOx, $PM_{2.5}$ and NMVOC emissions were retrieved from the databases of the Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) (International Institute for Applied System Analysis, 2018) and multi-resolution emission inventory for China (MEIC) (Tsinghua University, 2018); CO_2 emissions were from China Emission Accounts and Datasets (CEADS) (Shan *et al*., 2017), Carbon Dioxide Information Analysis Centre (CDIAC) (Boden *et al*. 2016), Emission Database for Global Atmospheric Research (EDGAR) (Olivier *et al*., 2016) and Global Carbon Budget (GCB) (Le Quéré *et al*., 2016).

1.4. Ground-level ozone pollution and its formation regime in China

With focused control on primary $PM_{2.5}$, sulfur dioxide (SO_2) and nitrogen oxide (NOx), the average $PM_{2.5}$ concentration in 74 cities of key control decreased by 35% in 2017 (47 μg/m^3), compared to a level of 72 μg/m^3 in 2013 (China National Environmental Monitoring Centre, 2018a). Nevertheless, due to the lax control in NMVOCs, which is one of the key precursors of O_3 in the troposphere, O_3 level shows a worrying trend. The hourly concentration of O_3 in China increased by 16~27% from 2013 to 2017 (Figure 1-8), while the O_3 exposure metrics (cumulative O_3 concentration) increased even higher by 57~77% (Lu *et al.*, 2018). The present extent of O_3 pollution, in terms of the exposure of humans and vegetation, is found greater in China than in any other developed region of the world with comprehensive O_3 monitoring (Lu *et al.*, 2018). With initial progress being made from particulate control, China still has a long way to go to curb the rise of O_3.

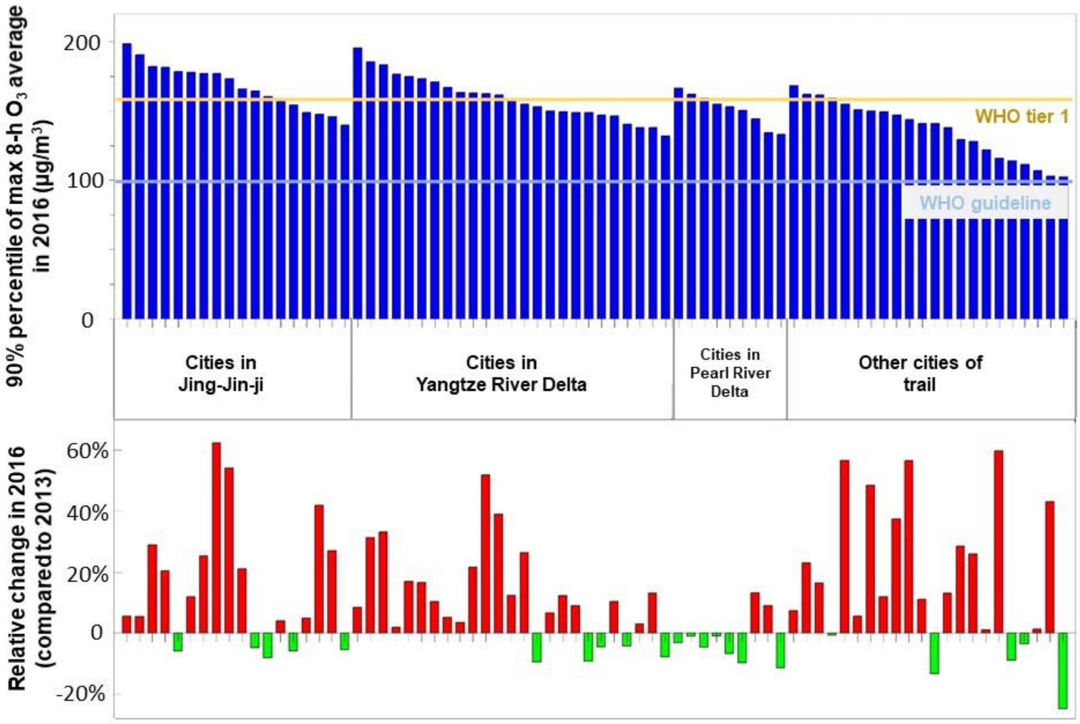

Figure 1-8 Ozone levels in 74 cities of key control in China in terms of (a) 90th percentile of max 8-h O_3 average in 2017 and (b) relative changes compared to 2013

Data source: Ozone levels in 74 cities were collected from China National Environmental Monitoring Centre (2018a).

Unlike most air pollutants, O_3 in the troposphere is not directly emitted by human activities. Rather, it is secondary photochemical pollutant formed via a series of complex chemical processes driven by sunlight. Figure 1-9 schematically shows the key players involved in the formation of O_3 in the troposphere (Jenkin *et al.*, 2000). The mechanisms have been well-established and can be found in previous studies (Atkinson, 1990&1994).

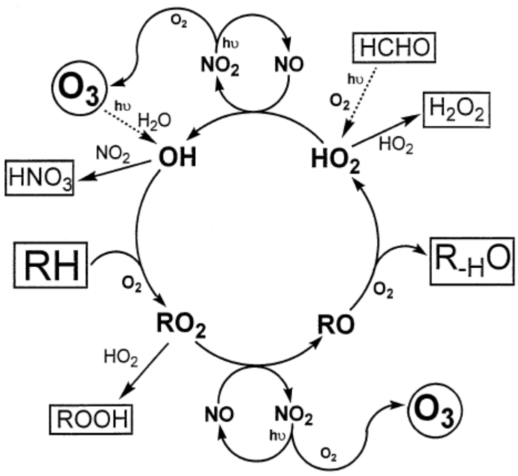

Figure 1-9 Schematic representation of the free radical-catalysed oxidation of a generic saturated hydrocarbon, RH, to its first generation oxidized product, $R_{-H}O$. The key role played by the NOx species in the chain-propagating process is also illustrated, which leads to the generation of O_3 as a by-product (Adapted from Jenkin *et al*. (2000)).

From the perspective of air pollution control, O_3 formation is mainly driven by two major classes of directly emitted precursors: NOx and NMVOCs. The relationship between O_3, NOx and NMVOCs is nonlinear and sensitive to the relative ratio of NOx and NMVOCs in the atmosphere. In other words, the maximum O_3 concentration that is ultimately formed is not directly proportional to the initial atmospheric concentrations of NO_X and NMVOCs. First proposed by Haagen-Smit and Fox (1954), O_3 isopleth shows the maximum O_3 concentration that result from initial mixtures of NO_X and NMVOCs. As shown in Figure 1-10, the contour lines represent the maximum O_3 concentration. For dots on the same contour line, their initial conditions (NMVOCs and NOx concentrations or emission rates) are different but would result in same peak O_3 concentration. An O_3 isopleth exhibits a diagonal ridge from the lower left to the upper right corner of the graph. The diagonal ridge divides the graph into two areas characterized by different O_3-NOx-NMVOCs relationships. Figure 1-10 shows a typical set of O_3 isopleths developed by empirical kinetic modelling approach (Dodge, 1977). It should be noted that Figure 1-10 uses the term of volatile organic compounds (VOC) instead of NMVOCs. VOC in Figure 1-10 thus includes methane and NMVOCs. However, the relationship between O_3, NOx and VOC illustrates in Figure 1-10 is generally applicable to NMVOCs as well.

When the initial conditions are to the right of the ridge line, lowering NOx concentration either at constant VOC concentration or in conjunction with lowering VOCs leads to lower peak O_3 concentration. Such an O_3 formation regime is generally observed in rural areas and suburbs downwind of cities (Ou *et al.*, 2016), and it is said to be "NOx-limited". Under such a regime, the supply of organic peroxy radicals (RO_2) and peroxy radicals (HO_2) is ample to convert nitric oxide (NO) to nitrogen dioxide (NO_2). The photolysis of NO_2 serves as the only important source of O_3 formation and the decrease of NOx directly results in a decrease in O_3. When the initial condition is to the left of the ridge line, lowering VOC at constant NOx will result in lower peak O_3 concentration. Peak O_3 concentration will also decrease if VOCs and NOx are reduced proportionately and simultaneously. However, lowering NOx at constant VOC will result in increased peak O_3 concentration until the ridge line is reached. In other words, NOx reduction in some conditions could lead to increased O_3, as a result of the complex chemistry of O_3 formation (Atkinson, 1990&1994; Jenkin *et al.*, 2000). Such an O_3 formation regime is usually found in highly polluted urban areas with low VOC/NOx ratio and is called "VOC-limited" (or "NMVOC-limited" hereinafter).

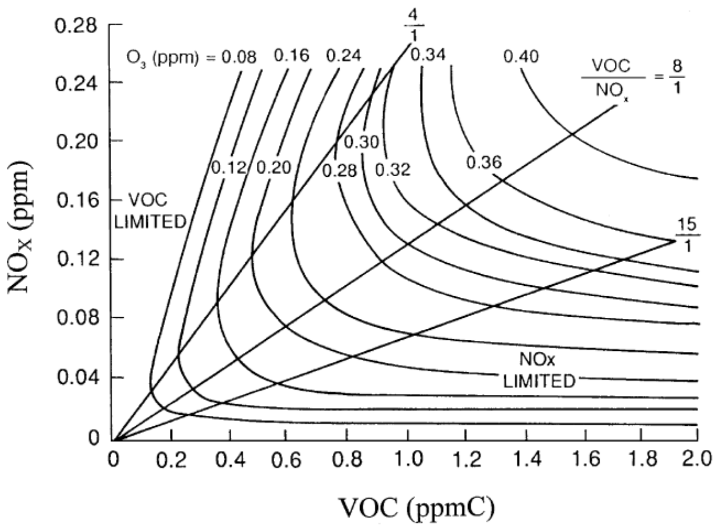

Figure 1-10. Example of an isopleth diagram illustrating calculated peak ozone concentrations generated from various initial concentrations of NOx and a specified VOC mixture using the empirical kinetic modelling approach (Adapted from (Dodge, 1977)). It should be noted that this figure uses the term of VOC instead of NMVOCs. VOC here thus includes methane and NMVOCs. However, the relationship between O_3, NOx and VOC illustrates here is generally applicable to NMVOCs as well.

The O_3-NOx-NMVOCs relationship has important implications on the development of O_3 control strategies. The isopleth graph shows that NOx reduction will lead to significantly different effects on peak O_3 concentration depending on the initial NMVOCs/NOx ratio. The NMVOCs/NOx emission ratios are therefore crucial to determine the O_3 regime and consequently, the effectiveness of control strategies.

1.5. Research Aims, Objectives and Framework

1.5.1. Research aims and objectives

The past decade saw substantial changes in China's socioeconomic status, energy consumption patterns and pollution characteristics. The interactions between the three, however, are less understood. This study aims to advance the methodologies and knowledge in integrated assessment of energy, pollution and socioeconomic demands. Specifically, the focus will be on China as a whole and its provinces in various development stages. Great progress in China's socioeconomic development, its predominant role in global energy consumption and persistent pollution in the home land together make it a unique platform to demonstrate the methods and study the roles of socioeconomic demands in energy and pollution issues. Experiences in China will serve as real-world examples on how to reconcile the conflicts between socioeconomic development urges, limited energy, and environmental degradation.

The fulfilment of research aim is realized by objectives specified as follow.

- Develop an integrated assessment framework to depict material and emission flows between producers, consumers and environmental receptors;
- Demonstrate the proposed framework (the whole flow or part of it) in national and subnational studies;
- Identify the socioeconomic drivers of China's primary energy consumption and understand the mechanism of declined energy consumption in some provinces since 2011;
- Advance the understanding of pollution causes from the demand side, especially for the ever-rising O_3 problem;
- Evaluate the sustainability of China's production and consumption patterns, and explore the generalization of its experiences.

1.5.2. Research Framework and thesis structure

Emission and material flows are the keys to connect the environmental and socioeconomic systems. In this study, a four-stage research framework to capture the flows between producers, consumers and environmental receptors is proposed, as shown in Figure 1-11.

- Step 1 Primary energy consumption accounting

The first step aims to estimate the primary energy consumption by fuel types and sectors. Specifically, the method in Figure 1-9 is designed according to China's energy statistic systems. Energy Balance Table (EBT) and sectoral final energy consumption table in national and subnational levels are used. EBT provides aggregate information on energy indigenous production, input & output of transformation, regional flows and final consumption. On top of this, sectoral final energy consumption table is used to provide the final energy consumption of 40 manufacturing sectors, which are aggregated as one single number in EBT. Detailed methods can be referred to Section 3.1. This step eventually produces a primary energy consumption matrix with a dimension of 4 fuel types (coal, petroleum products, natural gas and non-fossil fuels) and 46 sectors (including primary industry, 41 secondary industrial sectors, 2 tertiary industrial sectors, urban and rural household consumption).

- Step 2 Direct emission accounting

The second step identifies the entities that emit the air pollutant emissions by development and validation of production-based emission inventories. The primary energy consumption matrix is one of the key inputs to estimate emissions from fossil fuels combustion. Besides, industrial output, consumption of raw material and others are also used to study the process-based emissions (more details can be found in Section 3.1). Given the inherent uncertainty of emission inventories, validation should be carried out where possible. This study explores the possibilities of inventory validation using ambient measurement data. Validation is carried out for NMVOCs, one of the air pollutants with highest uncertainty in terms of production-based emissions (See Section 3.2).

- Step 3 Linkage between emission and socioeconomic accounts

Energy and emission accounts are connected to the socioeconomic account through multi-regional input-output (MRIO) analysis and decomposition analysis (DA). MRIO tracks down emissions along the supply chain, and consequently, reveals the demands (from intermediate sectors and final consumers in local or from other regions) that drive local production activities with air pollutant emissions. A consumption-based inventory is developed and used for further analysis in environmental simulation platform. DA is used as a complement to identify the socioeconomic drivers of energy consumption or emissions. While MRIO provides an explicit depiction of emissions from producers, intermediate sectors and final demands, DA decomposes the aggregated energy consumption or emissions to a number of pre-defined factors of interest such as population growth, economic growth, industrial structure, energy intensity and energy mix.

- Step 4 Measuring environmental outcomes and alternative paths

The consumption-based emission inventory in Step 3 reveals the emissions driven by different demands and is used to develop the model-ready emission profiles for environmental model. In this study, an air quality simulation platform configured by Sparse Matrix Operator Kernel Emissions (SMOKE) Model, Weather Research and Forecasting (WRF) Model and Community Multiscale Air Quality (CMAQ) Model is adopted. The adoption of air quality modelling platform transforms the demand-attributed emissions into ambient concentrations, followed by health impact estimation such as excess premature death due to elevation of air pollutant concentration. In this way, environmental consequences in association with socioeconomic demands are measured. Key demands driving environmental degradation are identified and mitigation potentials can be measured following similar work flow.

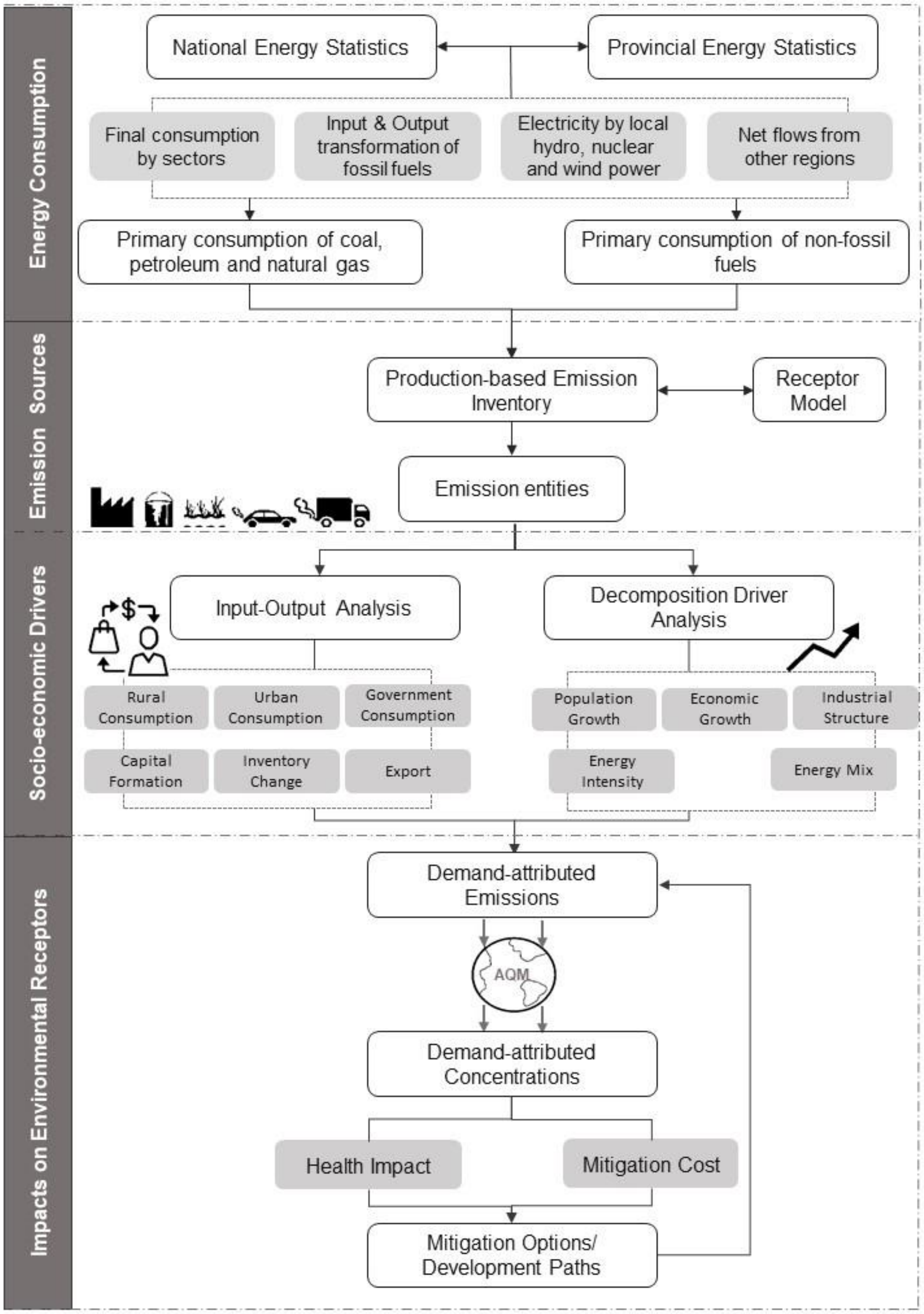

Figure 1-11 Research framework to capture material and emission flows between producers, consumers and environmental receptors

The structure of thesis is organized in accordance with the proposed framework. Chapter 2 reviews the established methods and knowns in energy-pollution-socioeconomic assessment and identifies the research gaps. Chapter 3 and 4 propose the integrated assessment framework to depict material and emission flows between producers, consumers and environmental receptors. In particular, Chapter 3 focuses on the data and methods to compile the energy and emission accounts. Chapter 4 elaborates how energy consumption and emissions are used to connect the socioeconomic and environmental systems and the methods to measure environmental consequences in association with socioeconomic demands. Chapter 5 to 8 demonstrate the proposed framework (the whole flow or part of it) in national and subnational studies. Chapter 5 studies the production-based patterns of energy consumption in 30 provinces in China and their drivers for growing, plateaued and declined consumption. Chapter 6 and 7 investigates the demand-driven emissions of Guangdong and Tibet, respectively. The former one serves as an example of more developed regions in China while the later one reflects the status of less developed ones. Chapter 8 presents a national study on the nexus of demand-emission-pollution-health. It reveals the socioeconomic demands driving the rising ground-level O_3 pollution in China, its health impacts and the cost and benefits of mitigation pathways. Chapter 9 summarizes the key findings, contributions, innovation of this study, along with limitations and suggestions for future work.

Chapter 2 Research Background

2.1. China's energy consumption and uncertainty

To study the issues concerning energy consumption in China, official statistics provided by the National Bureau of Statistics (NBS) and the Bureau of Statistics of the local governments are the exclusive data sources, especially for studies over a long time span. This subsection first induces the national and provincial energy statistics available in China, followed by a review of current studies on the uncertainties and data quality.

2.1.1. Primary and secondary energy consumption

The concept of primary and secondary energy is crucial in energy statistics in the course of compilation of energy balances. In one sense, it is important to separate new energy entering the system (primary) and the energy that is transformed within the system (secondary) in order to avoid double counting. In another sense, the definitions greatly affect the measuring and recording of energy flows in the energy balances, and hence, altering long-range policy design and analysis of broader energy or environmental issues. Despite its importance, there is lack of a clear and internationally agreed definition of primary and secondary energy.

According to the Concepts and Methods in Energy Statistics by the United Nations (UN) (United Nations, 1982), "*Primary energy should be used to designate those sources that only involve extraction or capture, with or without separation from contiguous material, cleaning or grading, before the energy embodied in that source can be converted into heat or mechanical work.*" By contrast, *"Secondary energy should be used to designate all sources of energy that results from transformation of primary sources"*. The Energy Statistics Manual by Organisation for Economic Co-operation and Development, International Energy Agency and statistical office of the European Union (hereinafter referred to as "OECD/IEA/Eurostat") (OECD/IEA/EUROSTAT, 2004) explains the concepts of primary and secondary energy commodities as "*Energy commodities are either extracted or captured directly from natural resources (and are termed primary) such as crude oil, hard coal, natural* *gas, or are produced from primary commodities*" and "*Secondary energy comes from the transformation of primary or secondary energy"*, respectively.

These sets of definitions have agreements on the most important factor distinguishes the primary and secondary energy. It is the process or activity involved for humans to make use of the energy in the source (Øvergaard, 2008). From the very beginning, all the energy on earth originates from the sun. It is through the natural energy chains that energy from the sun is transferred to other forms. "*Energy can neither be created nor destroyed*", as stated in the first law of thermodynamics. Therefore, energy transformations happens naturally all the time. The line between primary and secondary energy, however, is the first time when human factors are involved to extract, collect or transform the energy. Regarding primary energy, it generally refers to the process of extraction or capture. The physical and chemical characteristics of the energy is not changed. For instance, hard coal is extracted from the ground. It is then cleaned and separated from rocks and other non-energy substances, but its physical and chemical property such as calorific value remain constant. As for secondary energy, it is identified by the process of transformation. It includes any process of transforming one form of energy to the other. A quintessential example is the conversion of fossil fuels to electricity and heat that are used by end users such as household.

The line between primary and secondary energy can be relatively ambiguous when it comes down to electricity and heat from sources other than fossil fuels. Table 2-1 adapts the summary from (Øvergaard, 2008) on how the UN and OECD/IEA/Eurostat definitions diverge on electricity commodities.

Table 2-1 Classification of electricity in two international manuals (Øvergaard, 2008)

	Hydro, Wind Solar, Tide Wave	Nuclear fusion	Geothermal and Solar Thermal	Coal, natural gas, oil, renewables
UN manual	Primary	Primary	Primary	Secondary
OECD/IEA/Eurostat manual	Primary	Secondary	Secondary	Secondary

In this study, the definition of a Chinese study (Shan *et al.*, 2017) was adopted, which is generally in line with the UN definition. Figure 1 presents a schematic illustration of primary versus secondary energy used throughout this work. There are 30 types of fuels under China's energy statistics systems. Among them, raw coal, crude oil, natural gas and other energy are classified as primary energy sources. The other 26 types of fuels, including but not limited to cleaned coal, briquettes, gasoline, diesel oil, fuel oil, liquefied petroleum gas, are defined as secondary energy.

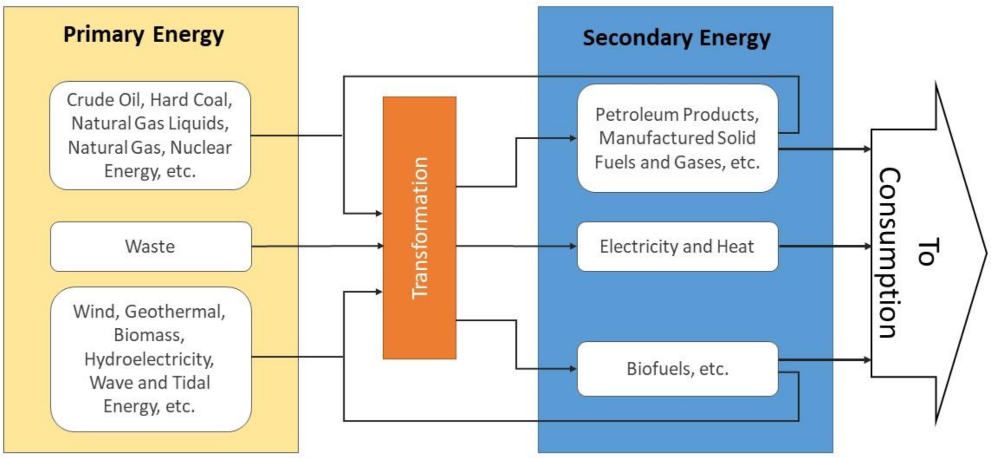

Figure 2-1 Schematic illustration of primary and secondary energy

2.1.2. Data quality and uncertainty

As a developing country, data quality of official statistics in China is subject to considerable uncertainties and limitations. Such concerns have resulted in quite a few studies that tried to understand the causes of poor data quality, and its impacts in energy planning, emission mitigation target and other socioeconomic analysis.

Statistical corruption is one of the factors that undermine the credibility of official data (Junguo and Hong, 2009; Ma *et al.*, 2014). It has been found in China for years. Two reasons account for that. First, economic growth is the measure to evaluate the performance of local officials. Statistical data such as GDP and value added are used as a reflection on economic growth. Second, the statistical bureau is not an independent entity in China. Rather, it is regulated by or dependent on local government. It is not surprising that statistics are vulnerable to government interference and tailored for different purpose. This is called "numbers make leaders" phenomenon. Things are improving with a new regulation "Rules on Punishment for Violation of Laws in Statistics". It was put in effect by the Ministry of Supervision, Ministry of Human Resources and Social Security and National Bureau of Statistics.

Reliability of energy statistics in China is also questioned due to the inconsistency in its national and provincial statistics. As mentioned above, the National Bureau of Statistics (NBS) and the Bureau of Statistics of the local governments in provincial or even city-level compile their own statistics on energy consumption as well as other socioeconomic data. Due to the different scopes and methods, large gaps were found between statistics from different levels. A previous study has developed two CO_2 emission inventories for China using the national and the sum of provincial energy statistics (Guan *et al.*, 2012). While the activity level data were both publicly available official energy data, the difference of CO_2 emissions was found to be 1.4 gigatonnes for 2010. This figure is equivalent to Japan's annual CO_2 emissions, which was the world's fourth largest emitter or 5% of the global total. Such a large gap was mainly introduced by the differences in coal consumption in coal washing and manufacturing. An earlier study investigated the same issue by examining the sectoral discrepancies between national and provincial statistics (Ma *et al.*, 2014). It was also found that industrial sectors were the major contributors to discrepancies in both GDP and total energy consumption. Another study has used satellite-based measurements of nitrogen dioxide (NO_2) concentration and noted substantial differences in coal consumption as reported in three different sets of official statistics, with a perceived underreporting of coal consumption (Hajime *et al.*, 2006).

Understanding the inconsistency in its energy statistics system, China has retrospectively revised the statistics, which reflects both improvement and uncertainty inherent in China's data (Qi *et al.*, 2016). The national energy statistics in China has been revised three times since 2000 (2006, 2010 and 2015). Table 2-2 summaries the total energy consumption and raw coal consumption extracted from three revisions, which was adopted from (Zheng *et al.*, 2018b). The first revision in 2006 increased total energy consumption by an average of 5% from 1999 to 2003. It was mainly due to the adjustment in raw coal and other petroleum products, which was increased by 4% and four-fold, respectively. The second revision took place in 2010. It raised the total energy consumption by an average of 7% from 2000 to 2007, in comparison with the 2006 data. Raw coal and coke were the focuses with an average increase of 8% and 3%, respectively. The most recent revision was in 2015, with an average increase of total consumption of 2%. Impact of energy data revisions on China's ability to achieve its carbon mitigation targets has been investigated (Zheng *et al.*, 2018b). It was shown that the achievement of national mitigation targets (as well as international pledges) might be postponed by two years. The peak value of total CO_2 emission is also highly uncertain, with the uncertainty varying from 12% to 29%.

Table 2-2 Comparison between energy data in three revisions (Zheng *et al.*, 2018b)

Year	**Total Energy consumption (Mtce)**				**Raw coal (Mt)**			
	2015 data	**2010 data**	**2006 data**	**Original data**	**2015 data**	**2010 data**	**2006 data**	**Original data**
2000	1159	1205	1101	1036	1047	1107	1022	967
2001	1231	1239	1135	1085	1106	1129	1049	1017
2002	1330	1318	1217	1173	1212	1209	1108	1090
2003	1562	1528	1384	1318	1436	1412	1305	1253
2004	1799	1768	1638		1644	1615	1495	
2005	2034	1964	1873		1856	1774	1650	
2006	2243	2151	2053		2053	1953	1803	
2007	2412	2292	2231		2207	2088	1936	
2008	2484	2349			2277	2136		
2009	2671	2458			2448	2241		
2010	2861	2625			2590	2358		
2011	3141	2845			2886	2605		
2012	3258	2939			2978	2669		
2013	3388				3092			
2014	3319				2928			

It is noted that only revisions on national levels were carried out. After revisions, the gaps between national and provincial statistics have been narrowed. In this study, the provincial energy statistics were used to develop the primary energy consumption matrix. Their uncertainty and comparison with the most up-to-date national statistics are discussed in Section 3.1.1.

2.2. Production- and consumption-based emission accounting

This study relies heavily on two approaches of emission estimation: production and consumption-based accounting. The concepts of such two methods, and their application and limitations are introduced here with selected studies.

2.2.1. Definitions of production- and consumption-based emissions

In general, emission –be it GHG or air pollutant discharge– from a geographic area can be varied from definitions of emission boundaries (Barrett *et al.*, 2013) :

- Territory-based emission: The administrative-territorial emission refers to emission "*taking place within national (including administered) territories and offshore areas over which the country has jurisdiction (page overview.5)*" (IPCC., 1996). It excludes the emissions from international transport such as aviation, shipping, and tourism (Barrett *et al.*, 2013). Territory-based emission, therefore, reflects the anthropogenic emission by domestic production and resident activities within one's boundary (Kennedy *et al.*, 2009, 2010).
- Production-based emission: It is relatively similar to territory-based emission but in a wider scope. Specifically, it encompasses not only "*emissions from international aviation and shipping are typically allocated to the country of the relevant vessel's operator (page 453)*" (Barrett *et al.*, 2013), but also the "*emissions from international tourism are allocated based on where individual tourists are resident, rather than their destination (page 453)*" (Barrett *et al.*, 2013).
- Consumption-based emission: Emission from consumption is fundamentally different from the above two methods. It breaks the geographical boundary of where emission is discharged and attributes the emission to final consumer of products. As quoted, "*all emissions occurring along the chains of production and distribution are allocated to the final consumer of products (page 211)*" (Wiedmann, 2009).

It can be observed that the boundaries of territory- and production-based emissions overlap with each other to a large extent. In practices, these two terms are used interchangeably in many circumstances. In this study, the term – "production-based"–

is used. The production-based emission in this study, nevertheless, only reflects part of the emissions from international aviation and shipping and neglects the emissions from international tourism. This is due the energy statistics employed in this study cannot reflect the energy consumed by Chinese vessels operated outside its boarder and emissions from international tourism is hard to allocate to the nationalities of individual tourists.

In a generalized form, the production-based emission of a region includes the emissions from resident institutional units analogous to GDP (Peters and Hertwich, 2007),

$$\text{Production} = \text{Emissions from resident institutional units} \qquad \text{Eq. 2-1}$$

The construction of consumption-based emission, emissions embodied in exports are excluded while the emissions embodied in imports are included,

$$\text{Consumption} = \text{Production} - \text{Exports} + \text{Imports} \qquad \text{Eq. 2-2}$$

In both equations, the expression “emission embodied” refers to all the missions required to produce the product. It includes all steps in production from raw material extraction through to final assembly and ultimately the final sale of the product. These emissions can be calculated either by the input-output analysis (Leontief, 1970) or allocation through the global production networks with similar methodologies (Wiedmann *et al.*, 2007).

2.2.2. Applications and limitations

Depending on the definition and system boundary, emission and shared responsibility of the same geographic area may vary. Despite the increasing recognition of consumption-based accounting, territory- or production-based emissions remain dominant in international, regional and local efforts for GHG emission reduction and air pollution alleviation. International binding commitments under the United National Framework Convention of Climate Change (UNFCCC) and Kyoto Protocol, for instances, are territory-based. At the heart of the Paris Agreement, Nationally determined contributions (NDCs) record emission released by agents within the geographic borders of a nation. National emissions reported to the Convention on Long-range Transboundary Air Pollution (LRTAP Convention) in Europe follow similar methods. In local scale, production-based accounting is widely used to formulate emission reduction targets and pollution mitigation strategies. In China, the national emission ceilings for air pollutants such as SO_2, NOx, PM_{10} and NMVOCs, are based upon production-based accounting.

The widespread use of production-based accounting reflects its advantages in emission estimation. Firstly, it is relatively straightforward and easy for interpretation and implementation. It is because the boundary of production-based emission is clear and in line with the geographic boundary. The activity level data required by production-based accounting, is also consistent with the System of National Accounts, which is used for GDP and other socioeconomic accounts. The data needed for production-based accounting is therefore easier to attain and the capacity required is lower than that of consumption-based approach. Secondly, it is recognized that production-based emission is subject to lower uncertainty. As Equation 2-2 shown, the estimation of consumption-based emission is indeed based upon production-based accounting by subtracting the export-embodied emissions and including embodied emissions in the imports. It therefore inherites the uncertainty from production-based approach. In addition, segmentation of import- and export-embodied emissions introduces considerable uncertainty as trade flows and input-output tables are employed. Worse still, while quantitative assessment can be carried out for production-based inventory with well-established and feasible ways (Frey and Zheng, 2002; Zheng and Frey, 2005; Zheng *et al.*, 2009a; Li *et al.*, 2016), it is hard to measure how reliable consumption-based accounting is. Studies on the latter are sparse (Sato, 2014; Owen, 2017) though some attempts have been made with stochastic multivariate method and others (Rodrigues *et al.*, 2018). Thirdly, production-based emission can be seamlessly connected (once it is temporally and spatially allocated) with environment system models, integrated assessment models (IAMs) and other emission planning and simulation tools. It greatly extends the application of production-based emissions and their policy significances. Such applications are reviewed in more detail in Section 2.3.

However, there are two main critiques on production-based accounting. One is the difficulty to allow for the emissions from international air and sea transport and international tourism to countries. Since such emissions do not take place within a specific country, it is relatively difficult to allocate such emissions (Yoon, Yang and Kim, 2018). Currently, the UNFCCC has not reached an agreement on how to attribute the bunker fuels for international transport to individual countries. The other is the potential of carbon leakage. Carbon leakage refers to the phenomena that decreasing emission in one country can be directly linked to increasing emissions in the other country with looser environmental regulations (Franzen and Mader, 2018). Under the production-based accounting scheme, emission-intensive industries in countries with strict emission controls, regulations or taxes might relocate to territories with fewer restrictions. Then the goods produced in the less restricted area might be shipped to the more restrictive countries. The production-based emissions from more restrictive countries, therefore, might be reduced. In global scale, nevertheless, emissions might remain rather constant if not increase. Take the Kyoto Protocol for an example, it was estimated that around 5 Gt of CO_2 (~ 15% of the global budget) was relocated from Annex I to non-Annex I countries through the international trade of goods and services (Peter and Hertwich, 2007). Globally, 23% of CO_2 emissions were embodied in exports predominantly from developing countries such as China to developed nations in 2004 (Davis and Caldeira, 2010). A more recent study suggests that the proportion was increasing over time: CO_2 emissions related to international trade climbed to 26% in 2008 (Peters, Davis and Andrew, 2012).

Consumption-based accounting takes care of such problems, especially the potentials of carbon leakage. The use of consumption-based inventories subtracts export-embodied emissions but includes import-embodied emission. The outsourced emissions are thus under surveillance (Kondo, Moriguchi and Shimizu, 1998; Munksgaard and Pedersen, 2001; Lenzen, Pade and Munksgaard, 2004). Another advantage of consumption-based approach is its wider coverage of global emission with limited participation (Peters, 2008a&b). Using the Annex I countries in Kyoto Protocol as examples, if consumption-based emission were regulated instead of production-based emission, efforts by the Annex I countries could be in reducing emissions not only within their own territories but also the originating countries which produce goods for them. It would naturally stimulate cleaner production in wider scales and make polices such as the Clean Development Mechanism (CDM) a natural part of the NDC (Peters and Hertwich, 2007).

Accounting from the perspective of consumption is subject to three key disadvantages. First, consumption-based accounting requires much more complex calculation and the usage of surrogates to allocate emissions. As mentioned above, such an accounting approach is highly demanding in data concerning multilateral trade. In addition to the inherent uncertainty in the statistics on global trade flows, available data such as those from the Global Trade Analysis Project and other input-output tables are generally in monetary value. To transfer the monetary flow to emission flow, it requires the adoption of various surrogates such as energy consumption, industrial output, and consumption of raw materials (Sargento, Ramos and Hewings, 2012; Huo *et al.*, 2014; Meng *et al.*, 2015, 2017; Mi *et al.*, 2016). Considering the large uncertainty and the lack of recognized method for uncertainty assessment, the reliability of consumption-based emission is still under criticism. Second, it is argued that consumption-based approach violates the principle of product liability (Lenzen *et al.*, 2007; Franzen and Mader, 2018). It states that producers are responsible for the quality and safety of their productions. Third, binding commitment on consumption-based emissions would require political decision making to extend outside of the standard geo-political area (Peters, 2008a&b).

Debate around the issue of production- and consumption-based emission is ongoing. The key battle field is on the size of carbon leakages and its flowing direction, which determines whether switching from production- based accounting to consumption-based accounting is beneficial. From the league of consumption-based accounting, estimations of the export-embodied emissions show the significances of carbon leakage between countries under different regulations (Kondo, Moriguchi and Shimizu, 1998; Davis and Caldeira, 2010; Peters, Davis and Andrew, 2012). Advocates for production-based accounting argued that such empirical investigations are still sparse (Franzen and Mader, 2018). Some studies even suggested small or no evidence for strong carbon leakages. Branger and Quirion (2014) investigated EU countries before and after the implementation of the European Union Emissions Trading System (EU ETS) and reported that emission leakages were generally insignificant. It is noteworthy that such a finding might have resulted from the very low carbon price in the EU. Incentives for a relocation of carbon intensive industries such as cement or aluminium production were therefore small. Another study compared the production- and consumption-based CO_2 emission of 110 countries for the time span of 1997 to 2011 (Franzen and Mader, 2018). They concluded that within-country differences depending on accounting schemes are small. More importantly, they argued there exists no evidence on carbon leakage from the developed countries to the developing countries. Take the ratio of consumption- and production-based CO_2 emissions per capita by countries for instance, the top five countries with the largest ratios are almost all developing countries with the exception of Switzerland.

2.3. Energy consumption, pollution formation and environmental consequences

Energy sits at the core of many environmental problems the world is confronting today, be it climate change or harmful air pollutant levels in indoor and outdoor environment. There is an extensive body of literature that shows how energy system contributes to climate and air pollution issues. These studies can be divided into three categories according to the methodologies.

2.3.1. Emission Inventory

The first one is characterized by emission inventory. From the perspective of either production or consumption, emissions as by-products of fossil fuel combustion can be estimated. Regarding the sources of activity level data, emissions can be estimated from bottom-up or top-down approaches. The bottom-up approach starts with local data at municipal level or even from the specific object of the emissions (Kannari *et al.*, 2007; Beusen *et al.*, 2008; Lutsey and Sperling, 2008; Zhao *et al.*, 2011; Kuenen *et al.*, 2014; Shi *et al.*, 2014). In terms of emissions from energy sectors, it can be the fuels consumed by individual power plants, industrial boilers and household stoves. Along with fuel consumption, technology types, latitude and longitude, service years and other information are also required in some circumstances in order to select representative emission factors and allocate the emissions.

The top-down approach can be referred to the traditional emission inventories based upon activity level data at national/regional level and the top-down models emerged in recent years. The top-down emission inventories are compiled by similar methodology as that of bottom-up inventories. The key difference, however, is the usage of bulk activity level at national or regional scale and default emission factors instead of technology-specific ones (Liu *et al.*, 2016; Li *et al.*, 2017a; Liu *et al.*, 2018a). In other words, activity level data and emission factors used in top-down inventories are coarser and more applicable to areas with limited data.

Top-down models are fundamentally different since they involve the usage of satellite data (Arellano *et al.*, 2004; Levelt *et al.*, 2006; Bergamaschi *et al.*, 2009; Yurganov *et al.*, 2011; Wang *et al.*, 2012; Ghude *et al.*, 2013; Houweling *et al.*, 2017) and to a less extent, usage of ambient measurement (Lee *et al.*, 2011; Tang *et al.*, 2013). Such a method generally relies on the development of inverse algorithm between emissions and observations from satellite or ambient measurement and extrapolation to other grids and time spans of interests. Take NOx emission as an example, its emissions are produced during combustion processes and, thus may serve as a proxy for fossil fuel-based energy usage and greenhouse gases and other pollutants. Duncan *et al.* (2016) used high-resolution nitrogen dioxide (NO_2) data from the Ozone Monitoring Instrument (OMI) (Levelt *et al.*, 2006) to analyse changes in urban NO_2 levels around the world from 2005 to 2014. Based upon linear trend analysis used in Duncan *et al.* (2016) and exponential modified Gaussian methods, Liu *et al.* (2017) developed an advanced fitting function to relate the observation variations to bottom-up information and to evaluate the NOx emission trends over Chinese cities from 2005 to 2015.

Another stem of top-down models is represented by receptor models, which are mathematical or statistical procedures to identify and quantify the source of air pollutants at a receptor location (Henry *et al.*, 1984). It statistically apportions the measured ambient air pollutant concentrations, for multiple time periods at one or multiple monitoring sites, to the emission sources according to some pre-knowledge of their emission characteristics (primarily their chemical characteristics). The site- and time-specific ambient measurements are subject to sampling and analytical errors and to meteorological variability (Karagulian and Belis, 2012; Belis *et al.*, 2015).

These emission estimation methods serve as complementary tools and independent references to each other. On the one hand, emission inventories are often developed in an intermediate manner with both top-down and bottom-up approaches. This is due to the fact the availability of activity level data can vary by sources and sectors. For example, Dios *et al.* (2012) used a mix of top-down and bottom-up methodologies to develop a set of high resolution emission inventories for the European continent.

According to the data availability in China, Zheng *et al.* (2009a) estimated the emissions from power plants and industrial sources with a bottom-up approach. Emissions from on-road mobile sources, non-road mobile sources and others generally follow a top-down manner.

On the other hand, top-down inverse models have received increasing attention as crucial means to validate emission inventories that are developed from statistical analysis. Debate on the usage of top-down modelling results to validate emission inventories still continues and evolves with new evidences (Wang *et al.*, 2006a; Hsu *et al.*, 2010; Zhao *et al.*, 2012a; López-Aparicio *et al.*, 2017). A previous study discussed the possibility of introducing top-down models to assess the compliance with Kyoto Protocol (Rypdal *et al.*, 2005). They calculated the probable emissions using measured concentrations of gases in the atmosphere and meteorological models. Applicability of such top-down estimations were critically reviewed. It was found that inverse modelling results could be useful to monitor the global success of the protocol in particular those dealing with fluorinated gases. Nevertheless, Rypdal *et al.* (2005) concluded that top-down methods are still too inaccurate, cumbersome and politically problematic to be independent alternatives to the reported emission inventories for compliance assessment. As measurement methods have improved remarkably in recent years, some studies suggested that the regulation of greenhouse gas emissions can have integrity only if verified by direct atmospheric measurements (Royal Astronomical Society, 2009; Committee on Methods for Estimating Greenhouse Gas Emissions, 2010; Nisbet and Weiss, 2010). The emerging measurements include the continuous high-precision CO_2, CH_4, N_2O data with the advent of new optical method (Marquis and Tans, 2008), and the advancements in air pollutant monitoring in terms of spatial and temporal coverage, and speciated constituents (Molina *et al.*, 2007; Lin *et al.*, 2008; Park *et al.*, 2013; Bian *et al.*, 2014).

The usage of receptor models is less common than inverse modelling in terms of the cross-validation with emission inventories. Receptor models, however, have their own merits as independent references to validate the source contribution of $PM_{2.5}$ and NMVOCs. For example, quite a few of studies compared NMVOCs emission source identification results between the emission inventory and receptor models, and found significant inconsistencies in source contributions, especially for solvent use, Liquefied Petroleum Gas (LPG) uses, and biogenic sources (Watson *et al.*, 2001; Morino *et al.*, 2011; Wang *et al.*, 2014a). In China, Zheng *et al.* (2009b) compared the source apportionment by emission inventory with receptor modelling by Liu *et al.* (2008). General consistency was gained on the high contributions from gasoline vehicles, coating and solvents, but large discrepancies were observed in the contribution of LPG, and some specific areas with high emission loadings. Despite the observed discrepancies, the question of how to interpret the mixed and sometimes conflicting answers for source identification remains less studied. Reasons responsible for the discrepancies varied in different studies and they were proposed and studied in a somewhat biased way with the underlying assumption that one of the methods is more reliable and the discrepancies are mainly attributed by the limitation or flaw of the other. For studies focused on emission inventories, representativeness of sampling time and sites, photochemical loss and the tracers used in receptor model were questioned Zheng *et al.* (2009b) . As for studies based on receptor model, they argued that emission inventories may fall short of the data quality of activity level data, emission factor and potentially missing sources that lead to under- or over-estimations (Wang *et al.*, 2014b).

2.3.2. Life cycle assessment

Life-cycle assessment, or LCA, is an environmental accounting and management approach that considers all the aspects of resource use and environmental releases associated with an industrial system from cradle to grave (Tukker, 2000; Cabeza *et al.*, 2014). LCA differs from the above-mentioned emission accounting approaches in the way that it accounts for all emissions connected to goods or services, regardless of which industrial or economic activities or sectors produce these emissions (e.g., energy, mining, manufacturing, or waste sector) and when these emissions occur over time (US Environmental Protection Agency, 2010). The other emission accounting approaches mentioned above - be it production- or consumption-based – generally focus on the emissions by specific sectors or activities or consumers on annual basis.

LCA is an emerging tool to evaluate the emissions and other wastes stemmed from energy production, transportation and consumption. It is especially useful to provide a comprehensive comparison between different energy solutions in terms of their environmental benefits and drawbacks. Various energy alternatives are on the horizon, such as solar, wind, hydro power and hydrogen. They are promising clean energy when one considers the emissions during usage. However, it is questionable how clean these alternatives can be when we include all the emissions occur during extraction, infrastructure and retirement. The build-up of wind turbines, for example, requires considerable amount of rare-earth materials (e.g., neodymium and dysprosium), which is generally extracted in the developing countries with poor management and heavy emissions (Rademaker *et al.*, 2013; Zhou *et al.*, 2017). LCA is developed to take care of these problems. Pehnt (2006) developed the dynamic LCA of renewable energy technologies. Using Germany as a case study, they evaluated the emissions of CO_2, CH_4, N_2O, SO_2, NOx, NH_3 and HCl of electricity provided by hydropower, photovoltaics, wind, solar thermal, geothermal and wood. It was found that the inputs of finite energy resources and emissions of greenhouse gases for all renewable energy chains were extremely low compared with the conventional system. There exists, however, variabilities in LCA studies according to the size and the technology of the case (Evans *et al.*, 2009; Sherwani *et al.*, 2010; Blengini *et al.*, 2011; Asdrubali *et al.*, 2013; Vázquez-Rowe *et al.*, 2014). Efforts have been made to harmonize the results from literatures (Evans *et al.*, 2009; Cherubini, 2010; Ramesh *et al.*, 2010; Sesana and Salvalai, 2013; Turconi *et al.*, 2013). Wrapping up results of 100 different case studies, Asdrubali *et al.* (2013) found wind power with a lower overall environmental impact than other renewable technology. It had the lowest carbon dioxide equivalent (CO_2eq) emissions and the lower embodied energy (the energy that is consumed to produce the materials and devices for wind power generation). Geothermal power and photovoltaics, instead, had the highest overall environmental impacts and the widest range of variability. Evidences in favour of renewable energy technology are accumulating and laying the ground for the wide deployment of renewable energy. A recent study critically reviewed the trade-offs of increased up-front emissions and reduced operational emissions of renewable technologies (Hertwich *et al.*, 2015). They presented the first global and integrated LCA of long-term, wide-scale implementation of electricity generation from renewable sources (i.e., photovoltaic and solar thermal, wind, and hydropower) and of carbon dioxide capture and storage for fossil power generation. Considering the emissions causing PM exposure, freshwater eco-toxicity and eutrophication, and climate change effect, it was concluded that renewable energy yields more environmental benefits than fossil fuel systems. Bulk material requirement appear manageable but not negligible. Copper is the only material for which supply may be a concern.

2.3.3. Numerical modelling

The above two methods provide quantitative analysis on how energy-relevant sources and others contribute to GHG and air pollutant emissions. With the help of numerical modelling, source contribution to a wider range of environmental indicators can be assessed. In the context of climate and air pollution, a numerical model is a mathematical simulation of how GHGs or air pollutants disperse and react in the atmosphere and other earth-system modules such as ocean and land. Model outputs include temperature, ambient air pollutant concentrations and other environmental factors of concern (United States Environmental Protection Agency, 2016). The core of a numerical model is to reproduce the real-world systems with mathematical equations to reflect the law of physics, fluid motion, and chemistry. The real-world systems, however, are too complicated to be comprehensively represented in numerical models. Depending on the scope of study area, temporal and spatial resolution, and the environmental indicators of interest, different simplifications and compromises are made to ensure that numerical models are both reliable and computationally feasible. Since climate is generally an issue of wider scope, global or regional models are employed such as the Community Earth System Model (CESM) (Zveryaev, 2015; Kay *et al.*, 2016; Li *et al.*, 2018a) and general circulation model (GCM) (Oglesby and Saltzman, 1990; Kyselý, 2002; Ruosteenoja *et al.*, 2007). For air quality studies, multi-scale models are developed for global, regional or even street levels. GEOS-Chem, for example, is a global model of atmospheric chemistry driven by assimilated meteorological observations from the Goddard Earth Observing System (GEOS) of the NASA Global Modeling Assimilation Office (GMAO) (Bey *et al.*, 2001). It is widely used to study the global circulation and formation of $PM_{2.5}$ (Henze *et al.*, 2009; Kim *et al.*, 2015), O_3 (Fusco and Logan, 2003; Zhang *et al.*, 2011), black carbon (Cogan *et al.*, 2012), CO (Chen *et al.*, 2009) and other air pollutants (Wang *et al.*, 2014b) in the troposphere. On regional scales such as national and provincial levels, the Community Multiscale Air Quality Modeling System (CMAQ) (Binkowski and Roselle, 2003; Foley *et al.*, 2010) and

Comprehensive Air Quality Model with Extensions (CAMx) (Tesche *et al.*, 2006; Nopmongcol *et al.*, 2012) are widely used. They are photochemical grid models on fine resolutions, e.g., a few kilometres and per hour. The Operational Street Pollution Model (OSPM) (Kakosimos *et al.*, 2010) and other street-in-grid models were developed (Kim *et al.*, 2018) to study the dispersion of air pollutants in street canyons.

One of the key applications of numerical models is to study the casual relationship between emissions and the concentrations of either greenhouse gas or air pollutants in the atmosphere. The invention of such tools enable researchers and policy makers to explore the “what if” question. By designing emission scenarios that reflect the possible policy pathways, one can foresee the effectiveness of proposed mitigation strategy (Pallav *et al.*, 2010).

In the field of climate studies, numerical tools are used to assess the possible pathways or technologies to limit temperature rise or other climate impacts. For example, Tilmes *et al.*, (2016) used CESM to investigate climate outcomes applying stratospheric sulphur injection (SSI), one of the geoengineering techniques. They argued that SSI produces mean and extreme temperature in CESM comparable to an early decarbonisation pathway. Some critique the internal variability in climate models, and thus their reliability in future climate projections (Vidale *et al.*, 2003; Horton *et al.*, 2006; Knutti and Sedláček, 2013). To address such an issue, ensembles of simulations or models are used (von Deimling *et al.*, 2006; Tebaldi and Knutti, 2007; Meier *et al.*, 2012). Sanderson *et al.* (2018) had produced a 15 member ensemble conducted with CESM. Though internal variability is still a significant component of uncertainty, they reported that there is evidence of a significantly increased risk of extreme warm events in some regions as early as 2030 in RCP8.5 relative to RCP4.5. Another study combined the projections of sixteen GCM models to assess strategies for adaptation to climate change impacts in hydropower generation in Brazil (Lucena *et al.*, 2018).

For air quality research, the same work flows as climate modelling study are generally followed. The end-points for effectiveness assessment can be air pollutant concentrations, air quality exceedance rate, health exposure and even co-benefits (or trade-off) of climate effects.

The concentration of air pollutants and exceedance rate of air quality are key outputs provided by air quality models that can assist in control strategy formulation. Kinnon *et al.* (2016) presented a good example using the CMAQ model to investigate the air quality impacts of fuel cell electric hydrogen vehicles (FCEVs) in California. It covered the regional energy system projection, development of emission fields and atmospheric modelling. Such a modelling study provided evidence on the reduction potentials of FCEVs on O_3 and $PM_{2.5}$ concentrations and had assisted decision makers in developing effective air quality improvement strategies from the transportation sector. Similar studies are numerous concerning the air quality improvement potentials from emission reductions in power sector (Gégo *et al.*, 2008; Wang *et al.*, 2010a), industry (Cheng *et al.*, 2007; San José *et al.*, 2007), household (Gu *et al.*, 2018; Baykara *et al.*, 2019), open field biomass burning (Zhang *et al.*, 2006; Huang *et al.*, 2013) and others.

The output of air quality models are generally gridded concentrations. Combined with demographic data such as population density, age and gender distribution, one could assess the health risk driven by elevated air pollution. Pollutants with the strongest evidence for public health concern include PM, O_3, NO_2, SO_2 and air toxics such as mercury and hydrogen chloride (Ezzati and Kammen, 2002; Afroz, Hassan and Ibrahim, 2003; Zhang and Smith, 2007). Globally, 9 out of 10 people breathe air containing high levels of pollutants (World Health Organization, 2018). Air pollution from indoor and outdoor is responsible for a death toll of 7 million people every year (World Health Organization, 2019). Such estimations are built upon the evidence from epidemiology which develops the health-exposure relationships between air pollutant concentrations and the mortality rates for specific diseases. Currently, there are a growing number of studies to establish the concentration-response relations between $PM_{2.5}$ and mortality associated with cardiovascular disease (Schwartz *et al.*, 2002; Wyzga and Rohr, 2015; Limaye *et al.*, 2019), and to a lesser extent, on O_3 and respiratory diseases (Gelzleichter *et al.*, 1992; Atkinson *et al.*, 2012; Bae *et al.*, 2015). These studies generally develop the quantitative association between the historical air pollutant concentrations and the excess mortality by various regression models. (Jerrett *et al.*, 2009) used the air quality monitoring record and health statistic in the US from 1977 to 2000 to study the health risk of long-term exposure of $PM_{2.5}$ and O_3. The estimated relative risk of death from respiratory causes that was associated with an increment in O_3 concentration of 10 ppb was 1.040 (95% confidence interval, 1.010 to 1.067). Such epidemiology studies, however, are still limited in both their numbers and study areas, which generally focus on developed regions due to the high demand for historical data.

The impact of energy transition, emission control measures and strategies on public health is then computed by the outputs of air quality model and the established concentration-response relationship (Wang and Mauzerall, 2006; Fann *et al.*, 2009; Jackson *et al.*, 2010; Beevers *et al.*, 2013). Linking the outputs from CMAQ with census data and the concentration-response relationship, Atkinson *et al.* (2012) estimated the $PM_{2.5}$-related public health impact associated with the emissions for a set of power plants in the US. Zhao *et al.* (2018) reported that reduced usage of solid fuels in household fuels had led to a 42% decrease of integrated population-weighted exposure to $PM_{2.5}$ from 2005 to 2015 in China. Abel *et al.* (2019) studied the air quality-related health benefits of energy efficiency in the US. They used the AVoided Emissions and geneRation Tool (AVERT) to simulate plant-level generation and emissions, the CMAQ model to simulate air quality, and the Environmental Benefits Mapping and Analysis Program (BenMAP) to quantify mortality impacts. A 12% summertime reduction baseload electricity demand would result in 10~16% reduction of NOx, SO_2 and CO_2 emissions, and consequently, avoid 300 premature deaths annually. Such measures of the benefits on public heath are indeed important considerations in air pollution mitigation strategy formulation. Moreover, when energy-relevant emissions are involved, they also serve as evidence and extra incentives to combine the immediate and long-term benefits and makes no-regret or low-regret climate policy possible (Burtraw *et al.*, 2003; Dudek *et al.*, 2003; Amann *et al.*, 2011). It is in this way that numerical models play roles in the current and future air pollution and energy policies.

In some circumstances, air quality and climate models are used jointly to study the interaction between climate and air quality and the effectiveness of mitigation pathways under such complex dynamics (Hogrefe *et al.*, 2004; Groosman *et al.*, 2011; Glotfelty *et al.*, 2017; Hong *et al.*, 2017). Stowell *et al.* (2017) used a hybrid downscaling approach evaluate the separate impact of climate change and emission control policies on O_3 levels and associated excess mortality in the US in the 2050s.

With a combination of climate, air quality and epidemiological models, Orru *et al*. (2017) estimated that climate change would adversely affect future air quality for more than 85% of China's population, with an increase of 3% and 3% of the population-weighted average concentrations of $PM_{2.5}$ and O_3, respectively. Such studies, nevertheless, are highly dependent on the climate change scenarios and on projections of future air pollution emissions, with relatively high uncertainty (Ebi and McGregor, 2008; Liao *et al.*, 2009; Davis *et al.*, 2011). Another limitation is the lack of projections on the effects on morbidity (Orru *et al.*, 2017).

2.4. Incorporation of socioeconomic factors in environmental studies and integrated assessment

Climate change and air pollution are deeply woven into human society. There are a multitude of studies on their complex interactions. Here, focus will be on two strands of research. One is the "cause-focused" research, which investigates how human demands and activities fuel the climate and air quality problems. Another strand is "impact-focused" research that measures the socioeconmic impact of climate change and air pollution.

Strictly speaking, the emission inventory and life cycle assessment reviewed above can be categorized into the caused-focused research, and the numerical modelling addresses both the causes and impacts. The studies reviewed below, however, have more focus on specialized socioenomic analysis. While emission inventory and life cycle assessment reveal the human activities that are directly responsible for pollution precursors, caused-focused literature digs deeper in the socioecomic drivers in macroeconomic level. Compared to the health burden calculated by numerical models, impact-focused studies estimate the direct and indirect socioeconomic impacts in monetary term. Some studies can even investigate how climate and air pollution contribute to social issues such as inequality.

Here, cause- and impact-focused studies are reviewed in Section 2.4.1 and 2.4.2, repectively. They are followed by a review of integrated assessment studies in Secion 2.4.3, which are interdiscipinary works that combine socioecnmic analysis with conventional environmetal tools.

2.4.1. Socioeconomic drivers of climate problem and air pollution

There is a proliferation of studies to uncover the socioeconomic drivers of GHG and air pollutant emissions. One of the perennial questions in the centre of energy and environmental policy is how to reduce emissions (or energy consumption) while maintaining stable economic growth (Coers and Sanders, 2013). To answer this question, causal relationship between emissions (or energy consumption) and real GDP growth should be investigated (Ozturk, 2010; Wagner *et al.*, 2016). A major strand of studies on energy and emission socioeconomic drivers, therefore, is to study the causality between these two. Empirical studies are accumulating concerning the existence and direction of causality. Tang *et al.* (2016a) used a neoclassical Solow growth framework to test Granger Causality between energy consumption and economic growth in Vietnam from 1971 to 2011 and reported the causality running from energy consumption to economic growth. With Panel Vector Autoregressive and impulse response function, Antonakakis *et al.* (2017) studied the energy consumption, economic growth and CO_2 emissions in 106 countries classified by income groups over the period of 1971 to 2011. They found that causality between total economic growth and energy consumption is bidirectional. However, they cannot certify a statistically significant relationship between renewable energy consumption and economic growth. There is a lack of evidence that renewable energy consumption is able to promote growth in a more efficient and environmentally sustainable way. Results from literature, however, have been inconclusive. Ghoshray *et al.* (2018) proposed that the inconsistency can be explained by some methodological flaws. One is the use of bivariate models, which fail to detect more complex causal relations and neglect the effects from other driving factors. The other is the use of liner causal models. The second flaw can be partly overcome by the usage of non-linear causal relationships or other noble methods such as Flexible Fourier (Ghoshray *et al.*, 2018).

The above review on causality or decoupling studies highlights the need of a multivariate framework. Such a need gave rise to methodological and empirical studies regarding panel data analysis, Index decomposition analysis (IDA) and Structural Decomposition Analysis (SDA). First, panel data analysis is a statistical method to analyse two dimensional data. In the context of energy consumption and emission data, the object is typically time series data with sectoral details (Marques *et al.*, 2010; Jiang *et al.*, 2014; Du *et al.*, 2016). Given the immense difference in the shares of renewable energy in total primary energy supply among OECD countries, Gan and Smith (2011) applied panel data modelling approach to identify the drivers of renewable energy development in OECD countries. Common drivers were GDP per capita and market deployment policies, and country-specific drivers revealed different pathways for bioenergy development. A similar study was conducted by Chen (2018) to study the factors influencing renewable consumption in 30 provinces in China from 1996 to 2013. They studied the effects of economic growth, CO_2 emissions, foreign trade and urbanization on the renewable energy consumption. Results were similar to that of Gan and Smith (2011), in which economic development was an important positive driver with heterogeneous effects across regions. The links between socioeconomic indicators, energy consumption and emissions can be investigated following similar methods (Andrés and Padilla, 2018; Du *et al.*, 2018; Feng *et al.*, 2018; Pao and Chen, 2019). While empirical evidences covering more countries and longer time span are accumulating over time, findings are not conclusive. Chen (2018) reviewed nearly 90 pieces of literature on the driving effects from economic growth and urbanization to energy consumption and CO_2 emissions. These studies found divergence in the multivariate relationships. Indeed, results of nearly 90 literatures can be divided into 7 groups in favouring of different types of causal relationships. Such divergences show that results are country- and time- specific and can vary from case to case.

Second, IDA is widely used to analyse change in energy consumption and emissions over time. It is used to analyse changes in indicators such as energy use, CO_2-emissions, labour demand and value added (Ang and Liu, 2007; Ang and Xu, 2013). The changes in these variables are decomposed into determinants such as technological, demand, and structural effects. Similar to panel data analysis, such a technique is applicable to deal with multidimensional and multilevel data. The family of IDA includes additive and multiplicative analyses. Both of them are based upon the chain computation method and the Divisia (log-change) decomposition method (Ang, 1994). It was first used to study electricity consumption trends in industry in the late 1970s. Growth of studies has been tremendous since then. While it is hard to numerate all the studies, a comprehensive review covering both the methodological and application fronts was provided by Ang and Zhang (2000). More specific reviews on sub-areas are also provided recently. Liu and Ang (2007) reviewed the studies that decomposed changes in aggregate energy intensity of industry to the relative impacts arising from energy intensity change and product-mix change. Xu and Ang (2013) focused on the decomposition studies on energy related CO_2 emissions.

SDA is another decomposition method that has developed independently from IDA. IDA and SDA have the same aims but apply different models. IDA uses only aggregate sector information, while SDA relies on the input-output framework and is also quoted as "IO SDA" (Rose and Casler, 1996). SDA is based on input–output coefficients and final demand per sector from the IO tables. SDA can therefore distinguish between a range of technological effects and final demand effects that are not possible in the IDA framework (Rutger and van der Bergh, 2003). Earlier studies are dated back to the late 1980s (Rose, 1984; Gould and Kulshreshtha, 1986), and the application of SDA has been developed into a major analytical tool lately. A majority of SDA studies on energy and emissions use additive decomposition (Su and Ang, 2012). By additive SDA and the conjunction of global and regional IO tables, Meng *et al.* (2019) presented a good example on how SDA can be used to identify the socioeconomic driver of environmental issue. Given the fact that the growth of global emissions of $PM_{2.5}$ and many of its precursors slowed down from 2004 to 2011, Meng *et al.* (2019) reported that improvements in energy intensities and production efficiency were the major drivers.

Reviewing the existing studies, IDA and SDA have been demonstrated as useful complements to device/process level, engineering-based industrial energy analysis and macro-level econometric analysis that relates energy consumption or emissions to some explanatory variables. While the objectives and techniques are basically the same among studies, there are great variations in the pre-determined variables and data set used. Such inconsistencies make it hard to compare the results from different studies even for the same study area. Take China as an example, there is an extensive body of literature on driver analysis of China's energy consumption at the national level and, to a lesser extent, at the provincial level. At the national level, these studies cover a wide time span from 1970 to 2015 but are generally inconsistent in the number of decomposed factors, time lag and sectors of interest (Song and Zheng, 2012; Xu *et al.*, 2014; Zhang *et al.*, 2016a; Fan *et al.*, 2017; Zhao *et al.*, 2017; Guan *et al.*, 2018; Wang *et al.*, 2018a).

2.4.2. Impacts of climate and air pollution in socioeconomic context

The impacts of climate and air pollution to human society can be understood in two ways. One is the direct impact or cost, which is caused by the direct consequences of climate and air pollution problems. Typically, it is the short-term physical impacts on natural resources, people and tangible assets. Take air pollution as an example, the direct impact would be the death toll, decreased morbidity, increased national burden of health care, corrosion of susceptible materials and infrastructure, reduced crop yield and others. Direct impacts studies, therefore, translate such outcomes into monetary loss. Given the data availability and epidemic evidences, impact studies of air pollution are mainly on measuring the direct impacts of mortality and morbidity (Venners *et al.*, 2003; Kan and Chen, 2004; Meng *et al.*, 2016a). Based upon an exposure-response relationship, relative risks for a particular disease are associated with air pollutant concentration levels (Wong *et al.*, 2002; Meng *et al.*, 2016a). Health cost is then measured either by evaluating patients' willingness-to-pay (WTP) to avoid disease risk (Alberini and Krupnick, 2000; Carlsson and Johansson-Stenman, 2000; Wang and Mullahy, 2006) or by applying the productive years of life loss (PYLL) (Miraglia *et al.*, 2005; Matus *et al.*, 2012; Xia *et al.*, 2016). From the perspective of climate, impacts from drought, flood, heat wave and other natural disasters that are intensified by climate can be measured (Whetton *et al.*, 1993; Yang *et al.*, 2012; Gleick, 2014). The direct impact of flood, for example, includes the expected annual damage (EAD) from river flooding events, which is estimated to be 6.4 billion Euro in 2012 and may increase to 14 to 21.5 billion Euro (constant 2006 prices) by 2100 (Feyen *et al.*, 2012).

The indirect impacts, by contrast, investigates the cascading effects triggered by negative nature of climate and air pollution problems. It refers to the economic impact or loss resulting from labour delay, capital loss, disruption of economic activities in the whole production supply chain and costs for physical capital reconstruction (Hallegatte and Przyluski, 2010; Baghersad and Zobel, 2015; Hallegatte, 2015, 2017). The quantification of indirect impacts are an emerging field. To track down cascading effects along the supply chain, IO or computable general equilibrium (CGE) is adopted. For example, Xia *et al.* (2018) used MRIO table for 30 provinces in China to study the disease-induced working-time reduction in 2012. Such an indirect impact was estimated to be CNY 398.23 billion, equivalent to ~1% of China's GDP in 2012. Nam *et al.* (2010) applied CGE to measure the welfare loss caused by air pollution in Europe. Even for European countries where air quality is relative high, they still experienced an annual loss in consumption of about 222 billion Euro in year 2000 prices (~3% of total consumption) and a total welfare loss of about 370 billion Euro. Nam *et al.* (2010) constructed an econometric and IO joint method and estimated that the indirect economic loss for the transportation sector caused by representative haze pollution of Beijing in 2013 was 23.7 million yuan. Methods in this field, however, are still building up.

2.4.3. Integrated assessment

Integrated assessment is an interdisciplinary approach to combine, interpret and communicate knowledge from diverse scientific disciplines to expose an entire cause-effect chain of a problem from a synoptic perspective. By integrating a broader set of studies, approaches and points of view coming from different scientific areas interacting each other, integrated assessment strives to provide more and better information on the issue assessed than single disciplinary studies added up (Jakeman and Letcher, 2003; Van Delden *et al.*, 2011; Voinov and Shugart, 2013). In the context of climate and air pollution problems investigated here, integrated assessment should embrace the social, economic, technical and environmental perspectives (Toth, 1998; Kalaugher *et al.*, 2013; Welsh *et al.*, 2013).

Energy system models (ESMs) and integrated assessment models (IAMs) represent one dominant strand of integrated assessment in terms of energy and climate policy (Cantore, 2011; van Vuuren *et al.*, 2011; Harfoot *et al.*, 2014). The underlying philosophy of ESMs and IAMs is similar with AQMs, which is to explore the "what if" or "how to" questions by a wide range of numerical experiments embodied in the models. The ESMs and IAMs, however, are simplified replicates of the material and energy flows inside human society and economy, rather than the physical and chemical laws depicted in AQMs. More specifically, ESMs and IAMs contain with them a representation of fuel extraction, transformation of fuels into useful energy forms such as electricity, hydrogen, heating and transport fuels, delivery of this energy to end users, and the use of this energy to provide services such as transporting people and freight, heating buildings, and powering factories (Gambhir, 2019). They cover the economic and technical perspectives by the integration of cost (e.g., infrastructure and maintenance cost), tax, carbon prices, performance and availability of technologies, and other technical parameters. In some circumstances, ESMs and IAMs are linked to a CGE model to produce a better reflection on the economic system such as the price and demand elasticity (Messner and Schrattenholzer, 2000; Klaassen and Riahi, 2007; Kypreos and Lehtila, 2015). Social considerations are generally embodied in the design of socio-economic growth. Environmental aspects are reflected by the pre-determined emission constraints and climate targets. Since their development, ESMs and IAMs have been used widely to explore low-carbon pathways. Their prominences have been well documented in the latest (5^{th}) assessment report by Intergovernmental Panel on Climate Change (IPCC), which is an ensemble of over 1000 modeled future emissions pathways (Intergovernmental Panel on Climate Change, 2014). The existing models include the TIMES Integrated Assessment Model (TIAM) (Loulou and Labriet, 2008; Gracceva and Zeniewski, 2013; Selosse and Ricci, 2014), MESSAGE Integrated Assessment Model (MESSAGE) (McCollum *et al.*, 2011; Rogner and Riahi, 2013; Sullivan *et al.*, 2013), and their extensions (Messner and Schrattenholzer, 2000; Huppmann *et al.*, 2019).

It can be observed that such integrated models are designed for energy-relevant GHG emissions and climate targets. Air pollutant emissions are not standardized components with such models. To enable integrated assessment for the sake of air quality, ESMs and IAMs can be connected to other simulation models via external links. Some studies have used the inputs and outputs from MESSAGE and the Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) model in an iterative manner to explore the energy pathways under air pollutant emission constraints. Specifically, energy scenarios provided by MESSAGE are used as inputs for GAINS to quantify the air concentration and health benefits. By iteration, a pathway with minimum cost from the energy system (optimized by MESSAGE) to reach a certain air quality target (controlled by GAINS) will be provided as output. Following such a methodology, Maragatham and Rafaj (2012) facilitated an impact assessment of simultaneous control of air pollution and GHG abatement under energy projections by 2050.

Another strand refers to a wider range of studies in looser forms. It represents the efforts to combine the above cause-focused and impact-focused socioeconomic studies with conventional environmental studies. Instead of a nested structure embodied in one single model, they combine the approaches from different disciplines via soft links. The advantages of such studies include flexibilities and transparencies. For ESMs and IAMs, many of their model parameters are not open and the optimization functions and other settings are generally fixed (McMichael, 1997; Cocks *et al.*, 1998; Ackerman *et al.*, 2009). There is no consensus on how such loose-form studies should be constructed. They can vary from research question, data availability, involved expertise and other factors. Kumar and Saroj (2014) proposed a simplified framework to study the nexus between energy production, related water consumption and air pollution under the backdrop of growing population and urbanisation. The key idea was to integrate production, consumption, emissions and control into one single assessment framework. Similarly, Griggs *et al.* (2014) developed an integrated framework to incorporate six sustainable development goals (SDGs) which included both development and environmental considerations. Numerous studies of the kind have emerged in recent years to advocate the idea of integrated assessment (Camagni *et al.*, 1998; Ezzati *et al.*, 2001; Nair *et al.*, 2014; Li *et al.*, 2017b). Many of them, however, are in conceptual stages and qualitative manners. There are still enormous gaps in both methodologies and data to facilitate a feasible integrated assessment framework.

Quantitative studies are accumulating to overcome the methodological and data gaps in integrated assessment. Some studies used mathematical constraints to ensure optimization was reached with multiple targets. For example, (Zeng *et al.*, 2017) developed the population-production-pollution nexus for Beijing, China, with eight constraints touching the factors of population, incomes, emission penalty, loss from reduced production activities, cost for environmental retreatment and inter-regional transportation. It identified the optimized policies to reconcile the conflicts from demand, production and pollution mitigation. The introduction of mathematical constraints in these studies have limited their usage, however. While a mathematically optimal solution can be provided, it is not necessarily the optimal option in the real world considering other socioeconomic barriers. More importantly, it is hard to quantify the cause and effect relationship between the environment and socioeconomic systems.

Studies aiming to capture the material and emission flows between energy, environment and socioeconomic systems have emerged accordingly. To break the systems' boundaries, the input-output (IO) framework is used. More specifically, the environmentally-extended input-output (EEIO) framework is adopted. Compared to the traditional IO method, EEIO integrates material or emission flow data into the monetary input-output relation (Tukker *et al.*, 2009; Kitzes, 2013; Hawkins *et al.*, 2015). With EEIO and complex network analysis, Chen *et al.* (2018) studied the global energy flows embodied in international trade. Wang *et al.* (2019) combined the EEIO framework and ecological network analysis to depict the sectoral embodied consumption of water and energy and their inter-sector flows. The impact of the energy–water linkage on energy and water systems was investigated and results showed that nexus impact on the water system was larger than that on the energy system. In term of air pollution, attempts have been made to connect EEIO with atmospheric transport models for a better understanding of pollution causes and responsibility. Lin *et al.* (2014) provided an influential work to study the emissions embodied in the international trade between US and China and the environmental impacts in both countries. Specifically, emissions of SO_2, NOx, CO and black carbon were analysed, followed by simulated concentrations of $PM_{2.5}$ and O_3. It exposed an interesting integrated assessment work on the causes and impacts of bilateral trade. One limitation of this study, however, was the simulation of O_3, in which NMVOCs emissions were remained constant across scenarios. Later on, Zhang *et al.* (2017) provided a more throughout study that addressed all the global economies. In addition, they extended the analysis to public health, which linked the drivers of global consumption to premature mortality associated with $PM_{2.5}$ outdoor exposure. Integrated assessments on other pollutants, such as black carbon (Meng *et al.*, 2018) and mercury (Hui *et al.*, 2017; Li *et al.*, 2017c; Chen *et al.*, 2019) were also carried out. Nevertheless, studies of this kind are still sparse and applications on other secondary pollutants such as O_3 are very limited.

2.5. Research Gap

With respect to energy, pollution and socioeconomics, each of them is an area with a multitude of studies that are hard to numerate exhaustively. This chapter strives to review studies relevant to the proposed methodological framework (See Figure 1-9 in Section 1.4.2). Research gaps in data, methodology and knowledge are identified and discussed below.

2.5.1. Methodology and data gaps

The merits of integrated assessment have received more attention recently. Such an interdisciplinary approach can combine, interpret and communicate knowledge from diverse scientific disciplines and provide more and better information on the issue than single disciplinary studies added up. This is especially true for climate and air pollution problems, which have their roots and fruits in the economic, social and ecological systems. Towards an integrated assessment of energy, pollution and socioeconomics, different models, conceptual frameworks and quantitative methods have been proposed. Nevertheless, each of them has their own limitations. Since integrated assessment models are generally designed to reach optimal solutions of energy systems under the predetermined climate targets, they are less applicable to explore the full chain of cause and impact in energy, pollution and socioeconomic system. To enable integrated assessment for the sake of air quality, they also need to connect to other simulation models via external links. Concerning integrated assessment frameworks, a lot of studies have advocated the importance to introduce different perspectives in order to better understand the trade-offs and synergies. Many of them, however, are in conceptual stages and qualitative manners. Quantitative studies are accumulating but still limited. Some studies used mathematical constraints to ensure optimization was reached with multiple targets, which are indeed similar to the underlying logic of integrated assessment models. The others try to connect the social and economic system with the environmental system by the IO framework. They have succeeded in providing quantitative evidence on the emission and material flows between different systems and renewing the understanding on the cause and effect of climate and air pollution (Lin *et al.*, 2014; Zhang *et al.*, 2017b; Meng *et al.*, 2018; Chen *et al.*, 2019). Nevertheless, studies in such quantitative manners are still sparse. Recognizing the central role of IO in the integrate assessment, this study develops an integrated assessment framework to depict material and emission flows between producers, consumers and environmental receptors. Such a framework is comprised by EEIO analysis, decomposition techniques, air quality modelling, health exposure evaluation, and a comprehensive set of technical and cost parameters. It is argued that production- and consumption-based emissions can serve as the keys to connect different systems and allow a quantitative assessment on the full chain of cause and effect.

In addition, this study attempts to overcome some of the limitations in energy and emission data and the MRIO table in China. First, existing studies have exposed the mixed quality of energy consumption and emission data in China (Marland, 2008; Junguo and Hong, 2009), which is also a common issue for other developing countries. Statistical corruption, inconsistency between statistic systems in different administrative levels, and frequent revisions of energy statistics have been identified as three of the key factors responsible for questionable quality of energy consumption statistics. The uncertainty in energy data would be propagated into the compilation of production- and consumption-based emission inventories and consequently, undermines the reliability of integrated assessment. According to the existing studies, uncertainty is especially large for air pollutants such as $PM_{2.5}$ and NMVOCs. This raises data and methodology gaps with respect to the reliability of energy and emission data and their validation. This study tries to overcome such research gaps by a comparison of energy statistic in national and provincial levels (See Section 3.1.1) and an attempt to validate NMVOCs emission inventories with ground-level measurements of speciated NMVOCs (See Section 3.1.3). Second, the central role of an IO framework in quantitative integrated assessment has been acknowledged. Currently, the MRIO table is available for 30 mainland provinces in China (Mi *et al.*, 2017). While such a MRIO has captured the major economic activities between provinces, there is still a need to extend the current table to cover the whole national economy. The extension of the MIRO would enable an integrated assessment in wider coverage and expose the production and consumption characteristics of some regions that are generally neglected. This study tries to advance the development of China's MRIO table by extending it to cover all the provinces in mainland.

2.5.2. Knowledge gaps

The above methodologies and data gaps partly result in insufficient knowledge on the complex interaction between energy consumption, pollution formation and socioeconomic demands in China. This study identifies the research gaps in terms of subnational studies and the causes and effects of some emerging trends in energy consumption and pollution.

First, studies in subnational levels for a vast country as China are vital but are still lacking. As a country that comprises more than 30 administrative regions, provinces in China are widely divergent in their development statuses as shown in Section 1.1. Due to the data availability and work load, studies in subnational levels are generally less than those in national levels. However, the overall trends for China as a whole can disguise some interesting and contradictory pictures between Chinese regions, as demonstrated in studies on the determinants of carbon intensities (Guan *et al.*, 2014) and regional emission drivers (Mi *et al.*, 2017).

With respect to energy consumption, the dominance of national studies or the grouping of regions have overlooked the crucial transitions in provincial levels. The energy elasticity (the percentage change in energy consumption to achieve one per cent change in national GDP) (Shimi and Reji, 2013; Giraud, 2014) in China had decreased continuously from 2003 to 2015. Starting at a level of 1.11 from 2003 to 2007, the energy elasticity dropped to 0.58 during 2007 to 2011, followed by an even lower value of 0.46 from 2011 to 2015. China seems to be on the way towards more energy-efficient growth. The slowdown of energy consumption growth is even more prominent in provincial level. Eight of its provinces have seen declines in their total primary consumption (including coal, petroleum, natural gas and non-fossil fuels) from 2011 to 2015. The other five provinces, in addition, have decreased their combined consumption of coal and petroleum though their total primary consumption has slightly increased. Collectively, nearly half of China's 30 inland provinces are making positive transitions in their energy consumption. However, the drivers behind such transitions and the possibility to sustain them are not covered in current studies. There is an extensive body of literature on driver analysis of China's energy consumption at the national level, and to a lesser extent, at the provincial level. At the national level, these studies cover a wide time span from 1970 to 2015 but are generally inconsistent in the number of decomposed factors, time lag and sectors of interest (Gu*an et al*., 2008, 2018; Liu *et al*., 2012; Zhang and Da, 2015; Wang and Feng, 2017). Such inconsistencies make it hard to compare the results from different studies. At the provincial level, many of the studies are focused on energy-related CO_2 emissions (Jiang *et al.*, 2017; Ye *et al.*, 2017), energy intensity (Song and Zheng, 2012; Elliott *et al.*, 2017) and CO_2 emission intensity (Tan *et al.*, 2011; Wang *et al.*, 2018a). They missed the declines of some provinces in energy consumption due to the grouping of provinces or lack of sub-period analysis. For example, some studies only targeted the start and end years (e.g., 2000 and 2015, 2005 and 2010), which obscured the emerging trend in between. The others grouped the provinces by their spatial locations or types of drivers for ease of discussion. In a previous study, for instance, provinces were grouped into East, Central and West (Wang and Feng, 2017). The energy-related CO_2 emissions for the Central provinces have levelled off since 2011. Among them, it is highly likely that some of their emissions had already declined. It is a pity that the trend was smoothed and omitted.

Third, there is a worrying trend on the ground-level O_3 in China yet its causes and effects are still poorly characterized. While China has made enormous progress in combatting the fine particulate matter ($PM_{2.5}$) pollution, ozone (O_3) pollution is on the rise. With focused control of primary $PM_{2.5}$, sulfur dioxide (SO_2) and nitrogen oxides (NOx) (Chinese State Council, 2013), the $PM_{2.5}$ concentration decreased by 35% in 2017 (47 $\mu g/m^3$), compared to a level of 72 $\mu g/m^3$ in 2013 (China National Environmental Monitoring Centre, 2018b). Meanwhile, the hourly concentration of O_3 in China increased by 16~27% from 2013 to 2017. The O_3 exposure metrics (cumulative O_3 concentration) increased even more by 57~77% (Lu *et al.*, 2018). The present extent of O_3 pollution, in terms of the exposure of humans and vegetation, is greater in China than in any other developed region of the world with comprehensive O_3 monitoring (Lu *et al.*, 2018). Evaluation of past data in the United States and some other developed countries showed that O_3 pollution became more prominent after initial progress on particulate control had been made (Coordinating Research Council, 2015; Fujita *et al.*, 2016). Few earlier studies in China also highlighted the threat of worsening O_3 pollution following the strong $PM_{2.5}$ control policies (Xing *et al.*, 2011a; Xue *et al.*, 2014; Ou *et al.*, 2016). Still, the surge of O_3 in recent years is surprising in terms of its extent. There is an awareness of simultaneous reductions of

NMVOCs and NH_3 with NOx control to enhance the effectiveness (Xing *et al.*, 2018), but more investigation on the increased O_3 and evidence-based policy recommendation are still needed. China's initial success on air pollution control is marked by strong end-of-pipe treatments based on the production-based knowledge. As China is undergoing crucial transitions of economic and social growths ("new normal"), the drivers and consumption patterns behind air pollutant emissions should be understood. Such knowledge may enable coordination of emission control and China's supply- and demand- side reform. To this end, an integrated assessment from both the production- and consumption-based perspectives is needed.

Chapter 3 Method and data of energy-pollution-socioeconomic integrated assessment

In accordance with the methodological framework proposed in Section 1.4.2 (See Figure 1-9), the methods and data sources involved are introduced in this Chapter. Section 3.1 describes the compilation of the primary energy consumption matrix, production-based CO_2 and air pollutant emissions and source of socioeconomic data. Section 3.2 introduces how the socioeconomic drivers and demands driving the energy consumption and emissions are identified. Section 3.3 provides details on the construction of the air quality modelling platform and its validation. Evaluation of health impacts caused by elevated air pollution and the cost to introduce cleaner production measures is given in Section 3.4. Section 3.5 is a summary of methods and data sources. It is also a brief restatement on the proposed methodological framework and how the methods and data sources used here can support such a framework.

3.1. Energy consumption, emission and socioeconomic data

3.1.1. Compilation of primary energy consumption matrix by sectors and fuel types

To support the development of air pollutant and greenhouse gas emission inventories, primary energy consumption is a prerequisite. Primary energy consumption refers to the use of crude energy, which is the energy that has not been subjected to any conversion or transformation process. It differs from final energy consumption, which has a much higher proportion of electricity after transformation.

In most energy statistics in China, final energy consumption is recorded. The ways to estimate primary energy consumption are different for fossil fuels and non-fossil fuels. As for fossil fuels, final consumption in physical quantities are available for 8 aggregate sectors from EBT: (1) Agriculture, forestry, animal husbandry and fishery; (2) Industry; (3) Construction; (4) Transport, storage and post; (5) wholesale, retail trade and hotel, restaurants; (6) Others; (7) Urban residential consumption; and (8) Rural residential consumption. The final energy consumption in the above sectors except industry is indeed the same as primary energy consumption, as they do not involve any energy transformation activities. In the industrial sectors, however, there exist various activities of energy transformation, such as the input of coal and petroleum products in the thermal power sector for electricity generation, input of raw coal and cleaned coal for coke production and others. The final energy consumption of industrial sectors, therefore, reflects only part of the fuels that are actually consumed. To include the fuels used for transformation, statistics on the input and output of fuels used for transformation are collected and added up to the industrial sectors. Combined with the sectoral final energy consumption table which includes 40 manufacturing sectors, the input and output of fuels for energy transformation is added up to or deducted from the corresponding sectors, respectively.

In terms of non-fossil fuels, they are represented as electricity and other energy in the final energy consumption statistics. The electricity includes those from fossil and non-fossil fuels. The amount of electricity generated from non-fossil fuels are estimated by the indigenous production of electricity from non-fossil fuels, electricity moving in from other provinces and electricity sent out to other provinces, as shown in Equation 3-1.

$$ENF_i = I_i + M_i \times \Theta - S_i \times \Theta i \qquad \text{Eq. 3-1}$$

Where ENF_i is the electricity from non-fossil fuels consumed in province i, I_i is the indigenous production of electricity from non-fossil fuels in province i, M_i is the amount of electricity moving into province i from other provinces, Θ is the percentage of non-fossil fuels in the total electricity generated nationally, S_i is the amount of electricity sent out from province i to other provinces, Θi is the percentage of non-fossil fuels in the electricity generated in province i. Θ and Θi can be calculated from the national and provincial EBTs, respectively, from the information of primary energy supply.

Once the electricity from non-fossil fuels consumed by a province is estimated from the above equation, it is allocated to sectors based upon the sectoral consumption of total electricity. The underlying assumption here is that, proportions of non-fossil fuels and fossil fuels in the electricity used in end consumers are the same across sectors since one cannot tell the primary source of electricity once they are connected to grids.

The above procedures would provide the consumption of 30 types of fuels in physical quantities for 46 sectors (including primary industry, 41 secondary industrial sectors, 2 tertiary industrial sectors, urban and rural household consumption). The explicit lists of fuel types and sectors can be found in Table 3-1 and Table 3-2, respectively. In other words, every province could have a 30×46 matrix on primary energy consumption, which is used for emission estimation. For the decomposition analysis in Chapter 5, physical quantities are transformed to coal equivalent for an apt comparison across fuel types and the 30 types of fuels are aggregated into 4 categories as shown in Table 3-1.

Table 3-1 Energy types and their aggregation

<table>
<tr><th>Category</th><th>Fuel types</th><th>Category</th><th>Fuel types</th></tr>
<tr><td rowspan="11">Coal</td><td>Raw coal</td><td rowspan="10">Petroleum</td><td>Fuel oil</td></tr>
<tr><td>Cleaned coal</td><td>Naphtha</td></tr>
<tr><td>Other washed coal</td><td>Lubricants</td></tr>
<tr><td>Briquettes</td><td>Petroleum waxes</td></tr>
<tr><td>Gangue</td><td>White spirit</td></tr>
<tr><td>Coke</td><td>Bitumen asphalt</td></tr>
<tr><td>Coke oven gas</td><td>Petroleum coke</td></tr>
<tr><td>Blast furnace gas</td><td>Liquefied petroleum gas (LPG)</td></tr>
<tr><td>Converter gas</td><td>Refinery gas</td></tr>
<tr><td>Other gas</td><td>Other petroleum products</td></tr>
<tr><td>Other coking products</td><td rowspan="2">Natural Gas</td><td>Natural gas</td></tr>
<tr><td rowspan="4">Petroleum</td><td>Crude Oil</td><td>Liquefied natural gas (LNG)</td></tr>
<tr><td>Gasoline</td><td rowspan="2">Non-fossil fuels</td><td>Other energy</td></tr>
<tr><td>Kerosene</td><td>Electricity (after adjustment using Eq. 3-1)</td></tr>
<tr><td>Diesel oil</td><td colspan="2">Heat</td></tr>
</table>

Table 3-2 Sector number and names

No.	Category	Sector	No.	Category	Sector
1	Primary	Farming, Forestry, Animal Husbandry, Fishery & Water Conservancy	24		Chemical Fiber
2		Coal Mining and Dressing	25		Rubber Products
3		Petroleum and Natural Gas Extraction	26		Plastic Products
4		Ferrous Metals Mining and Dressing	27		Non-metal Mineral Products
5		Nonferrous Metals Mining and Dressing	28		Smelting and Pressing of Ferrous Metals
6		Non-metal Minerals Mining and Dressing	29		Smelting and Pressing of Nonferrous Metals
7		Other Minerals Mining and Dressing	30		Metal Products
8		Logging and Transport of Wood and Bamboo	31		Ordinary Machinery
9		Food Processing	32	Secondary-Manufacturing	Equipment for Special Purpose
10	Secondary-Manufacturing	Food Production	33		Transportation Equipment
11		Beverage Production	34		Electric Equipment and Machinery
12		Tobacco Processing	35		Electronic and Telecommunications Equipment
13		Textile Industry	36		Instruments, Meters Cultural and Office Machinery
14		Garments and Other Fiber Products	37		Other Manufacturing Industry
15		Leather, Furs, Down and Related Products	38		Scrap and waste
16		Timber Processing, Bamboo, Cane, Palm & Straw Products	39		Electric Power, Steam and Hot Water Production and Supply
17		Furniture Manufacturing	40		Gas Production and Supply

18	Papermaking and Paper Products	41		Tap Water Production and Supply
19	Printing and Record Medium Reproduction	42	Secondary-Construction	Construction
20	Cultural, Educational and Sports Articles	43	Tertiary	Transport, Storage, Postal & Telecommunications Services
21	Petroleum Processing and Coking	44	Tertiary	Wholesale, Retail Trade and Catering Service
22	Raw Chemical Materials and Chemical Products	45	Residential	Urban consumption
23	Medical and Pharmaceutical Products	46	Residential	Rural consumption

There are gaps between energy statistics at the provincial levels and those from national metrics. One previous work compared the CO_2 emission inventories compiled by national and provincial energy statistics for the period of 1997 to 2010 and found large inconsistency between the emissions calculated between these two official energy data sets (Guan *et al.*, 2012). Nevertheless, China has revised its energy statistics three times since 2000 to improve the self-consistency (Zheng *et al.*, 2018b). The gap between the national and provincial statistics is closing. This study uses the latest provincial energy statistics from 2000 to 2016, which is indeed the only available data covering all the mainland provinces in such a time frame. The provincial sum is compared to the national consumption in Table 3-3. The relative differences between the two were from -6% to 8%.

Table 3-3 Differences between national and provincial energy statistics

	Total Energy Consumption (10^4 tce)		
Year	National	Provincial Sum	Relative Difference
2003	197083	185264	-6%
2004	230281	212286	-8%
2005	261369	251521	-4%
2006	286467	278232	-3%
2007	311442	302576	-3%
2008	320611	320217	0%
2009	336126	336870	0%
2010	360648	375760	4%
2011	387043	418296	8%
2012	402138	415851	3%
2013	416913	413406	-1%
2014	425806	435637	2%
2015	429905	441905	3%
2016	435819	455357	4%

Though the sum of provincial statistics is compared with the national energy budget, the uncertainty (or variability) of energy consumption of a single province is hard to fathom since there is no other available data source to reflect the provincial consumption. All that can be concluded is that the sum of provincial statistics is generally consistent with the national one. The sum of provincial statistics presents a similar trend as that of the national value.

3.1.2. Production-based emissions of CO_2

The production-based CO_2 emission inventories for subnational levels in China developed by previous studies (Shan *et al.*, 2016a, 2017) are adopted. These inventories are compiled with a consistent methodology and data sources using the energy consumption data from China's Energy Statistical Yearbooks and the best available local emission coefficients (Liu *et al*. 2015a; Mi *et al*. 2016).

Specifically, the primary energy consumption matrix is used to estimate the emissions from combustion sources. For CO_2 emissions, the well-established methods for China are adopted from previous studies (Shan *et al.*, 2016a, 2017). In brief, CO_2 emissions from energy-related combustion is estimated as below,

$$CE_{i,k,j} = AD_{i,k,j} \times NCV_j \times CC_j \times O_{jk} \qquad \text{Eq 3-2}$$

Where $CE_{i,j,k}$ refers to the CO_2 emissions from fossil fuel j burned in sector k of province i; $AD_{i,j,k}$ is the consumption of fossil fuel j in sector k; NCV_j is the net caloric values; CC_j is the CO_2 emissions per net caloric value produced by fossil fuel j; and O_{jk} is the oxygenation efficiency.

The process-based CO_2 emissions, which are produced by physical-chemical reactions in production process other than combustion, are estimated as in Equation 3-3.

$$CE_{i,k} = ADP_{i,k} \times EFC_k \qquad \text{Eq. 3-3}$$

Where $CE_{i,k}$ refers to the process-related CO_2 emissions from sector k in province i; and $ADP_{i,k}$ is the activity level of sector k in province i such as industrial outputs, EFC_k is the CO_2 emission factor of sector k. Details on the methods and emission factors used refer to (Shan *et al.*, 2016b, 2017).

3.1.3. Production-based emissions of air pollutants

Subnational emissions of seven pollutants (SO_2, NOx, PM_{10}, $PM_{2.5}$, NMVOCs, CO and NH_3) were adopted from previous studies (Bian *et al.*, 2019). Validations with ambient measurements (this section) and modelling results (See section 3.3) were carried out in this study.

Air pollutant emissions from the major known sources were included, including power plants, industrial combustion, residential combustion, on-road mobile source, non-road mobile source, dust source, industrial process sources, non-industrial solvent use, storage and transportation, agriculture source, biomass burning, and others.

- Power plants, industrial combustion and residential combustion

Air pollutant emissions from fuel combustion in power plants, industrial sources and residential usage can be estimated by either mass balance or emission factor methods. For SO_2 emissions, mass balance method is adopted.

$$PE_{i,j,k,p} = AD_{i,j,k} \times C_j \times SC_{i,j,k} \times \Sigma_q(PR_{i,j,k,p,q} \times (1-\eta_{p,q})) \qquad \text{Eq 3-4}$$

Where $PE_{i,j,k,p}$ refers to the emissions of pollutant p (which is SO_2 in this case) from fossil fuel j burned in sector k of province i; $AD_{i,j,k}$ is the consumption of fossil fuel j in sector k; C_j is the fuel-based coefficient, which is 0.8 for coal and 1 for petroleum; $PR_{i,j,k,p,q}$ is the penetration rate of air pollutant emission treatments q for pollutant p (which is SO_2 in this case) from fossil fuel j burned in sector k of province i; $\eta_{p,q}$ is the removal efficiency of air pollutant emission treatments q for pollutant p (which is SO_2 in this case).

For NOx, CO, PM_{10}, $PM_{2.5}$ and NMVOCs, emissions from fossil fuel combustion are calculated by emission factor as follows.

$$PE_{i,j,k,p} = AD_{i,j,k} \times EF_{j,k,p} \times \Sigma_q (PR_{i,j,k,p,q} \times (1-\eta_{p,q})) \qquad \text{Eq 3-5}$$

Where $PE_{i,j,k,p}$ refers to the emissions of pollutant p from fossil fuel j burned in sector k of province i; $AD_{i,j,k}$ is the consumption of fossil fuel j in sector k, province i; $EF_{j,k,p}$ is the unabated emission factor for pollutant p using fossil fuel j in sector k; $PR_{i,j,k,p,q}$ is the penetration rate of air pollutant emission treatment q for pollutant p from fossil fuel j burned in sector k of province i; $\eta_{p,q}$ is the removal efficiency of air pollutant emission treatment q for pollutant p.

Emission factors are adopted from Bian *et al.* (2019), Zheng *et al.* (2018a), Lu *et al.* (2013) and Zheng *et al*. (2009a). Energy consumption matrix developed in Section 3.1.1 is used as activity level data.

- Industrial process source

Some of the NOx, CO, PM_{10}, $PM_{2.5}$ and NMVOCs emissions are from non-combustion processes in industries. Here, emission actor approach is adopted.

$$PE_{i,k\,p} = ADP_{i,k} \times \Sigma(X_{i,k,p,t} \times EF_{i,k,p,t}) \qquad \text{Eq 3-6}$$

Where $PE_{i,k,p}$ refers to the non-combustion emissions of pollutant p from sector k of province i; $ADP_{i,k}$ is the activity level of sector k in province j such as industrial outputs; $X_{i,k,p,t}$ is the application rate of technology t (relevant to different emission levels of pollutant p) in sector k of province i; $EF_{i,k,p,q}$ is the emission factor of pollutant p for technology t in sector k of province i.

Emission factors are adopted from Bian *et al*. (2019), Zheng *et al.* (2013, 2018a), Yin *et al*. (2015) and Ou *et al*. (2015). Activity level data are from National Bureau of Statistics (2018a&c) as well as point-source data from the industries.

- On-road mobile sources and dust source

Emissions from on-road mobile sources and dust are estimated as Eq. 3-7.

$$PE_{i,p} = \Sigma_v(P_{i,v} \times VKT_{i,v} \times EF_{v,p}) \qquad \text{Eq 3-7}$$

Where PE_i is the emission of pollutant p from on-road mobile sources in province i; $P_{i,v}$ is the population of vehicle v in province i; $VKT_{i,v}$ is the annual average mileage travelled of vehicle type v in province i, with the unit of km; $EF_{v,p}$ is the emission factor of pollutant p of vehicle type v, with the unit of g km^{-1}.

Emission factors are adopted from Bian *et al*. (2019) and Zheng *et al.* (2009a&c, 2018a). Vehicle populations are from National Bureau of Statistics (2018d). Average mileage travelled by vehicle type is collected from local transport departments.

Dust source refer to the $PM_{2.5}$ and PM_{10} emissions from construction sites, which can be estimated by Eq. 3-8.

$$PE_{i,p} = S_i \times CT_i \times EF_p \qquad \text{Eq 3-8}$$

Where $PE_{i,p}$ is the emissions of pollutant p in province i from dust sources; S_i is the construction area in province i, in km^2; CT_i is the average construction time per site in province i, in the unit of day; EF_p is the emission factor of pollutant p, in $g{\cdot}km^{-2}day^{-1}$.

Emission factor for dust sources and average construction time are from Bian *et al*. (2018) and Zheng *et al*. (2018a). Statistics of construction area are from National Bureau of Statistics (2018a).

- Household solvents

Household consumption of paints, consumer products and other can result in NMVOCs emissions. Such emissions are estimated by an emission factor method.

$$PE_{i,p} = POP_i \times EF_p \qquad \text{Eq 3-9}$$

Where $PE_{i,p}$ is the NMVOCs emissions from household in province i; POP_i is the total population in province i; EF_p is the emission factor, in the unit of g per capita. Emission factors are collected from Ou *et al.* (2015) and Zheng *et al.* (2018a). Population data are from National Bureau of Statistics (2018a).

- Other sources

Given the data availabilities and workloads, emission inventories for other sources are retrieved from previous studies. For off-road mobile source, inventories developed by Li *et al*. (2018b) are adopted. Biomass burning emissions are from Xu *et al*. (2019). NH_3 emission inventories are adopted from Zheng *et al*. (2020). NMVOCs emissions from biogenic sources are estimated by Model of Emissions of Gases and Aerosols from Nature (MEGAN) (Jiang *et al.*, 2018).

3.1.4. Validation of NMVOCs emission inventories

Among the air pollutants studied here, NMVOCs is one of the groups with the highest uncertainty. Validation of emission inventories with independent measurements is an important procedure for data quality control if such measurements are available. Using the ambient measurement of speciated NMVOCs from a gridded sampling campaign (hereafter as "Grid Study"), NMVOCs emission inventories in Guangdong province are validated. The Grid Study collected air samples simultaneously in 84 grids with the grid size of 20 × 20 km^2, at 5 am and 10 am on four days (29 October 2008 and 1 March, 26 September and 5 December 2009) in Guangdong province. A total of 672 samples were collected and analysed using gas chromatography (GC) with a multi-detector system and high-pressure liquid chromatography (HPLC) with a photodiode array detector for NMVOCs and oxygenated VOCs (OVOCs), respectively. Details of the sampling and analysis methods utilized in Grid Study can be found in Louie *et al.* (2013).

To enable cross-validation of emission inventories and ambient measurement, data from the Grid Study were first analysed with a receptor model (RM) -- positive matrix factorization (PMF) model (version 3.0). RM generally follows the top-down based methodology. It statistically apportions the measured ambient air pollutant concentrations, for multiple time periods at one or multiple monitoring sites, to the emission sources according to some prior-knowledge of their emission characteristics (primarily their chemical characteristics). The site- and time-specific ambient VOC species measurements are subject to sampling and analytical errors and to meteorological variability (Belis *et al.*, 2015). Following the protocol of previous studies (Yuan *et al.*, 2013), twenty base runs and 100 bootstrap runs were performed to select the best solution and estimate the stability and uncertainty. Nine factors were identified, after which they were mapped onto the emission sources according to the abundances of various tracers, i.e., combustion, diesel exhaust, gasoline exhaust, gasoline evaporation, liquefied petroleum gas (LPG)-related sources, mixed solvents, industrial emissions, biogenic emissions and secondary and aged air masses.

The results obtained from both the emission inventory and PMF were unified in terms of their source classification, sampling time, and temporal and spatial resolutions. Regarding the source classification, the bottom-up emission inventory method incorporates a much more detailed source classification system, while the RM technique provides a general delineation of multiple sources based on the similarities among source profiles. Therefore, the deliberately classified sources in the EIs were grouped to match the 8 RM-based source categories, including combustion, gasoline exhaust, diesel exhaust, industrial processes, mixed solvents, LPG-related sources, gasoline evaporation and secondary and aged air masses. While secondary and aged air mass sources were classified within the RM, no primary emission sources in the EIs were assigned to this category. Hourly VOC emissions of the 8 sampling periods, i.e., 5 am and 10 am on 29 October 2008 and on 1 March, 26 September and 5 December 2009, were extracted from the EIs of 2008 and 2009 for comparison. To unify the spatial scale, the spatial surrogates used in the 3×3 km^2 emission inventory were used to develop the 20×20 km^2 spatial factors for the emission allocation. The source characterization results acquired using the emission inventory and the PMF therefore had the same sampling time and spatial resolution and were ready for comparison in terms of source contribution percentages at both different temporal variations (i.e., hourly and annual) and different spatial scales (i.e., 20×20 km^2, 40×40 km^2, and 200×200 km^2).

The discrepancies between emission inventory and RM varied from different temporal and spatial resolutions. As expected, the discrepancies were the largest in the finest temporal and spatial resolution, which was hourly and 20 × 20 km^2, respectively. As shown in Figure 3-1a, 57% of the results between two methods varied >3 times, i.e., the EI result was >3 times of RM or the other way around (RM result was >3 times of EI). 24% of the estimations even had differences >15-fold, and almost all source categories contributed to these extreme values.

If comparisons were made in larger temporal and spatial resolutions, e.g., combined the 8 sampling periods as annual average or combined every 4 grids to a bigger grid of 40 × 40 km^2, the discrepancies between the two methods seemed to be smoothed in some degrees. As Figure 3-1b illustrates, the percentage for those with variations >3 times decreased to 46% when comparison was made for annual average in 20 × 20 km^2 resolution. Similarly, when the grid size was increased to 40 × 40 km^2, the percentage dropped to 46% (Figure 3-1c). If both spatial and temporal enhancements were adopted, only 38% of the results remained in the range of >3 times, i.e., 62% of the results fell in the range between 1/3 and 3 (Figure 3-1d). If the grid size further increased to cover the entire region and samples in all eight events averaged, 78% of the percentage ratios (7 out of 9 sources) fell in the range between 1/3 and 3 (Figure 3-1e). Only biogenic emission and LPG-related sources still had percentage ratios >3, implying other factors may contribute to discrepancies for the two categories.

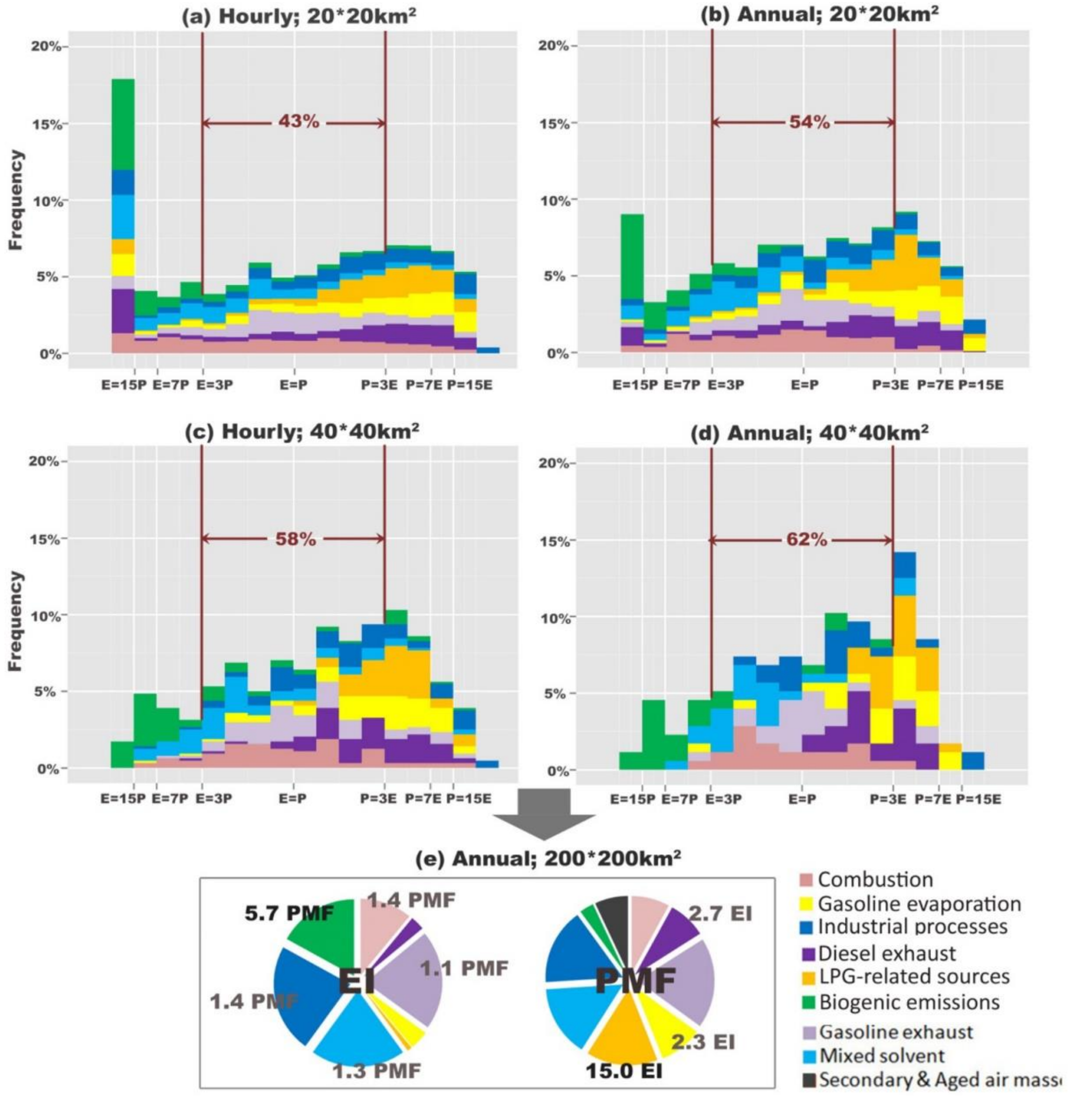

Figure 3-1 Summary of the differences in source contributions between emission inventory (EI) and RM in different temporal and spatial resolutions. The y-axis is the frequency of contribution estimates that fall within a specific range. The middle of the x-axis (E = P) represents the case that there is no difference between two methods' estimations. As the x-axis approaches the right side, PMF estimates were 3, 7, 15, and >15 times higher than those of EI, and the opposite as the x-axis approaches to the left. The percentage of samples with E/P from 1/3 to 3 increased from 43% in (a) all the way to 78% in (e) along with spatial and temporal averaging enhancements.

Even after reconciling the spatiotemporal resolution as discussed above, substantial disagreements still existed for biogenic emissions and LPG-related sources. Two reasons explained the discrepancies.

The first one is chemical loss, which might be the key factor explaining the disagreements of biogenic emissions. RM uses isoprene as the tracer to identify biogenic source. But isoprene is highly reactive, which is one to two orders higher than those of other species in an RM (Harley and Cass, 1995). Substantial loss is expected from source to the receptor where measurements are made. Figure 3-2 shows that the discrepancy between emission inventory and RM correlated well with the source reactivity. By combining the reactivity (k_{OH}) of different NMVOC species with their proportions in a source, the source reactivity can be estimated. As shown in Figure 3-2, biogenic emissions (point 9) in the upper-right corner constituted the most reactive source, and it was associated with the largest difference between emission inventory and RM. As the source reactivity decreased, the relative differences of source contributions by emission inventory and RM declined as well, with the exception of LPG-related sources and secondary and aged air masses. Secondary sources exhibited the lowest reactivity, as it is composed of long-lived species. Since a secondary source cannot correspond to any source in an emission inventory, its associated discrepancy was expected to be high. If LPG-related sources and secondary and aged air masses were removed, the source reactivity showed a positive relationship with the relative differences of two methods (r^2 = 0.59). Therefore, chemical loss constituted the single most important factor in the disagreement between EI and RM. Accordingly, some adjustment methods have been developed to account for the chemical losses of VOC species in the atmosphere to reconcile the results acquired using emission inventories and RMs (Na and Pyo Kim, 2007; Yuan *et al.*, 2012).

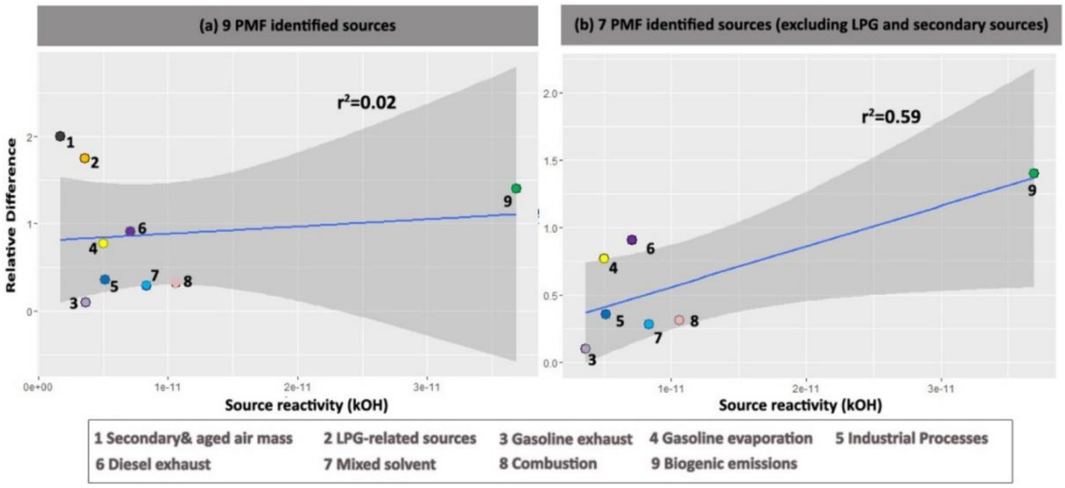

Figure 3-2 Relationship between source reactivity and the relative differences in SAs between EI and RM (a) for the nine sources and (b) excluding LPG and secondary sources. The number near the dot represents the ranking of source reactivity (1 is the lowest and 9 is the highest). The shaded area represents the 95% confidence interval of the fitting.

The above factors failed to explain the significant discrepancy in the contribution of LPG-related sources. Its source contribution estimated using the RM was 15 times that by emission inventory. The disagreement in the LPG-related source contributions from EI and RM has been reported elsewhere in China (Zhang *et al.*, 2009; Zhao *et al.*, 2012b), Japan (Morino *et al.*, 2011) and North America (Blake and Rowland, 1995; Fujita *et al.*, 1995), suggesting that this discrepancy is globally pervasive.

One possible cause is the usage of propane and *i/n*-butane in the RM as unique tracers of LPG sources. Propane and *i/n*-butane are ubiquitous in the atmosphere and generally make up large portions of the measured NMVOCs. These species were generally treated as tracers of LPG sources due to their higher percentages in the source profiles (percentage of a species in a source's emission). Propane and *i/n*-butane each comprises 40%, 4% and 9% of the NMVOC emitted from LPG exhaust (Ou *et al.*, 2015), much higher than their percentages in other sources. With the measurements of high concentrations of propane and *i/n*-butane in ambient samples and the underlying assumption that propane and *i/n*-butane came dominantly from LPG sources, LPG was constantly apportioned with high source contribution by RM. However, if the emission intensity was considered, industrial processes, which dominated the emissions in Guangdong, would contribute 47%, 29% and 54% of the total propane and *i/n*-butane emissions. Regardless of whether these percentages were accurate or not, it should be cautious to use propane and i/n-butane as the tracers of LPG. More efforts are needed to measure the local source profiles, especially the presence of propane and *i/n*-butane, in a wide variety of industrial processes.

Another possibility is underestimation of LPG emissions in the current emission inventory. A previous study suspected that usage of LPG might result in significant leakage (Blake and Rowland, 1995), with leakage rate of 1–5% depending on the boundary conditions. Evaporative emissions from LPG usage and gasoline evaporation during vehicle movement and parking were absent in the current emission inventory. A recent study in China highlighted that vehicular evaporative emissions (predominantly from gasoline) constituted a missing yet significant part of NMVOC emissions in emission inventory, and estimated that one vehicle in China emitted 1.6 kg of NMVOC emissions per year (Liu *et al.*, 2015b). If these two potentially missing sources were taken into account in EI, the source contributions by EI would change as those shown in Figure 3-3. It was noted that the large discrepancy in LPG-related sources was reconciled by inclusion of vehicular evaporative emissions and 2% LPG leakage rate. This highlighted that the need to review and improve emission estimations from evaporative sources in emission inventory.

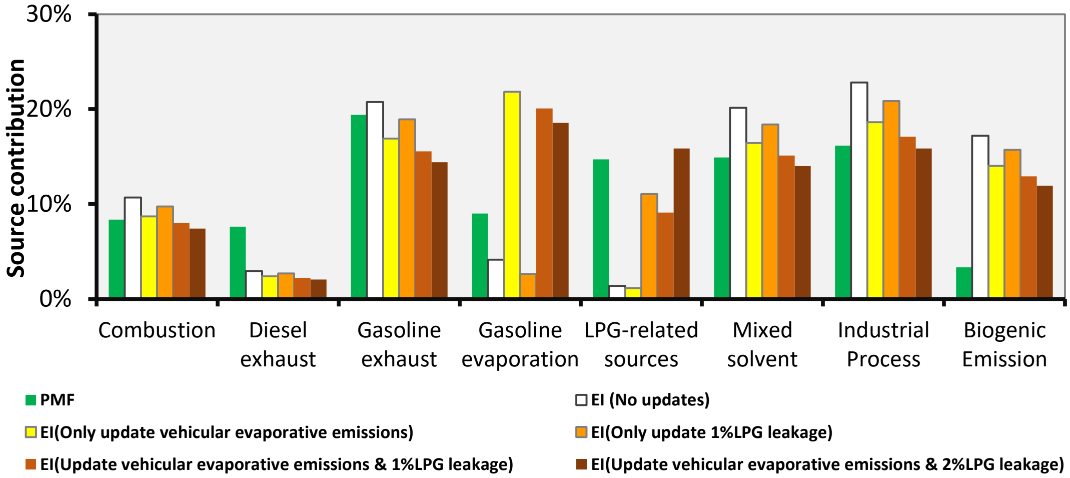

Figure 3-3 Comparison of source contributionss by RM and emission inventories with different vehicular evaporative emissions and LPG leakage scenarios.

Though the inclusion of vehicular evaporative emissions and 2% LPG leakage rate led to the least discrepancy between emission inventory and RM, only vehicular evaporation emissions were incorporated in the current NMVOCs emission inventories. It is because the LPG contribution from RM was also subject to its own limitation, which was the usage of propane and *i/n*-butane as the tracers of LPG source. Until more evidences are collected, it would be reckless to manipulate the current estimation of LPG emission in the inventory. As for vehicular evaporation emissions, the finding in this study echoes another study which provides strong evidences of this missing source (Liu *et al.*, 2015b). Therefore, it was included in the inventories for further analysis.

3.1.5. Socioeconomic data

Other socioeconomic data were collected from China's statistical yearbooks and the Statistical Communiqué of Economic and Social Development by provinces. Specifically, provincial GDP data by primary, secondary, tertiary industry were attained from the statistical yearbooks. The division of GDP from light and heavy industries were based upon the statistics by the provincial Statistical Communiqué.

All the GDP data were in constant price of 2015 according to the indices of real GDP growth. Population by provinces within the study period was obtained from the China's Statistical Yearbooks.

3.2. Identification of socioeconomic drivers and demands

Energy and emission accounts are connected to the socioeconomic account through decomposition analysis and MRIO analysis. In section 3.2.1, the method of decomposition analysis is introduced. It reveals the driving force by the pre-selected socioeconomic factors, which are population growth, economic growth, change of industrial structure, energy efficiency and energy mix. Section 3.2.2 presents the methods for the compilation of the MRIO table for 31 provinces in China for the year of 2012. Section 3.2.3 introduces the methods of environmentally-extended MRIO based upon the MRIO table for 31 provinces, which identifies the intermediate and final demands behind production-based emissions.

3.2.1. Driver decomposition analysis

Decomposition analysis is a recognized method of quantitatively characterizing the socioeconomic drivers of energy and environmental issues. Among the current DA methods, the logarithmic mean Divisia index (LMDI) is adopted in this study due to its path independence, consistency in aggregation, ability to handle zero values and demonstrated suitability in time series analyses of energy data (Ang & Liu, 2001; Ang, 2005; Cansino *et al.*, 2018; Goh *et al.*, 2018; Román *et al.*, 2018). The provincial energy consumption EC_i was decomposed as follows:

$$EC_i = \sum_j \sum_k POP_i \times \frac{GDP_i}{POP_i} \times \frac{GDP_{i,k}}{GDP_i} \times \frac{EC_{i,k}}{GDP_{i,k}} \times \frac{EC_{i,j,k}}{EC_{i,k}} = \sum_j \sum_k POP \times Eco \times InS \times Eff \times M \quad \text{Eq.3-10}$$

where EC_i represents primary energy consumption in province i, POP_i is the population of province i; GDP_i is the GDP of province i; $GDP_{i,k}$ is the GDP of sector k in province i; $EC_{i,k}$ is the total energy consumption by sector k in province i; $EC_{i,j,k}$ is the consumption of fuel j in sector k of province i. Thus, according to Eq. 3-10, E can be decomposed into the following five factors:

(1) *POP* is the population of province *i*.

(2) $Eco = GDP_i/POP_i$ is the per capita GDP of province i, which is a gauge of economic growth.

(3) $InS= GDP_{i,k} /GDP_i$ is the share of GDP associated with sector k and reflects the industrial structure of province i.

(4) $Eff = EC_{i,k} /GDP_{i,k}$ is the energy consumed by sector j per unit GDP growth and measures the energy efficiency in province i.

(5) $M = EC_{i,j,k} /EC_{i,k}$ is the proportion of fuel j in sector k and represents the energy mix. M_1, M_2, M_3 and M_4 are the effects of the coal share, petroleum share, natural gas share and non-fossil fuel share, respectively.

The changes in provincial energy consumption and its drivers every four years can be calculated as follows:

$$\begin{aligned}
\Delta EC_{tot} &= \sum_{i=1}^{4}\sum_{j=1}^{5} L\left(w_{ij}^{t}, w_{ij}^{t-4}\right)\ln\left(\frac{POP^{t}}{POP^{t-4}}\right) + \sum_{i=1}^{4}\sum_{j=1}^{5} L\left(w_{ij}^{t}, w_{ij}^{t-4}\right)\ln(\frac{Eco^{t}}{Eco^{t-4}}) + \sum_{i=1}^{4}\sum_{j=1}^{5} L\left(w_{ij}^{t}, w_{ij}^{t-4}\right)\ln(\frac{InS^{t}}{InS^{t-4}}) \\
&+ \sum_{i=1}^{4}\sum_{j=1}^{5} L\left(w_{ij}^{t}, w_{ij}^{t-4}\right)\ln(\frac{Eff^{t}}{Eff^{t-4}}) + \sum_{j=1}^{5} L(w_{1j}^{t}, w_{1j}^{t-4})\ln(\frac{M_{1j}^{t}}{M_{1j}^{t-4}}) + \sum_{j=1}^{5} L(w_{1j}^{t}, w_{1j}^{t-4})\ln(\frac{M_{1j}^{t}}{M_{1j}^{t-4}}) \\
&+ \sum_{j=1}^{5} L(w_{2j}^{t}, w_{2j}^{t-4})\ln(\frac{M_{2j}^{t}}{M_{2j}^{t-4}}) + \sum_{j=1}^{5} L(w_{3j}^{t}, w_{3j}^{t-4})\ln(\frac{M_{3j}^{t}}{M_{3j}^{t-4}}) + \sum_{j=1}^{5} L(w_{4j}^{t}, w_{4j}^{t-4})\ln(\frac{M_{4j}^{t}}{M_{4j}^{t-4}}) \\
&= \Delta E_{POP} + \Delta E_{Eco} + \Delta E_{Eff} + \Delta E_{coal} + \Delta E_{petroleum} + \Delta E_{gas} + \Delta E_{non-fossil}
\end{aligned}$$

Eq.3-11

Individually, L or w does not refer to specific mathematical operation here. Rather, they should be understood in a combination which refers to a weighting factor called the logarithmic mean weight $L(w_{ij}^{t}, w_{ij}^{t-4}) = (EC_{ij}^{t} - EC_{ij}^{t-4}) / (\ln(EC_{ij}^{t}) - \ln(EC_{ij}^{t-4}))$. $\Delta E_{POP}, \Delta E_{Eco}, \Delta E_{InS}, \Delta E_{Eff}, \Delta E_{coal}, \Delta E_{petroleum}, \Delta E_{gas}, \Delta E_{non-fossile}$ are the energy consumption changes due to population changes, economic growth, industrial structure adjustments, efficiency gains, and changes in the energy mix associated with coal, petroleum, natural gas and non-fossil fuels, respectively.

Recent studies have combined the decomposition analysis with cumulative sum (CUSUM) test (Guan *et al.*, 2018). Such a combination would determine whether the changes in energy consumption drivers is statistically significant (Kuan and Hornik, 1995). A standard linear regression model for a time series was introduced as follows:

$$y_t = x_t^T b_t + u_t \quad (t = 1,...,T) \qquad \text{Eq. 3-12}$$

where y_t is the dependent variable, x_t is a $K \times 1$ vector of independent variables, t is time, and β_t represents the $K \times 1$ vector of estimated coefficients. The structural change test determines the validity of the hypothesis that the estimated coefficients remain unchanged.

$$\mathrm{H}_0 : \beta_t = \beta_0 \quad (t = 1, \ldots, T) \qquad \text{Eq. 3-13}$$

If the null hypothesis is rejected, the occurrence of one or more structural changes must be considered. In practice, it is common to assume that there are m structural breaks that change coefficients. Additionally, the transition points can rarely be predetermined. Thus, it is reasonable to adopt a generalized fluctuation framework that does not assume a particular pattern of deviation from the null hypothesis (Kuan and Hornik, 1995). The core of this technique is to separate deviations from consistent trends in a graphical manner rather than by assuming any specific parametric relations while the central limit theorem holds.

To identify the structural break for each specific province, an empirical analysis was conducted by fitting a constant to a vector of time series energy consumption for a certain province. In this model setting, we can determine whether a statistically significant structural change occurred and when the associated transition occurred. Thus, an OLS-based CUSUM test based on the cumulated sums of standard OLS residuals was conducted (Ploberger and Krämer, 1992; Zeileis, 2002).

$$W_n^0(h) = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{i=1}^{nh} \hat{u}_i \quad (0 \le h \le 1) \qquad \text{Eq. 3-14}$$

In Eq. 3-11 the limiting process of $W_n^0(h)$ follows the standard Brownian bridge $W^0(h) = W(h) - hW(1)$, where *W(1)* is the standard Brownian motion.

After identifying the occurrences of structural changes, the transition points (i.e., how many structural changes occurred) are identified according to a previously published method (Bai, 1997). The algorithm follows a dynamic programming procedure based on the Bellman principle. The transition points are determined by Residual Sum of Square and Bayesian Information Criteria. The empirical analysis portion of the CUSUM test and the associated tests were performed using R software.

3.2.2. Multi-region Input-Output (MRIO) Table for 31 provinces

The MRIO table for 31 provinces is compiled based on the input-output tables (IOTs) for 31 provinces, which are released by the National Statistics Bureau of China. (National Statistics Bureau of China, 2013) These IOTs include 42 economic sectors and five final demands, namely, rural household consumption, urban household consumption, government consumption, fixed capital formation and inventory change. Exports and imports are also reported and divided into international and domestic amounts.

The above IOTs depict the sectoral inputs and outputs in monetary terms for a given region. However, their interactions with other regions are unknown. To simulate inter-regional flows, a gravity model is adopted. The standard gravity model expresses the inter-regional flow as a function of the total regional outflows, total regional inflows, transfer cost and distance, as shown in Eq. 3-12.

$$y_i^{rs} = e^{\beta 0} \frac{\left(x_i^{rO}\right)^{\beta 1} \left(x_i^{Os}\right)^{\beta 2}}{\left(d^{rs}\right)^{\beta 3}} \qquad \text{Eq. 3-15}$$

where y_i^{rs} is the trade flows of sector i from region r to s; $e^{ß0}$ is the constant proportionality factor; x_i^{ro} is the total outflows of sector i from region r to s; d is the distance between region r and s, which is approximated by the distances between capitals; $ß_1$ and $ß_2$ are weighting coefficients assigned to the masses of origin and destination, respectively; and $ß_3$ is the distance decay parameter. Taking the logarithm of both sides, Eq. 3.15 can be expressed as follows:

$$\ln\left(y_i^{rs}\right) = \beta_0 + \beta_1 \ln(x_i^{rO}) + \beta_2 \ln(x_i^{Os}) - \beta_3 \ln\left(d^{rs}\right) + \varepsilon \quad \text{Eq. 3-16}$$

Considering the dimensions of the matrix, Eq. 3-17 is constructed.

$$\mathbf{Y} = \beta_0 \mathbf{L}_0 + \beta_1 \mathbf{X}_1 + \beta_2 \mathbf{X}_2 - \beta_3 \mathbf{X}_3 + \varepsilon \qquad \text{Eq. 3-17}$$

where $\boldsymbol{Y}$ is an $\boldsymbol{N}\times\boldsymbol{1}$ matrix of the logarithm of the trade flows of product i between regions; $\boldsymbol{L_0}$ is an $\boldsymbol{N}\times\boldsymbol{1}$ matrix with all elements equal to 1; $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are the logarithms of the total outflows from origin regions and total inflows to destination regions, respectively; and $\boldsymbol{X_3}$ is the logarithm of the distance between two regions. Eq. 3.17 is solved by multiple regressions.

Based upon the above standard gravity model, two ratios, namely, the impact coefficients and impact exponent, are introduced to reflect varying inter-regional competition and cooperation relationships for different sectors (Mi *et al.*, 2017). The modified trade flow is written as follows:

$$Y' = \hat{Y} / \left(c_i^{gh}\right)^{\theta i} \quad \text{Eq. 3-18}$$

where Y' is the modified trade flow and $\hat{Y}$ is the trade flow obtained from the standard gravity model. Due to data availability, 42 sectors in the IOTs are aggregated into 30 sectors before the gravity model is applied.

With the above adjusted gravity model, an initial trade flow matrix that describes the flows between every pair of economic sectors for 31 provinces in monetary terms is constructed. Such an initial trade flow matrix does not match the double sum constraints, i.e., the total output and input of a specific sector do not match. Therefore, an RAS approach was adopted to adjust the initial trade flow matrix to ensure agreement with the sum constraints (Jackson and Murray, 2004; Miller and Blair, 2009). The error terms of the adjusted flow matrix were generally within 5%.

3.2.3. Intermediate and final demands from environmentally-extended input-output analysis

Environmentally-extended input-output (EEIO) analysis is an established method to understand how emissions are associated with demands from a given economy. The total outputs of sectors in a given economy $\boldsymbol{X}$ can be understood as the sum of the intermediate input to other sectors $\boldsymbol{Z}$ and the finished goods for final consumers $\boldsymbol{Y}$. For an economy with M regions and N industries. In each region, x_i^r represents the total output of industry i in country r and can be expressed as

$$x_i^r = \sum_{s=1}^{31} \sum_{j=1}^{30} z_{ij}^{rs} + \sum_{s=1}^{31} y_i^{rs} \quad \text{Eq. 3-19}$$

Where z_{ij}^{rs} (r, s=1, 2, …, 31) represents the intermediate product sold from industry i in country r to industry j in country s, y_i^{rs} represents the finished goods sold from industry i in country r to final consumers in country s.

A technical coefficient $a_{ij}^{rs} = z_{ij}^{rs}/x_j^s$ is defined as the input from sector *i* in region *r* needed to produce one unit of output from sector *j* in region *s*. Eq. 3-16 can therefore be formulated as follows:

$$X = AX + \gamma \qquad \text{Eq. 3-20}$$

where X, A, and γ are the matrices of x_i^r, a_{ij}^{rs} and y_i^{rs}, respectively.

Then, a vector of direct emission intensity, *h*, is introduced to describe the sector-specific air pollutant or GHG emissions per unit of economic output as follows:

$$h = E'/X' \qquad \text{Eq. 3-21}$$

where *E'* and *X'* are the vectors of production-based emissions and total output in monetary terms for 30 industries and 31 regions, respectively.

The air pollutant or GHG emissions associated with final consumption in region *r* can be calculated as follows:

$$F = h(I - A)^{-1}\gamma \qquad \text{Eq. 3-22}$$

Where *h* is a row vector representing direct emission intensity, *I* is a 930×930 identity matrix, *A* is the matrix of technical coefficient, and γ are final demands vector of all the regions. In this way, the air pollutant or GHG emissions attributable to five final demands (from local as well as other provinces or countries), i.e., rural consumption, urban consumption, governmental consumption, capital formation and inventory change, and export, can be estimated. By linking China's MRIO table for 30 provinces with global trade analysis project (GTAP) database, the originating countries driving the export demand were identified (Mi *et al.*, 2017, 2018).

3.3. Air quality simulation

An air quality modelling platform was developed for mainland China to support the case study for ground-level O_3 pollution in Chapter 7. The air quality modeling platform coupled the Weather Research and Forecast (WRF) model (Thaxton *et al.*, 2017), SparseMatrix Operator Kernel Emissions (SMOKE) model (Vukovich *et al.*, 2006), and CMAQ model (Hong *et al.*, 2017), with a spatial resolution of 27×27 km^2. The Weather Research and Forecast (WRF) model v3.9 was used to provide meteorological data. The CMAQ v5.0.2 with the CB-05 gas-phase chemical mechanism was used to simulate the ambient O_3 mixing ratios under different precursor emissions scenario. The SMOKE provided model-ready emission data by allocating the annual emissions at province level into hourly interval and grid cell. Species allocations were also involved. The model-ready meteorological and emission data was then fed into air quality model. The model was spun-up for 3 days in each month to eliminate the impact of initial conditions. Detailed model configurations of CMAQ and WRF are shown in Table 3-4.

Table 3-4 Details on model configuration

WRF v3.9	
Horizontal resolution	27km
Number of sigma level	26
Longwave Radiation	Rapid Radioactive Transfer Model (RRTM)
Shortwave Radiation	Dudhia scheme
Microphysics	WRF Single-Moment 6-class (WSM6)
Land-surface	Noah
Advection	global mass-conserving scheme
Planetary boundary layer (PBL) scheme	MRF
Cumulus option	Kain-Fritsch
CMAQv5.0.2	
Horizontal resolution	27km
Number of sigma level	18
Gas-phase chemistry	Carbon Bond 05 (CB05)
Aerosol module	AERO6
Horizontal advection module	Yamo
Vertical diffusion module	Asymmetric Convective Model version 2 (ACM2)
Photolysis calculation module	In-line
CMAQ cloud module	ACM
C CTM generalized -coordinate driver modul	Yamartino
Vertical layer Number	18 layers

Ground-level O_3 measurements were used to validate the modeling performance. In China, ambient O_3 mixing ratios were not regularly measured nation-wide until 2013. The records of ambient O_3 from China's national air quality monitoring network were adopted for the reference year 2013 (Figure 3-4). Specifically, the performance of modeling platform in July and October 2013 were evaluated. These two months represented two typical O_3 seasons in China. Normalized mean bias (NMB), normalized mean error (NME), and correlation coefficient (R) were used as indicators of model performance. According to recommended benchmarks for photochemical model performance statistics, the NMB for the 1 hour average or maximum daily 8 hour average ozone should be no larger than 15%, and the R should be higher than 0.50 (Emery *et al.*, 2017). The model performances of this work were within the above suggested range. The NME of this study was similar to those of previous studies in China (Liu *et al.*, 2010; Hu *et al.*, 2016; Zhang *et al.*, 2016b). For example, the NME for the 1 hour average O_3 over the eastern China in July was around 58.8~62.7% (Liu *et al.*, 2010). The modeling system can reproduce the O_3 mixing ratio reliably. In case study (Chapter 7), this study mainly refers to the maximum 8 hour average since it was reproduced well in the model and it is more relevant to the health impact.

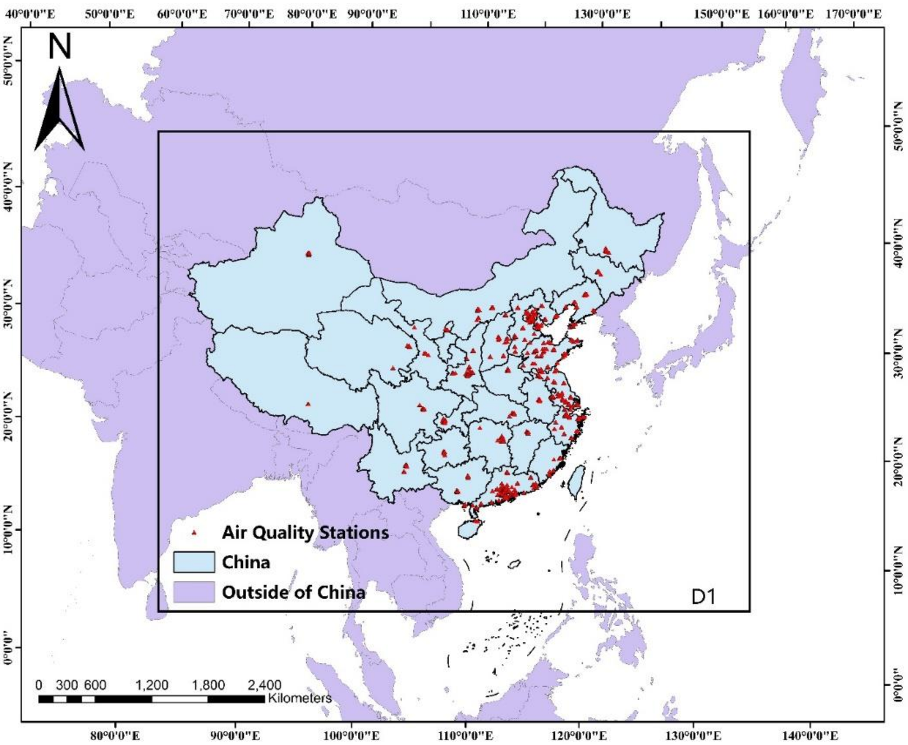

Figure 3-4 Locations of ambient ozone monitoring sites in China

Table 3-5 Statistics of model performances

	1 hour average O_3		Highest daily maximum 8 hour average O_3	
Indicator	**Jul 2013**	**Oct 2013**	**Jul 2013**	**Oct 2013**
NMB(%)	15.11	9.70	-1.26	-14.42
NME(%)	54.02	55.26	26.22	26.47
R	0.55	0.57	0.70	0.68

3.4. Health impact and mitigation cost evaluation

The risk of death from respiratory causes in association with an increase in ozone concentration has been documented in previous studies (Jerrett *et al.*, 2009). Here, number of premature deaths due to change of O_3 concentration was estimated as follows:

$$RR = exp\ (\beta\ (X\text{-}X_0)) \qquad \text{Eq. 3-23}$$

$$\Delta M = y_0 \left(\frac{RR-1}{RR}\right) POP \qquad \text{Eq. 3-24}$$

Where RR is the relative risk, β is the concentration-response factor (Jerrett *et al.*, 2009; Liu *et al.*, 2018b), $X\text{-}X_0$ is the change of O_3 concentration from different scenarios, M is the excess mortalities attributed to change of pollution, y_0 is the baseline mortality rate, and POP is the exposed population.

Costs of cleaner production in selected industrial sectors was evaluated. Given that local cost information was not available, the cost of such practices in Europe using IIASA-GAINS model data was adopted. Understanding the differences of cost of labour, infrastructure and others between China and Europe, the estimation here has large uncertainty in representing the exact cost in China. Interpretation of the estimated cost will be discussed later in Chapter 7 by comparison with an existing study.

3.5. Summary

The methods and data sources to support the methodological framework (Figure 1-9) were introduced in this chapter. To enable an integrated assessment of energy, pollution and socioeconomics, methods in environmental economics and environmental modelling were combined. Production-based energy consumption and emissions lay at the intersection of these two fields. On the one hand, the socioeconomic drivers and demands driving the production-based energy consumption and emissions were identified by decomposition analysis and input-output analysis. On the other hand, production-based emission inventories were fed into air quality simulation platform to quantify the environmental impacts by different production activities, followed by health impact assessment and cost estimation. Gripping the connection of production- and consumption-based emissions, production-based emissions and their impacts in environmental system model can be traced back to the underlying demands and drivers in socioeconomic system.

Understanding the inherent uncertainty in production-based emission inventories, this study tried to evaluate the reliability of NMVOCs emissions with ambient measurement record. It is true that bottom-up emission inventories and ambient measurements are not comparable in some senses. The concentration measured in the ambient is a mixed result of in-situ emissions and the physical and chemical transformations happen between emission sources and measurement site. Nevertheless, the results produced by receptor model, which is based upon ambient measurements, are widely used to inform policy makers and complement emission inventories. In addition, the ambient measurements used in this study evenly covered the whole study region, which are representative in terms of spatial coverage. Therefore, a trial to validate the speciated NMVOCs emission inventories with ambient records were conducted in this study. Discrepancies between two methods were quite large if comparison was made grid by grid (20×20 km^2). Cross-validation in regional scale such as 200×200 km^2 were much more reasonable. At the regional scale, the existing discrepancies between two methods were mainly explained by source reactivity. It draws caution on the implication of receptor model, which tends to underestimate the contribution of sources with higher reactivity. These two methods have fundamental differences in the relative contribution of LPG-related and vehicular evaporative source, indicating at least one of the methods were significantly flawed. After reviewing evidence from existing studies, vehicular evaporation emissions were added into the current emission inventories, with an emission factor of 1.6 kg of NMVOCs emissions per vehicle per year. No solid conclusion can be reached for LPG-related sources. It is urged that both the emission inventory and receptor model need to critically review their estimations on LPG-related contribution.

As a standard procedure of air quality simulation, the reliability of production-based inventories were also validated by evaluating the reproduction of ambient concentration in the air quality model. Ground-level O_3 measurements from China's national air quality monitoring network were used as independent references. Indicators of model performance suggested that modeling system can reproduce the O_3 mixing ratio reliably.

Chapter 4 China's provincial energy consumption and its socioeconomic drivers

Primary energy consumption for 30 provinces in China from 2003 to 2016 was analysed in this Chapter. As mentioned above in Section 1.2, energy elasticity declined dramatically from the peak value of 1.67 in 2004 to 0.14 in 2015, indicating that every 1% growth of GDP in 2015 was sustained by only 0.14% growth of energy consumption. It is crucial to understand the drivers behind such transitions and how feasible they are to sustain in the future. In the first section of this Chapter, energy consumption and economic growth in provincial levels are first reviewed. Provinces were classified into a few groups according to their patterns in energy consumption and elasticities. Section 4.2 shows the decomposition analysis results of provinces with declined energy consumption. The key drivers responsible for negative energy elasticity are identified. Decomposition analysis results for provinces with increasing consumption are presented in Section 4.3. Comparison between these two groups and their transition pathways towards energy-efficient growth are discussed in Section 4.4. The last section is a summary of the key findings and limitations of this Chapter. In terms of data source, this chapter uses the energy consumption compiled in Section 3.1.1 and other socioeconomic data as described in Section 3.1.5.

4.1. Energy consumption and economic growth in provincial levels

The years from 2003 to 2016 chronicle China's three distinct periods, characterized by fast economic expansion from 2003 to 2007, the fall and recovery of the economy under the strike of the global financial crisis from 2007 to 2011, and the strategic adjustment from 2011 to 2016 known as "China's new normal" period (a slowdown of economic growth to around 7%) aimed at "low but high-quality growth". According to the economic cycle, the period from 2003 to 2016 were divided into three phases for analysis.

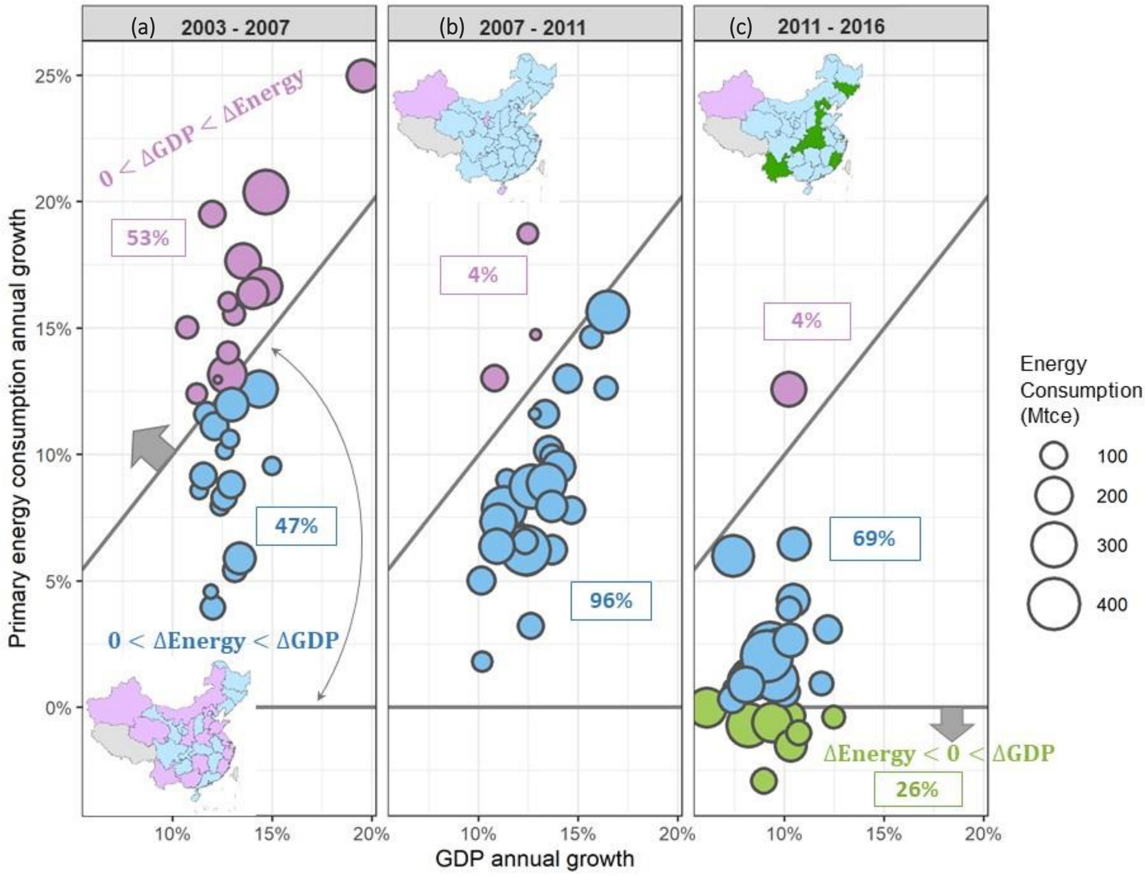

Figure 4-1 Comparison of energy annual growth and GDP annual growth in three periods, i.e., (a) 2003-2007, (b) 2007-2011 and (c) 2011-2015. The upper left area with dots in pink includes provinces with high energy elasticity (0 < ΔGDP < ΔEnergy). The middle area in blue indicates that provinces are with moderate energy elasticity (0 <ΔEnergy < ΔGDP). The lower right area in green stands for other province with low elasticity (ΔEnergy < 0 < ΔGDP). The percentages within each area represent the contribution to the national energy consumption. For example, 53% in the upper left area of (a) indicates that provinces within this area together contributed to 53% of the energy consumed nationally. The map within each subfigure shows the locations of provinces with different energy elasticity.

Data source: National Bureau of Statistics, 2018 a&b.

During the time from 2003 to 2007, as shown in Figure 4-1, 13 out of the 30 provinces had energy growth rate higher than their economic growth (energy elasticity larger than 1), accounting for 53% of the total energy consumed in China. Energy consumption in these provinces kept growing and its increase rate outpaced that of GDP. Regarding the other 17 provinces, their energy consumption were also climbing, but at a rate that was lower than that of GDP. Both the economic and energy consumption growth slowed down after 2007, and the deceleration of energy consumption were more noticeable in most provinces. Only 3 provinces, or 4% of the total energy consumption, had energy elasticity larger than 1. The energy elasticity of the other provinces was between 0 to 1. As China entered the “new-normal” period after 2011, the economic and energy consumption grew at even lower rates. Xinjiang was the only one with energy elasticity larger than 1. The other 21 provinces had energy elasticity between 0 and 1, which together made up 69% of energy consumed in this period. Energy consumption in 8 provinces in 2016 was found lower than the value in 2011, with negative energy elasticity. They were Jilin, Hebei, Henan, Hubei, Chongqing, Shanghai, Fujian and Yunnan.

4.2. Socioeconomic drivers for provinces with declined consumption

Drivers responsible for the initial decline of energy consumption in the eight provinces were revealed by the decomposition analysis. Here, the pre-defined factors were population growth, economic growth, industrial structure, energy intensity, and energy mix (i.e., the share of coal, petroleum, natural gas and non-fossil fuels).

Despite the variations in absolute contributions, the extensive body of literature agree that economic growth is always the predominant driver of increased energy consumption, while energy intensity is the most significant factor of decreased energy consumption in China (Guan *et al.*, 2009; Zhang and Cheng, 2009; Chong *et al.*, 2015; Jiang *et al.*, 2017; Liu *et al.*, 2018c). Nevertheless, the decreasing effect of energy intensity on energy consumption is hardly close to the increasing effect of economic growth. This phenomenon is observed in previous studies as well as in the analysis before 2011 in this work. However, changes began to occur during the period from 2011 to 2016. In eight provinces, the decreasing effect of energy intensity exceeded or approximated the increasing effect of economic growth (‘catch-up’ of energy intensity). In six of these provinces, energy intensity alone offset all the increased consumption triggered by the economy (Figure 4-2a). Collectively, the decrease in energy intensity in six provinces, i.e., Fujian, Chongqing, Jilin, Henan, Hubei and Yunnan, led to a decrease of 473 million tonnes of coal equivalent (Mtce), surpassing the increase caused by economic growth (419 Mtce). For the other two provinces, i.e., Hebei and Shanghai, the decrease from energy intensity compensated 95% and 73% of the increased consumption led by economic growth, respectively (Figure 4-2b). Detailed decomposition results by province can be found in Appendix Table A1.

Moreover, new drivers that decrease consumption are emerging. One driver is the share of coal. All the eight provinces with declined consumption are found to have decreasing consumption triggered by a decreased share of coal in the energy mix (Grey in Figure 4-2a). In Hubei, Shanghai, Fujian and Yunnan, the decreasing effect from the share of coal was particularly significant, which offset 27%, 21%, 21% and 16% of the increase from economic growth, respectively. It is true that part of the decreased consumption was offset by the increase of petroleum, natural gas or non-fossil fuels. However, the net effect of the changes caused by coal, petroleum, natural gas and non-fossil fuels were not zero (Guan *et al.*, 2018). Take Hubei for an example, share of coal was responsible for a decrease of 16 Mtce energy consumption, while share of petroleum, natural gas and non-fossil fuel accounted for an increase of 13, 1.7 and 1.7 Mtce, respectively. Their net effects came down to a decrease of 0.4 Mtce. In some circumstances, the decreased effect of coal was not followed by a decreased net effect. This is because only the quantity of fuel (i.e., weight) was considered here. Quality of fuel, e.g., content of carbon or caloric value, cannot be reflected (Guan *et al.*, 2018). Despite the small net effects in many cases, it is still worthy to investigate the driving effects by fuel types to understand the changes entailed by different fuels (Du *et al*., 2016; Jiang *et al*., 2017, Goh *et al*., 2018). Indeed, the decreasing effect of share of coal was rarely observed in provinces with climbing energy consumption (see Figure 4-3 b,c&d) while it was a common decreasing driver for provinces with decreased consumption.

The other driver is the change of industrial structure. With the exceptions of Chongqing, Yunnan and Hubei, industrial structure is a driver that decreases consumption featured by a reduced share of heavy industries (Dark blue in Figure 4-2b).

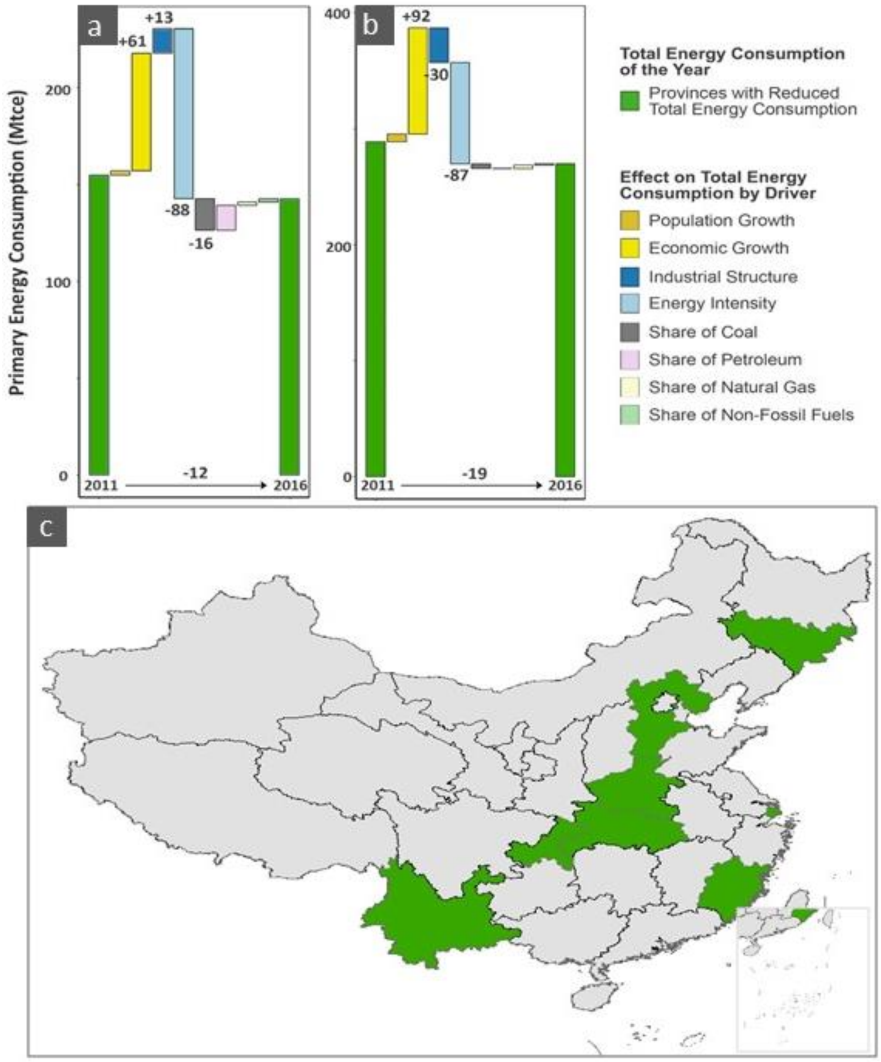

Figure 4-2 Key negative drivers leading to reduced consumption (a&b) and the locations of provinces with reduced total energy consumption in China (c). (a) and (b) are the so-called "waterfall" diagrams to show the driving effects by factors, which are population growth, economic growth, industrial growth, energy intensity, share of coal, share of petroleum, share of natural gas, and share of non-fossil fuels. The bars plotted represent changes in consumption and in a sequential way to provide a cumulative consumption. Despite the two dark green bars at the beginning (total consumption in 2011) and the end (total consumption in 2016), the 8 bars in-between represents the driving effects of the above 8 factors. For bars going up such as the bright yellow one of economic growth in (a), they are factors that lead to increased consumption. As for bars going down such as the light blue one of energy intensity in (a), they stand for factors that are responsible for decreased consumption. (c) shows the locations of provinces with reduced total energy consumption in China, which are coloured in dark green.

Drivers of reduced consumption, mainly from energy intensity, have caught up with the drivers that increase consumption and have led to reduced energy consumption in Shanghai, Hubei and other provinces (Fig. 1d in dark green). Similar patterns are observed in Beijing and in the other five provinces (Fig. 1d in light green), which were able to reduce their combined consumption of coal and petroleum.

In a deeper sense, the catch-up might be attributed to either the slowdown in economic growth or the significant reduction in energy intensity (or both). Indeed, both drivers contribute, but the effect of the energy intensity is more dominant. Economic growth was responsible for 283, 386 and 419 Mtce growth in energy consumption for the eight provinces from 2003 to 2007, from 2007 to 2011 and from 2011 to 2016, respectively. The driving effect from the economy kept growing but at a slower pace. Meanwhile, the decrease from energy intensity was dominant. Within the same time frame, energy intensity had led to decreases in energy consumption of 42 (from 2003 to 2007), 209 (from 2007 to 2011), and 473 Mtce (from 2011 to 2016). In the most recent six years from 2011 to 2016, the decreasing effect from energy intensity alone (473 Mtce) was able to offset all the increasing effect of economic growth on energy consumption (419 Mtce)– not to mention the additional decreases by the share of coal and the change of industrial structure. It can be concluded that the catch-up is more attributable to the enhancement of drivers that reduce consumption rather than the slowdown of the economy.

The observed declines in consumption are encouraging, but it is important to know the possibility of sustaining such trends. If there is a structural break in the consumption pattern, the nascent decline is likely to last and can be interpreted as a 'structural decline' (Guan *et al.*, 2018). Here, an econometric (cumulative sum) test was used to identify structural break points in provincial energy consumptions from 2003 to 2016.

For the 8 provinces analysed above, unfortunately, only two of them (Shanghai and Hubei) have structural breaking points during the period from 2011 to 2016. This finding suggests that the strong decreasing forces featured by energy intensity and, to a lesser extent, by the change of industrial structure and share of coal, are likely to be sustained. Regarding the other provinces, the changes in their energy drivers are not structurally significant.

4.3. Socioeconomic drivers for provinces with increasing consumption

Although new drivers that decrease consumption, i.e., share of coal and industrial structure, are emerging, a thorough review of the energy drivers from 2003 to 2016 in Chinese provinces shows that energy intensity was always the first driver of reduction that developed and applicable to provinces in various development states. Figure 4-3 illustrates the evolution of energy drivers for a province with an initial decline in consumption (e.g., Chongqing in a) and for provinces with growing consumption (e.g., Shaanxi in b and Inner Mongolia in c). Figure 4-3a shows how the decreasing effect of energy intensity emerged in Chongqing and quickly intensified to a magnitude comparable to that of economic growth, accompanied by the emergences of new drivers such as share of coal. Shaanxi and Inner Mongolia also reflect the enhancement of energy intensity but at a much slower rate. The effects from industrial structure change and share of coal were minor or even increasing. In addition, a reduction in energy intensity did not severely compromise economic growth. Provinces with increasing consumption were able to reduce their energy intensity by 7% while maintaining an 8% GDP annual growth from 2011 to 2016. As the only province with energy elasticity larger than 1, the driving effect of energy intensity in Xinjiang distinguishes with others. It remained as the positive driver throughout the study period, with no sign of decreasing (Figure 4-3d).

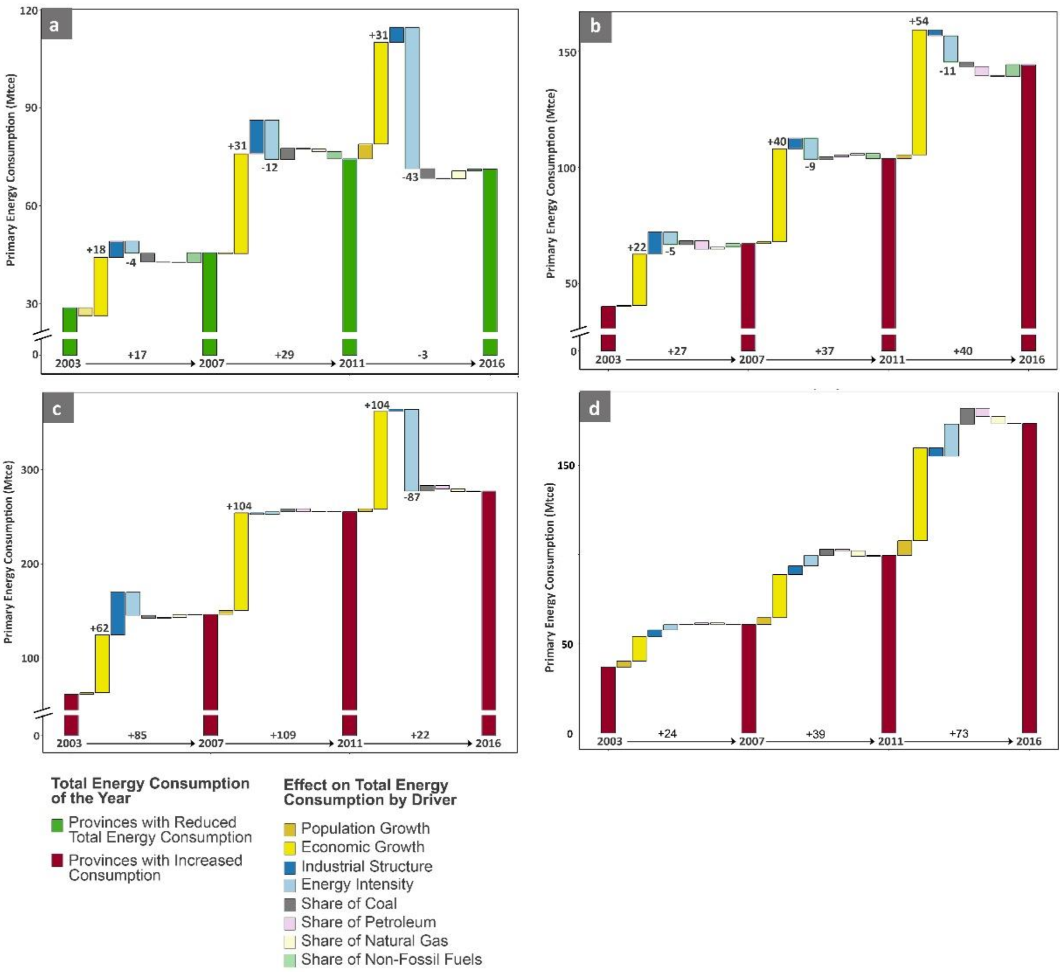

Figure 4-3 Evolution of energy drivers in provinces with (a) reduced and (b, c&d) increased consumption. (a) provides an example of a province with reduced consumption since 2011. The dark green bars represent the total energy consumption in 2003, 2007, 2011 and 2016. The 8 bars in-between show the driving effects by factors, which are population growth, economic growth, industrial growth, energy intensity, share of coal, share of petroleum, share of natural gas, and share of non-fossil fuels. For bars going up such as the bright yellow one of economic growth in (a), they are factors that lead to increased consumption. As for bars going down such as the light blue one of energy intensity in (a), they stand for factors that are responsible for decreased consumption. (b), (c) and (d) show the other three examples with energy consumption that consistently increased from 2003 to 2016. Annual total consumptions in 2003, 2007, 2011 and 2016 were shown in red bars. Numbers above the bars in (a), (b), (c) and (d) represent the driving effects of factors in terms of energy consumption. For example, “+18” in (a) means that economic growth was responsible for 18 Mtc increase of energy consumption from 2003 to 2007. “-4” in (a) means that energy intensity led to a decrease of 4 Mtce of energy consumption from 2003 to 2007. Numbers above the arrow indicates the change of provincial total energy consumption. For example, “+17” above the arrow from 2003 to 2007 in (a) suggests that energy consumption increased by 17 Mtce in this period.

4.4. Province-specific transition pathways towards more energy-efficient growth

The above analysis shows that energy intensity is the most important factor determining the energy elasticity of a province. Such an observation indicates two potential reduction pathways. One path is to sustain the strong decreasing effect mainly from energy intensity. It might be applicable to Hebei, Liaoning, Jilin, Henan, Hubei and Yunnan, whose energy intensities are still high (3.0~5.8 tce/10^4 $USD in 2016). Regarding Xinjiang, the only province with climbing energy intensity, more efforts should be made to understand the key sectors driving the climb, and develop measures to curb the trend. This reduction pathway is feasible as energy intensity reduction seems to be a low-hanging fruit achievable even by less developed provinces (See Section 4.3).

Part of high energy intensities of less developed provinces are attributed to their locations in the upstream of the supply chain as energy suppliers and heavy industrial goods producers (Tang *et al.*, 2016b). For example, approximately 34% of the electricity produced in Inner Mongolia was sent out to other provinces in 2016. The less developed provinces will benefit from demand-side adjustments and decoupling from energy in developed provinces. Nevertheless, local technological improvements might be more practical in the short term and benefit the greener growth of China as a whole. A dynamic market for energy-saving technologies has been developed in China with 5800 energy service companies and energy performance contracts worth 15 billion USD (Voita, 2018). As a way to apportion the responsibility, subsidies from other downstream provinces with greater ability to pay might be considered to fasten technological improvement in these supporting provinces.

The other is to complement energy intensity with new decreasing drivers. This suits better the other eight provinces, which have achieved relatively low levels of energy intensity. Their energy intensities were reduced by 34% from 2011 to 2016, whereas the average rate for the other provinces was 24%. By 2016, the energy intensities of these eight provinces were among the lowest in China and were even comparable to that of the United States, although their per capita GDP were only 20~30% that of the United States. A prominent example is Beijing. With a per capita GDP at 30% that of the United States, the energy intensity in Beijing by 2016 was 7% lower than that of the United States. To maintain decreasing drivers neck to neck with economic growth, the decreasing effects from energy mix and, to a lesser extent, from industrial structure, should be exploited. As the Energy Supply and Consumption Revolution Strategy (2016-2030) (hereinafter as the Strategy) was launched in 2016, China will further reduce its energy intensity by 15% from 2015 to 2020. Such a reduction is less than the 23% achieved from 2011 to 2015, indicating that energy intensity might not be as strong of a decreasing driver as it was in the past.

The Strategy also targets the share of cleaner fuels (natural gas and non-fossil fuels) and production overcapacities. By 2030, the share of cleaner fuels should reach 35%, doubling the level in 2016. The share of coal and petroleum, in other words, will be capped at 65%. The decreasing effects from share of coal and petroleum could be greatly enhanced (Tang *et al.*, 2018). This is especially true for the provinces with declined consumption, whose reduction potentials from energy intensity are depleting. Their greater ability to pay and pressure on pollution alleviation also urge the transition. Phasing-out overcapacities is also highlighted in the Strategy, targeting inefficient capacities in coal mines, iron and steel, and cement industries. The decreasing effect of industrial structure might emerge in those energy-suppling provinces and heavy industrial hubs, such as Heilongjiang, whose share of heavy industries decreased from 23.9% in 2011 to 17.3% in 2016. The decreasing effect of industrial structure change on energy consumption (25 Mtce) even exceeded that of energy intensity (9 Mtce) from 2011 to 2016.

The total energy consumption of China will be capped as 5000 Mtce and 6000 Mtce by 2020 and 2030, respectively. The annual growth, as a result, must be no higher than 1.8%, comparable to the growth from 2011 to 2016 (1.7% annually). To achieve such a low growing rate, energy consumption of some provinces need to be reduced, or at least, plateaued. China should endeavour to secure the initial declines observed in some of its provinces and foster energy efficiency improvement and industrial reconstruction for more energy-efficient growth in the less developed provinces.

4.5. Summary

There is an extensive body of literature on driver analysis of China's energy consumption at the national level and, to a lesser extent, at the provincial level. Many of the studies at provincial level focus on energy-related carbon dioxide (CO_2)

emissions (Ye *et al.*, 2017), energy intensity (Elliott *et al.*, 2017) and CO_2 emission intensity (Tan *et al.*, 2011). However, they missed the declines in energy consumption of some provinces due to the grouping of provinces or lack of sub-period analysis. For example, some studies only targeted the start and end years (e.g., 2000 to 2015, or 2005 to 2010), which obscured the emerging trend in between these periods. Other studies grouped the provinces by their spatial locations or types of drivers for ease of discussion. In a previous study, for instance, provinces were grouped into eastern, central and western regions and energy-related CO_2 emissions for central regions have levelled off since 2011 (Jiang *et al.*, 2017). Among these provinces, it is highly likely that some of their emissions had already declined. It is unfortunate that the trend was smoothed and overlooked.

In this Chapter, results of decomposition analysis of primary energy consumption in the provincial level from 2003 to 2017 were presented. Specifically, changes in energy drivers for the provinces with observed declines in their primary energy consumption were revealed and compared with other provinces with increased consumption. These eight provinces differed from the others since 2011, when the decreasing effect of energy intensity was enhanced and, for the first time, surpassed or approximated the increasing effect of economic growth. The catching-up was more associated with the significant reduction of energy intensity rather than the slowdown of economic growth. New decreasing factors such as the share of coal and industrial structure change were also emerging to curb the growth.

It is found that the driving effect of energy intensity is the most important factor determining the energy elasticity of a province. Energy intensity reduction seems to be a low-hanging fruit achievable by provinces in different development states, but its potentials in some developed provinces are depleting. As China aims to continue aggressive cut in energy intensity, more reduction should be contributed by the less developed ones. For more developed provinces with relatively low energy intensity, potentials from the new decreasing drivers, such as energy mix and change in industrial structure, should be explored.

Chapter 5 Air pollutant emissions in a fast-developing region and its socioeconomic drivers

This Chapter demonstrates part of the proposed framework in a subnational study in Guangdong province, China. It one of the fast developing regions in China that confront the challenges of air pollution mitigation and sustainable economic development. Previous studies have focused on the production-based emission characterization for control strategy formulation, while the drivers of emission growth and pattern changes from the consumption side are rarely explored. This study used the environmentally extended input-output analysis to study the intermediate and final demands for seven air pollutants in year 2007 and 2012. The changes of air pollutant emissions in these five years and the roles of socioeconomic demands were studied.

Section 5.1 compares the sectoral contribution from production- and consumption-based perspectives. From the consumption-based perspective, the intermediate demands driving production activities were discussed. Section 5.2 studies the change of sectoral contributions and their intensities from 2007 to 2012. In Section 5.3, production activities were associated with final demands including urban and rural consumption, governmental consumption, capital formation and export. On the leveraging of the above analysis, implications on sustainable production and consumption in Guangdong are discussed in Section 5.4. This Chapter is closed by a summary Section 5.5.

5.1. Production- and consumption-based source characterization

To match the production-based emission inventories with input-output table (IOT), the 42 production sectors in Guangdong's input-output tables were aggregated into 16 sectors (see Table 5-1). During the mapping process, primary energy consumption matrix and the other socioeconomic statistics collected in Chapter 3 were used as proxies to allocate the aggregated emissions in residential and service sectors, and household solvents.

Table 5-1 Energy Category of the 16 sectors

No	Sector	Sectors in IOT [a]
1	Agriculture	(1) Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy
2	Food Processing	(6) Food Processing, Food Production, Beverage Production, Tobacco Processing
3	Garments	(8) Garments and Other Fibre Products, Leather, Furs, Down and Related Products
4	Timber Processing	(9) Timber Processing, Bamboo, Cane, Palm and Straw Products, Furniture Manufacturing
5	Paper Products	(10) Papermaking and Paper Products, Printing and Record Medium Reproduction
6	Chemical Products	(12) Raw Chemical Materials and Chemical Products, Medical and Pharmaceutical Products, Chemical Fibre, Rubber Products, Plastic Products
7	Non-metal Mineral Products	(13) Non-metal Mineral Products
8	Smelting and Pressing of Metal	(14) Smelting and Pressing of Ferrous and Nonferrous Metals
9	Transportation Equipment	(18) Transportation Equipment
10	Electric Equipment	(19) Electric Equipment and Machinery
11	Telecommunications Equipment	(20) Electronic and Telecommunications Equipment
12	Electric Power	(25) Electric Power and Heat; (26) Steam and (27) Water Production and Supply
13	Construction	(28) Construction Industry
14	Transport and Storage	(30) Transport, Storage and Post
15	Other Services	(29) Wholesale and Retail Trade; (31)Hotels, Catering Service; (32) Information Transmission, Computer services and Software; (33) Finances; (34) Real state; (35) Leasing and commercial services; (36) Research and Experimental Development; (37)Water conservancy, Environment and Public Facilities Management; (38) Service to Households and Other Service; (39) Education; (40) Health, Social Security and Social Welfare; (41) Culture, Sports and Entertainment; (42) Public Management and Social Organization
16	Others	(2) Coal Mining and Dressing; (3) Petroleum and Natural Gas Extraction; (4) Ferrous and Nonferrous Metals Mining and Dressing; (5) Non-metal and Other Minerals Mining and Dressing; (7) Textile Industry; (11) Petroleum Processing and Coking, (16) Ordinary Machinery; (17) Equipment for Special Purpose; (21) Instruments, Meters Cultural and Office Machinery; (22) Artworks and other manufactures; (23) Waste; (24) Metal Products and Maintenance;

[a] Number in the bracket was the order of the sector in the input-output tables.

Sectoral contributions from production- and consumption-based accounting in 2012 were shown in Figure 5-1. Regarding the consumption perspective, emissions driven by five final demands, i.e., rural consumption, urban consumption, government consumption, capital formation and export, were included. As shown in Figure 5-1, the production-based source contributions varied between pollutants, but the contribution patterns were roughly similar from the perspective of consumption except NH_3.

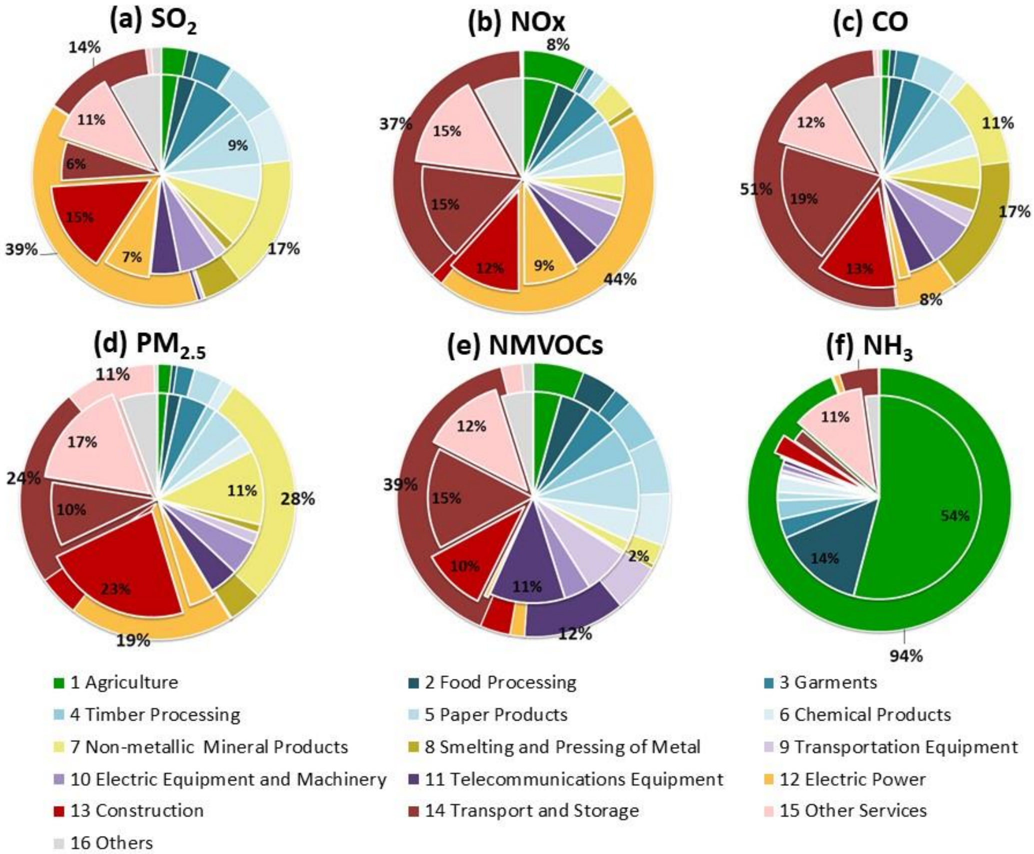

Figure 5-1 Evolution Source contributions from production (outer pie) and consumption (inner pie) perspectives for SO_2, NOx, CO, $PM_{2.5}$, NMVOCs and NH_3 in Guangdong in 2012

For SO_2, electric power, non-metal mineral products and transport were three dominant contributors in production, which constituted 39%, 17% and 14% of the production-based emissions (excluding rural and urban direct emissions), respectively. From the perspective of consumption, however, the contributions of these three sources decreased to 7%, 8% and 6%. Instead, construction and other services were the biggest contributors, responsible for 15% and 11% of the emissions. Similar characteristics were observed for NOx, CO, PM_{10} and $PM_{2.5}$. According to the production-based accounting, electric power, transport, non-metal mineral products, smelting and pressing of metal made up over 80% of NOx, CO, PM_{10} and $PM_{2.5}$ emissions. Their subtotal contributions decreased to less than 30% from the consumption perspective, while the proportions of construction, other services and transport took the lead.

With respect to NMVOCs, their production-based emissions are more related to vehicles and industrial processes that involve the extensive usage of NMVOCs-containing products such as paints and adhesives. Consequently, their production-based emissions were mostly from transport (39%) and light industries such as telecommunication equipment (12%). From the consumption perspective, light industries were still important contributors, but the proportion of transport dropped to 15%. Other services and construction accounted for 12 and 10% of the emission. For NH_3, agriculture dominated its production-based emission with 94% contribution. The contribution of agriculture declined to 54% from the consumption side, accompanied by increased proportions of food processing (14%) and other services (11%).

The differences between consumption and production perspectives were associated with the emission flows between sectors. Large amounts of SO_2, NOx, CO, PM_{10} and $PM_{2.5}$ emissions caused by fossil fuels combustion from electric power, non- metal mineral products and transport were indeed caused by the demands of construction and services. The NH_3 emission from agriculture was related to demands of the agriculture sector itself as well as those from food processing and other service sectors.

5.2. Change of sectoral emissions from 2007 to 2012

The seven pollutants saw different emission trends over the half decade from 2007 to 2012. Emissions of SO_2 (including urban and rural direct emissions) saw a decline of 28%, while NOx, CO, PM_{10}, $PM_{2.5}$, NMVOCs and NH_3 grew by 1.4, 26, 8.6, 8.5, 31 and 10%, respectively. Changes of sectoral emissions from consumption and production perspectives are discussed below (Figure 5-2).

From a production perspective, the decrease of SO_2 emissions were attributed to the substantial emission reductions in the three largest sources- electric power (Sector 12), transport (Sector 14) and non-metal mineral products (Sector 7), which dropped by 38, 19 and 9%. This is resulted from the stringent SO_2 control measures implemented during the 11th and 12th five-year plan (2006-2010 and 2011-2015), by increasing the penetration rates of desulfurization treatments and usage of low-sulphur coal in power plants and large industrial boilers. In terms of consumption, the largest contributor-construction (Sector 13) - experienced a drop of 42%. Other important contributors such as transport, non-metal mineral products, telecommunication equipment (Sector 11) also declined by varying degrees. The emissions of paper products (Sector 5) and other services (Sector 15), however, rose by 37 and 6.4%, respectively.

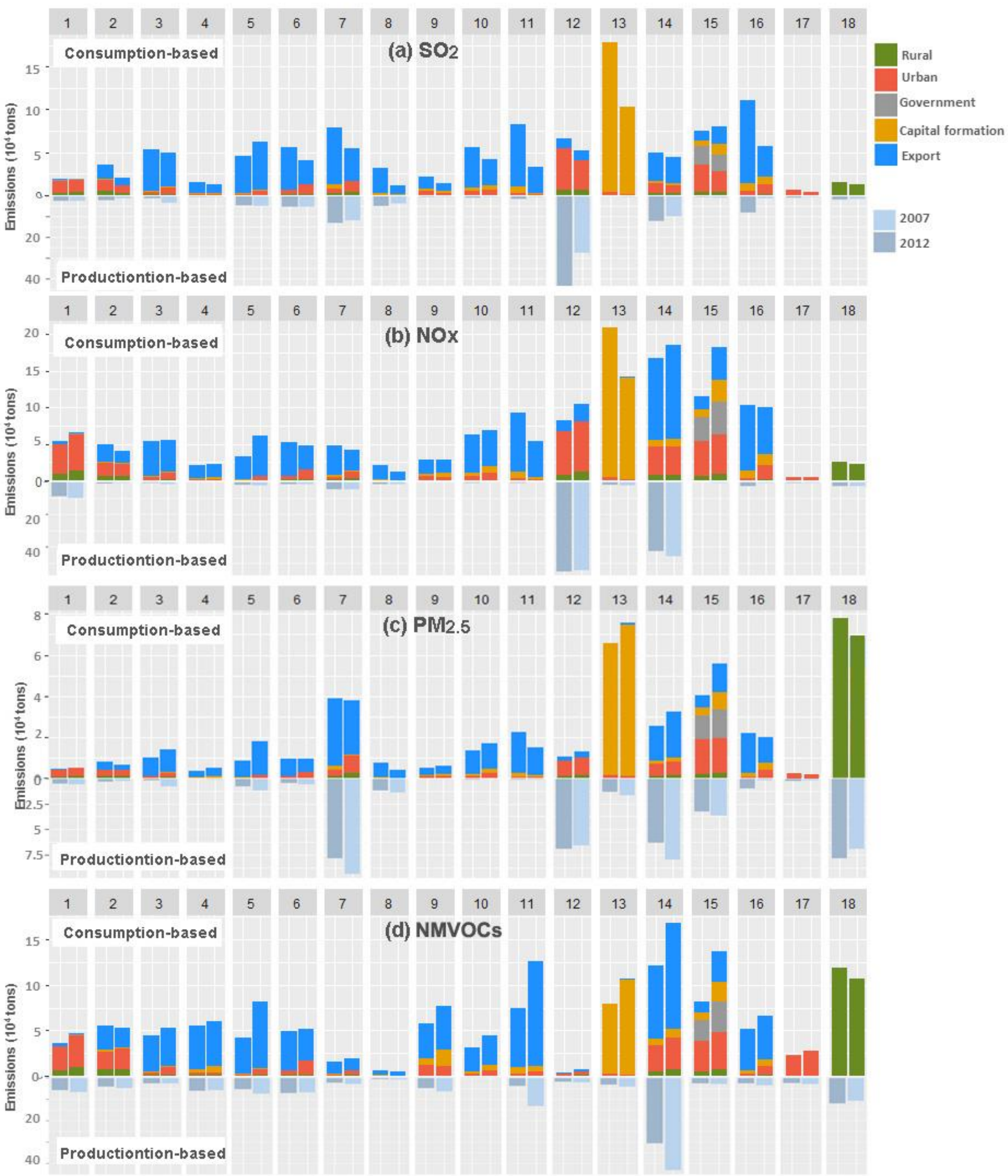

Figure 5-2 Consumption-based and production-based emissions of (a)SO_2, (b)NOx, (c) $PM_{2.5}$ and (d) NMVOCs in 2007 and 2012. Sector numbers from 1 to 16 refer to the orders of sectors in Table5-1. Sector 17 and 18 refers to urban and rural direct consumption,

respectively. For every subfigure, there are two bars in the upper frame (consumption-based emissions) and the lower frame (production-based emissions). The first bar represents the emissions in 2007 and the second one for emissions in 2012. In terms of consumption-based emissions, the final demands driven the emissions are shown in different colours: rural consumption (green), urban consumption (red), governmental consumption (grey), capital formation and inventory change (yellow), and export (blue).

With regards to NOx, the production-based emissions from power plants generally remained loosely controlled until 2010, when denitrifications such as selective catalytic reduction (SCR) were required for electric sectors and large industrial sources. Thanks to these measures, the NOx emissions from the electric sector decreased by 1.3%. Meanwhile, emission from transport increased by 7%. From the view of consumption, emission from construction and telecommunication equipment dropped by 32% and 41%, respectively. But emissions from other major contributors-other services, transport and electric power, experienced increases of 59%, 10% and 27%.

The production-based emissions of $PM_{2.5}$ were mainly made up by non-metal mineral products, transport, electric power and rural direct emissions from burning of woods and straw. From 2007 to 2012, emissions from the electric sector and rural consumption decreased by 5.2% and 12%, while those from non-metal mineral products and transport went up by 19% and 27%. Viewing from the perspective of consumption, most major contributors experienced an increasing trend except non-metal mineral products (-1.7%). Construction, transport and other services rose by 15%, 28% and 39%. PM_{10} exhibited similar trends as $PM_{2.5}$.

NMVOCs saw a surge of 31% during the five years. The production-based emissions from transport and telecommunication increased by 41% and 2.5 times, accompanied by varying increases from other light industries. Similar increasing trends were observed concerning the consumption-based emissions. Emissions from transport, construction, other services and telecommunication were 38%, 35%, 68% and 70% higher in 2012. As for CO, the increase was mainly attributed to transport from the production view, while construction, transport and other services explained the growth from the consumption perspective. Regarding NH_3, agriculture explained the emission growth from both perspectives.

The changes of emissions were attributable to different sources from the point of views of production and consumption. Viewing from production, the emissions from power plants displayed a decreasing trend for SO_2 and generally remained stable for other pollutants such as NOx and $PM_{2.5}$. Transport, non-metal mineral productions and other light industries kept growing for most pollutants except SO_2, serving as the drivers of the increasing emissions of NOx, PM_{10}, $PM_{2.5}$, NMVOCs and CO. From the consumption perspective, the varying trends by pollutants were contributed by construction, electric power, transport, other services, non-mental mineral productions and some light industries. The SO_2 and NOx emissions from construction decreased noticeably but its emissions of $PM_{2.5}$ and NMVOCs went up. With exception of SO_2, emissions from transport increased. It is noted that emissions from other services to all the pollutants kept growing over the years.

5.3. Change of source contributions and intensities from 2007 to 2012

As discussed above, the production-based emissions from the electric sector generally displayed a downward trend, while the emissions from transport, non-metal mineral products and some light industries grew by different levels. As a consequence, the source contribution patterns from the production perspective changed from 2007 to 2012. The contribution of electric power slightly decreased or remained stable, accompanied by increasing proportions from transport, non-metal mineral products and light industries, as shown in Figure 5-3a.

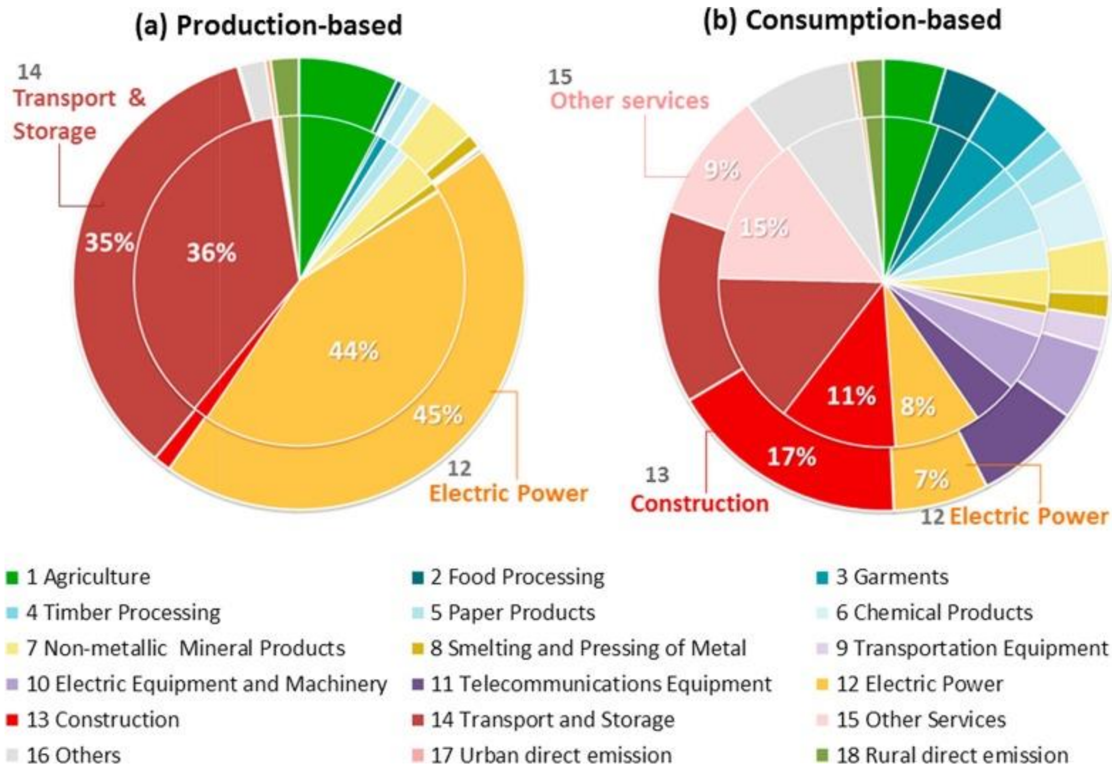

Figure 5-3 Changes in NOx source contributions from 2007 (outer pie) to 2012 (inner pie) from (a) production and (b) consumption perspectives

From the consumption perspective, the change in source contribution seems to be more notable than that in production. As a result of the change of emissions from key contributors, the contributions of construction to SO_2 and NOx decreased noticeably from 18 and 17% in 2007 to 14 and 11% in 2012, respectively. Meanwhile, the proportions of other services played a more prominent role for nearly all the pollutants. Its contribution to SO_2, NOx, PM_{10}, $PM_{2.5}$ and NMVOCs from consumption perspective increased from 8, 9, 8, 11 and 9% to 11, 15, 12, 14 and 11% in the five years, as illustrated in Figure 5-3b with NOx as an example.

Concerning the emission intensities by sectors, both the direct and embodied emission intensities showed a decreasing trend for most sources. Here, the sectoral embodied emission intensities were discussed in details.

Figure 5-4 showed that, for SO_2 and NOx, the emission intensity of power sector (Sector 12) was the highest, followed by that of transport (Sector 14), non-metal mineral products (Sector 7) and construction (Sector 13). All the four high emission-loading sectors saw a substantial decline from 2007 to 2012, especially for SO_2. The

SO_2 emission intensity of electric power decreased by 57%, and decrease rates for the other three sectors were in the range of 54-72%. For NOx, the intensity of power sector slipped down by 31% and other sectors by 43-67%.

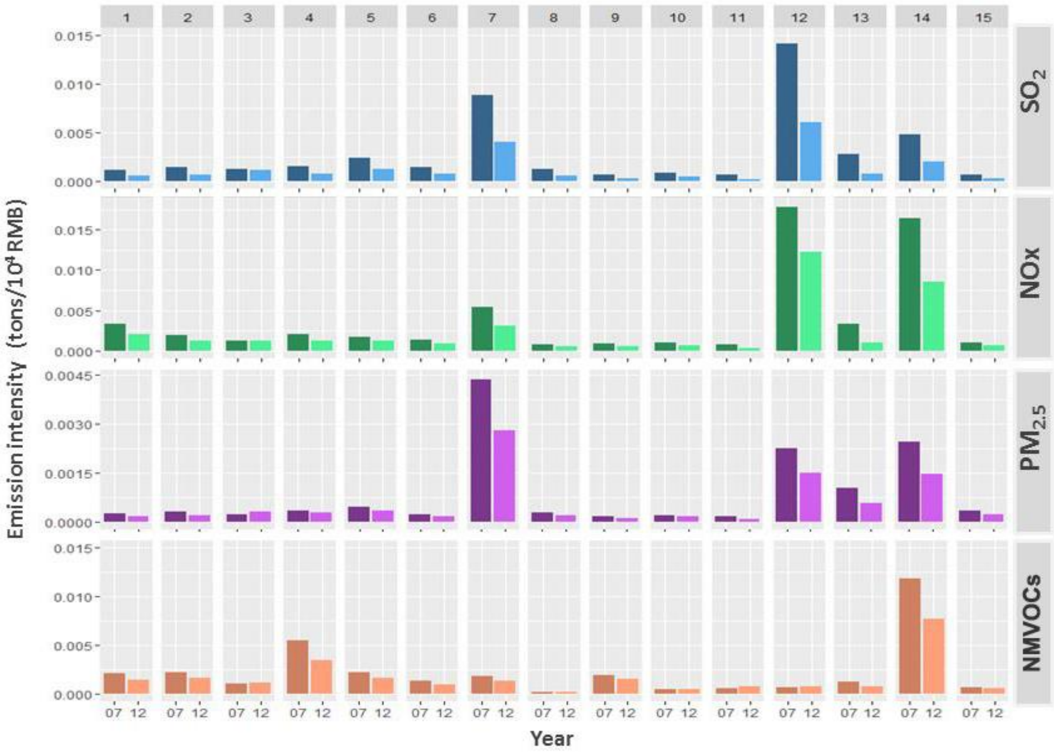

Figure 5-4 Embodied emission intensities of SO_2, NOx, $PM_{2.5}$ and NMVOCs in 2007 and 2012. Sector numbers from 1 to 15 refer to the orders of sectors in Table5-1.

Regarding PM_{10} and $PM_{2.5}$, non-metal mineral products and transport showed the highest emission intensities but dropped by 36-41% and 39-40% during the half decade. Electric power and transport also had high particulate emission loadings, which declined by 32-40%. With respect to NMVOCs, the intensity of transport and timber processing (Sector 4) stood out and saw a decrease of 35 and 36%, respectively. The intensities of CO were quite similar for most sectors, but they decreased by a much lower rate than that of other pollutants and some even increased. As for NH_3, the agriculture and food processing industry had outstanding intensities, which were reduced by 35 and 41%.

Noteworthy is that the sectors with high emission intensities were generally the same as those with high absolute emissions except other services. This sector took up 10-20% of the emissions from consumption perspective, but its emission intensity (Sector

15) was relatively low as shown in Figure 5-4. Take the SO_2 intensity in 2012 as an example, the intensity of electric power was 19 times that of other services. Combined with the fact that other services took a more prominent role in the emission of consumption end, it suggests that Guangdong is moving towards a greener consumption pathway. This might benefit from the efforts in emission reductions from the production end and the growing weight of other service industries in Guangdong, which increased from 17 to 24% of the provincial GDP from 2007 to 2012.

5.4. Final demands in 2007 and 2012

The emissions from the consumption perspective are driven by different final demands. Contributions of final demands to the 7 pollutants can be found in Table 5-2. As shown in Figure 5-2, with the exception of construction, which was mainly constituted by capital formation, other sectors were related to export and urban consumption. Indeed, export (including international export and interprovincial outflow) was the most important driver for the emissions of SO_2 (Figure 5-5a), NOx, PM_{10}, $PM_{2.5}$ and NMVOCs (Figure 5-5c) in Guangdong, accounting for 50% or more emissions from the consumption perspective. From 2007 to 2012, the proportion of export decreased for SO_2, NOx, PM_{10} and $PM_{2.5}$. As Figure 5-5c illustrated, the contribution of export declined from 56 to 50% for SO_2. But for NMVOCs and CO, the percentages of export were stable or slightly increased. For all the pollutants, urban consumption made up increasing contributions, e.g., its contribution to SO_2 and NMVOCs increased from 16 and 18% to 21 and 10% in five years. This is due much to the urbanization process in Guangdong. From 2007 to 2012, the proportion of urban population grew from 63.1 to 67.4%, reaching 71.4 million in 2012.

Table 5-2 Energy Contributions by final demands

Pollutants	Year	Rural [a]	Urban [b]	Governmental consumption	Capital formation	Export
SO_2	2007	4%	16%	2%	22%	56%
	2012	5%	21%	3%	20%	50%
NOx	2007	5%	20%	3%	21%	51%
	2012	6%	25%	4%	18%	48%
CO	2007	38%	10%	2%	11%	40%
	2012	28%	14%	2%	15%	42%
PM_{10}	2007	18%	13%	2%	22%	45%
	2012	16%	16%	3%	24%	42%
PM_{25}	2007	23%	13%	3%	21%	40%
	2012	20%	16%	3%	23%	38%
NMVOCs	2007	15%	18%	2%	13%	52%
	2012	12%	19%	3%	15%	52%
NH_3	2007	21%	44%	3%	5%	28%
	2012	22%	48%	3%	6%	22%

[a] Including indirect and direct consumption;
[b] Including indirect and direct consumption

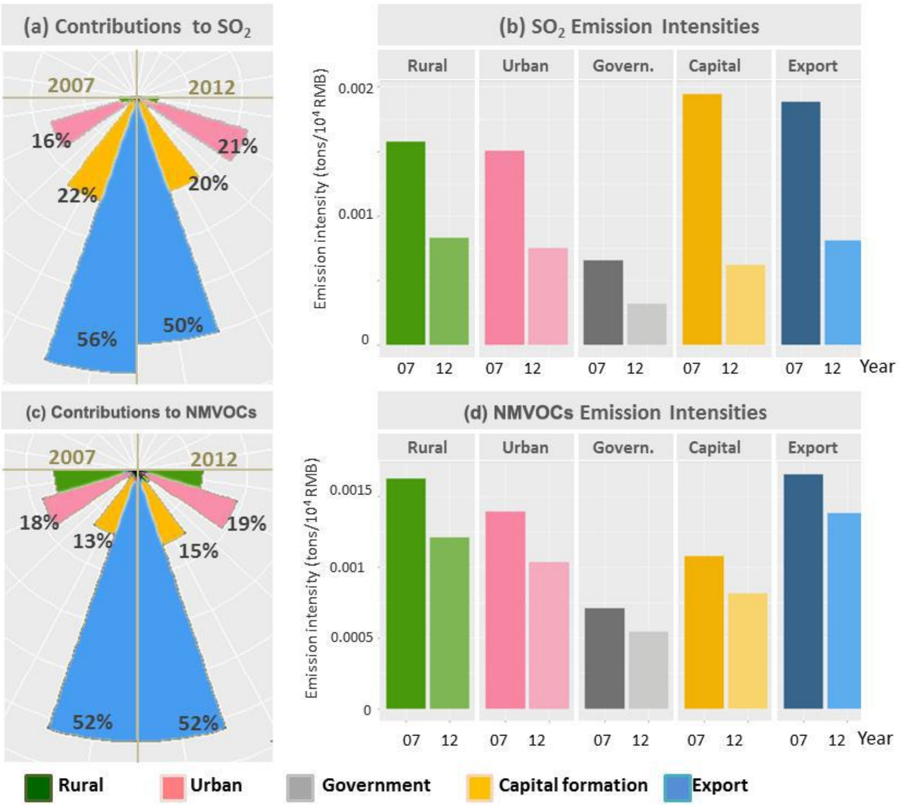

Figure 5-5 Contributions and emission intensities by final demands of (a, b) SO_2 and (c, d) NMVOCs in 2007 and 2012

In terms of emission intensities, capital formation and export stood out with high emission rates of SO_2, NOx, CO, PM_{10} and $PM_{2.5}$. For NMVOCs, the intensities embodied in export, rural and urban consumptions were high, while those of capital formation and government consumption were low (Figure 5-5d). As for NH_3, rural consumption was associated with the highest emission intensity, followed by that of urban consumption. During the half decade, the emission intensities of the five final demands generally experienced a decreasing trend with varying degrees for different pollutants. Again, SO_2 experienced the most notable decline, of which intensities from capital formation and export dropped by 68 and 57% respectively. Following SO_2, notable declines were also observed for NOx, PM_{10} and $PM_{2.5}$. The decreases of VOC and CO were in the least degree. For NMVOCs, the emission intensity embodied in export, rural and urban consumption were reduced by 24, 26 and 26% respectively, which accounted for only half their counterparts of SO_2.

Compared to the national average, export accounts for an unusually high share of Guangdong's consumption-based emission, suggesting that Guangdong bears an even higher cost of air pollution and related health loss due to the embodied emissions in export. As the "world factory", China is recognized as the largest embodied emission exporter in the world (Lin *et al.*, 2014; Zhang *et al.*, 2017) According to Huo *et al*. (2014) (Huo *et al.*, 2014), export explained 24, 24, 15 and 19% of the SO_2, NOx, $PM_{2.5}$ and VOC emission in China in 2010. The proportion of export in Guangdong, which accounted for half of the emissions, double the national average. A recent study has linked the embodied emission with health impacts and showed that the number of premature mortality as a result of international trade can be higher than those as a result of long-distance atmospheric pollution transport (Zhang *et al.*, 2017). It indicates that a probably huge external cost was borne by the people of Guangdong in producing the various products for export.

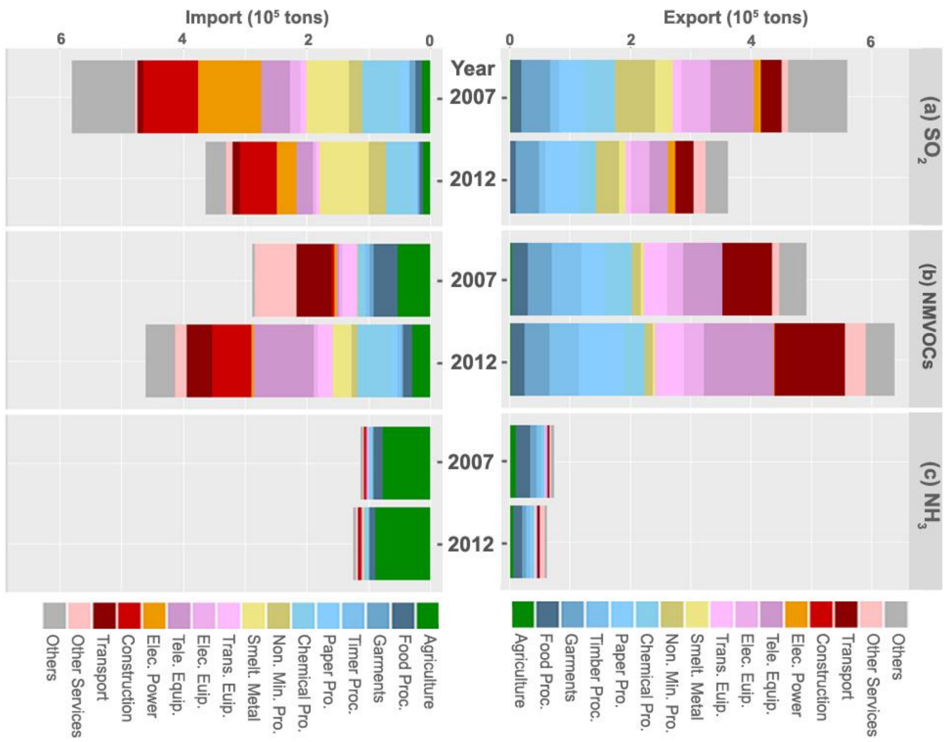

Figure 5-6 Air pollutant emissions embodied in import and export in 2007 and 2012

Intriguingly, Guangdong also had high emissions embodied in import (including international import and interprovincial inflow). As shown in Fig.6, the embodied emissions in import were close to those in exports for SO_2, NOx, CO, PM_{10} and $PM_{2.5}$. For NH_3, the emissions from import surpassed those from export, which were 1.55 and 2.04 times of export in 2007 and 2012. With respect to VOC, of which a large proportion of production-based emissions (nearly 45%) were emitted from light industries for export commodities, the embodied emissions in export remained higher than that in import but the gap was narrowing. The embodied emissions of import equalled to 59 and 72% of export embodied emissions in 2007 and 2012, respectively.

The embodied emissions in import were generally associated with electric power, construction, agriculture, chemical products, smelting and pressing of metal, telecommunication equipment and transport. Meanwhile, substantial emissions were embodied in the export commodities from telecommunication equipment, transport and the several key light industries in Guangdong, i.e., paper products, timber processing, garments and chemical products. The differences between the contributing sectors to embodied import and export emissions reflected the trade characteristics in Guangdong, which relies on the electricity, raw materials for manufacturing and agricultural products from other areas to support local production and living demands while exports great amount of electrical equipment and machinery, wood furniture, paper products, ceramics, garments and others for interprovincial or international trades.

5.5. Implications for Guangdong's sustainble production and consumption

As revealed by this study and other existing emission inventories, the traditionally major emitters from production perspectives were electric power, transport, non-metal mineral products, and some equipment machinery and light industries. These sources are the targets of the current control measures that track the emissions from the production end. From the consumption perspective, however, the contributions from construction, transport and other services were the highest. Substantial emissions from the large production-based emitters were indeed caused by the demands of these sources, which should cause more concern in terms of their hidden responsibilities for local air pollution.

The major contributors from production and consumption perspectives were usually associated with high emission intensities, with the exception of other service sector. From 2007 to 2012, most of these major contributors saw a decrease of more than 30% in their emission intensities. Nevertheless, due largely to the dramatic growth in local population and economy, their emissions of air pollutants generally displayed an increasing trend except for SO_2. From the production perspective, thanks to the stringent desulfurization measures during the 11^{th} and 12^{th} five-year plan, SO_2 emissions saw substantial decreases in electric power, transport and non-mental mineral products. Emissions of the power sector remained stable for other pollutants. Transport, non-mental mineral products and other industries were the major production-based drivers for the increase of PM_{10}, $PM_{2.5}$, CO and NMVOCs. From the consumption perspective, construction had lower SO_2 and NOx emission in 2012, but its emissions to other pollutant kept increasing. Additionally, transport, other service, electric power and some light industries such as paper product were the major drivers of the increasing air pollutant emissions from final demand.

As one of the major emission contributors from consumption perspective, other service sector had very low emission intensity. Noteworthy is that, during the half decade, the contribution of construction to the emissions driven by final demands slipped down, while other service took a more prominent role. This coincides with the increasing share of other service industries in Guangdong's GDP, which grew from 17 to 24% during the five years. It suggests that Guangdong was making progress in industrial transformation and greener consumption.

Being the major exporting province in China, which was widely known as the "world factory", Guangdong had an unusually high share of export in the air pollutant emissions. More than a half of the air pollutant emissions were driven by export. This figure was twice of the national average. Telecommunication equipment, transport and the several key light industries in Guangdong, i.e., paper products, timber processing, garments and chemical products were the major industrial sectors responsible for the huge amount of export commodities. The share of export started to decrease for SO_2, NOx, PM_{10} and $PM_{2.5}$, but remained still for CO and NMVOCs.

This large emission exporter also relied heavily on the import of agricultural products, raw materials, electricity and others from other areas. Indeed, the embodied emissions of import for SO_2, NOx, CO, PM_{10} and $PM_{2.5}$ were close to those of export. The embodied emissions of import for NH_3 were nearly twice of those of export. But for NMVOCs, whose emissions were largely related to machinery and light industries of export commodities, its embodied emissions of export still outweighed the import emissions.

Analysis shows that that Guangdong was moving forward to cleaner production and consumption. Nevertheless, more concern should be laid on the NMVOCs and CO emissions embodied in export. The experience in Guangdong suggested that transformation of the industrial structure to clean industries and simulating urban demands would benefit from further emission reduction while maintaining economic growth and living standards of local people.

5.6. Summary

From 2007 to 2012, the GDP of Guangdong increased dramatically by 80%. Meanwhile, it saw a 28% decrease of SO_2 emissions, accompanied by stabilized NOx emissions and 26, 8.6, 8.5, 31 and 10% increase of CO, PM_{10}, $PM_{2.5}$, NMVOCs and NH_3, respectively. This Chapter tried to examine drivers of air pollutant emissions of this fast developing region in order to gain a better understanding of air pollution causes and their evolutions.

Changes of air pollutant emissions can be explained by the control measures from the production end, evolution of industrial structures and final demands. The control measures were generally focused on SO_2, followed by NOx, PM_{10} and $PM_{2.5}$, and to the least extent, NMVOCs and CO. This was reflected in the emissions from both production and consumption perspectives in the way that the emissions of key sectors generally saw the most significant decline for SO_2 but displayed a slightly or notably increasing trend for PM_{10}, $PM_{2.5}$ and NMVOCs. Meanwhile, due to the growth of service industries in the economy and the increasing urban consumption demand, the share of other service industries (excluding transport, storage and post) in Guangdong' GDP grew by 41% in five years, resulting in the increasing proportion of the low-emission-intensity service sector in the emissions of all the 7 pollutants. The service sector was taking a more prominent role in the emissions from the perspective of consumption.

Analysis revealed an astonishingly high contribution of export to the air pollutant emissions in this region. Export accounted for half of the emissions, doubled the national average. Fortunately, emission intensities of SO_2, NOx, PM_{10} and $PM_{2.5}$ in export commodities had declined significantly from 2007 to 2012. Intensities of NMVOCs and CO, nevertheless, remained consistently high and call for caution.

Chapter 6 Emissions from Tibet and its interactions with local and exogenous demands

This Chapter serves as another case study at subnational level in China. It provides the first consumption-based estimation of CO_2 emissions from Tibet, and shows how emissions were embodied within interregional trade. The organization of this Chapter is similar to Chapter 5. In Section 6.1, emissions from two accounting approaches – production and consumption – are compared. It was found that consumption-based emissions from Tibet were much higher than its production-based account. Section 6.2 digs into the emission patterns from the two approaches. Contributions by sectors and final demands are discussed. Section 6.3 focuses on the embodied emissions within interregional trade between Tibet and other provinces in China. Implications on regional sustainable production and consumption are discussed in Section 6.4. Key findings and limitations are summarized in Section 6.5.

6.1. Production- and consumption-based emissions

While production-based accounting calculates emissions within a territory, consumption-based estimations cross territorial boundaries and tracks the emissions embodied in the regional supply chain induced by the demands of the study area (Chen *et al*. 2013; Meng *et al*. 2016b; Mi *et al.* 2016). In this study, it was found that consumption-based emissions of Tibet were much greater than the production-based emissions and that emissions occurring in other regions accounted for a large proportion of Tibet's consumption-based emissions.

In 2012, the production-based emissions of Tibet were estimated to be 6.2 Mt of CO_2, accounting for 0.07% of China's total CO_2 budget. From the consumption-based perspective, Tibet's CO_2 emissions increased three folds, reaching 18.8 Mt (0.2% of the national total), which is equal to the emissions of Guinea in 2015 (20.75 Mt) (EDGAR, 2017). Consequently, the consumption-based emission intensity of Tibet was much greater than the production-based intensity. The production-based emission intensity was 0.41 $tCO_2/10^4$ RMB in 2012, ranking 23rd among the 31 provinces studied here. In contrast, the consumption-based emission intensity was 1.56 $tCO_2/10^4$ RMB in 2012, ranking 14th among the 31 provinces.

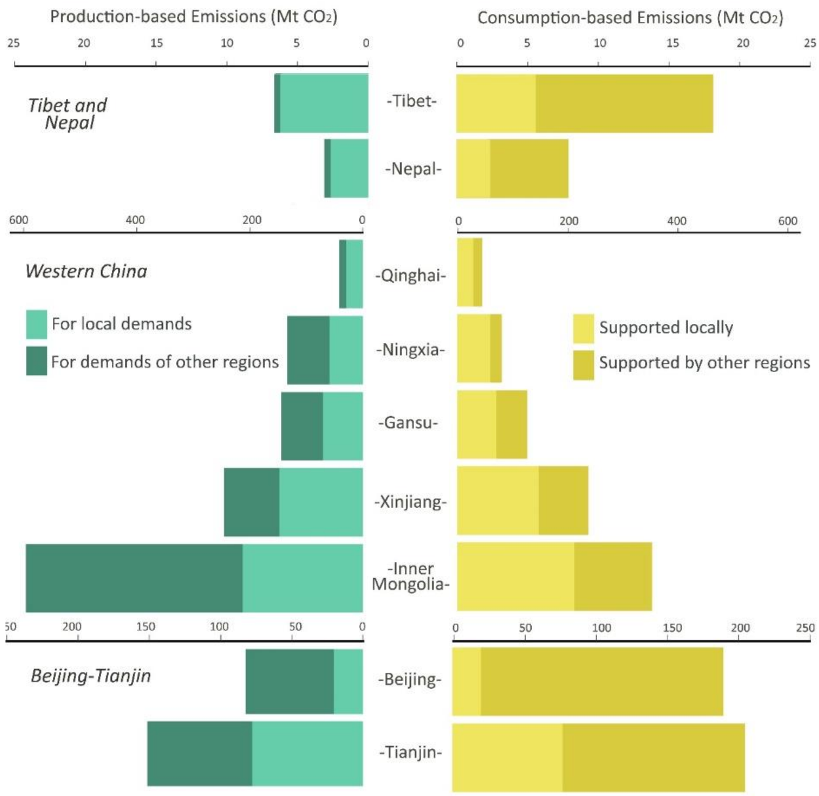

Figure 6-1 Composition of production- and consumption-based CO_2 emissions

The pattern of Tibet's consumption-based emissions was more similar to those of the more developed regions than those of its counterparts in western China. Figure 6-1 compares the production- and consumption-based emissions of Tibet, provinces in western China, developed regions in east China and Tibet's neighbor, Nepal. The production- and consumption-based estimates share one common emission component: the emissions emitted locally to satisfy local demand. The differences between these estimates are thus caused by the gap between local emissions induced by the exported emissions (in dark green in the left-hand side of Figure 1) and imported emissions (in dark yellow in the right-hand side of in Figure 1). In China, substantial CO_2 emissions are driven by the demands of the more developed provinces along the east coast. In addition, the emissions related to the goods and services consumed in these regions are imported from less-developed provinces in central and western China (Mi et al. 2017). As a result, the consumption-based emissions of developed regions are generally much higher than their territory-based emissions. As an example, the territory-based emissions of Beijing were 79.4 Mt of CO_2 in 2012, but its consumption-based emissions were 196.6 Mt, 2.5 times greater than the territory-based value. In sharp contrast, the territory-based emissions of the less-developed western provinces tended to exceed the consumption-based emissions. For example, the consumption-based emissions of Inner Mongolia and Ningxia were 334.9 and 87.2 Mt in 2012, respectively, each equal to 60% of the territory-based emissions. Indeed, approximately 66% and 54% of the emissions in Inner Mongolia and Ningxia, respectively, were emitted during the production of goods and services that were ultimately consumed in other regions.

In contrast, the consumption-based emission of Tibet far exceeded its production-based account. Of the 18.8 Mt of consumption-based emissions in Tibet, 69% were exported to other regions rather than emitted locally. This pattern distinguishes Tibet from other western provinces in China that are generally emission importers supporting the consumption and exports in the richer eastern regions. In fact, the ratio of consumption- based to territory-based emissions in Tibet (3.0) was the highest among the 31 provinces studied here, including greatly developed areas such as Beijing (2.5), Tianjin (1.5) and Guangdong (1.3). The neighbor of Tibet, Nepal, has very similar characteristics; the consumption-based emissions in Nepal were 2.8 times greater than the production-based emissions. These regions are both located near the Himalayas and have limited natural resources and fragile environments that make mass industrial production difficult. Such low self-sufficiency results in high dependencies on other regions.

6.2. Sectoral contributions and driving demands

The discrepancies between sectoral contributions from production- and consumption-based estimation were also substantial. As shown in Figure 6-2a, the production-based CO_2 emissions in Tibet were mainly attributed to non-metal mineral products (29%), other services (19%), transport (15%) and electricity and heat production (12%). Other services accounted for the second largest level of production-based emissions. This result is due to the high share of tertiary industry in Tibet, which accounted for 54% of its GDP in 2012, ranking the third highest in China after Beijing (76%) and Shanghai (60%) (National Bureau of Statistics of the People’s Republic of China 2013).

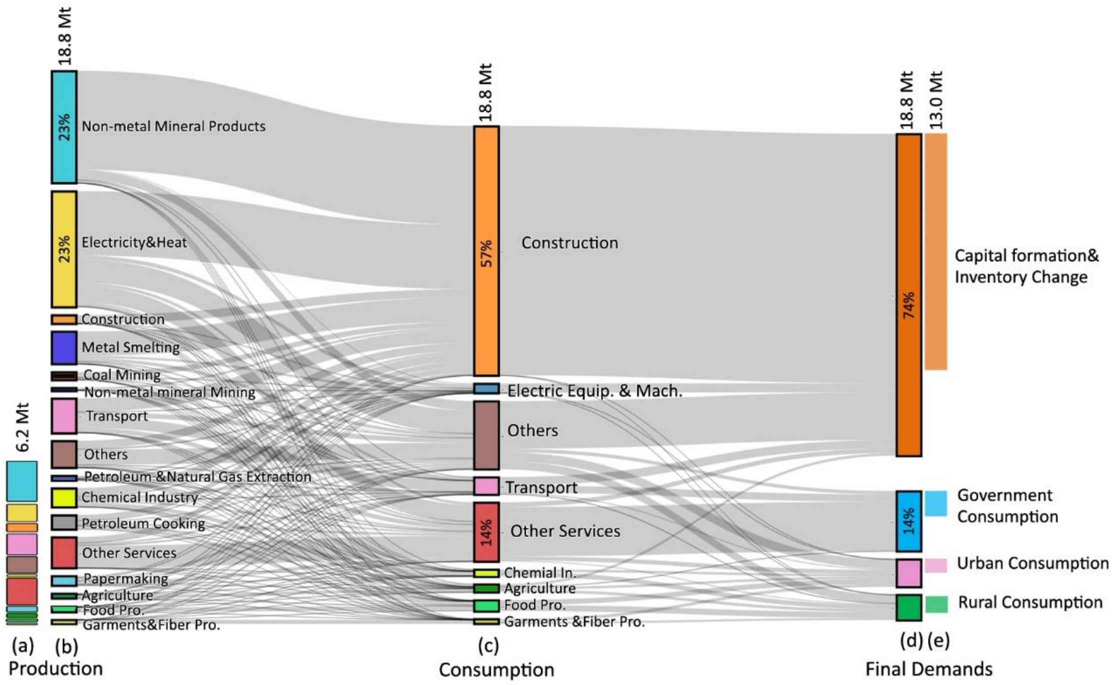

Figure 6-2 Emission flows from production to consumption and final demands. (a) CO_2 emissions from local production activities in Tibet – 6.2 Mt (production-based emissions), which is not sufficient to support Tibet's demands; (b) CO_2 emissions from production activities in Tibet and other regions in China that support Tibet's demands – 18.8 Mt; (c) Consumption-based sectoral CO_2 emissions totaling 18.8 Mt; (d) CO_2 emissions by final demand – 18.8 Mt; (e) CO_2 emissions supported by production in other regions by final demand – 13.0 Mt.

The local production activities and production activities in other regions in China (Figure 6-2b) collectively supported the consumption in Tibet (Figure 6-2c). From the consumption-based perspective, a large amount of emissions from non-metal mineral products, electricity and heat production, and metal smelting and processing were due to the demand for construction. Construction accounted for 57% of the consumption-based emissions followed by other services (14%) and transport (4%). Food processing, garments and fiber products, agriculture, the chemical industry, and electric equipment and machinery each contributed 2% to the total consumption-based emissions. Though the contribution of construction to consumption-based emissions is generally higher than its contribution to production-based emissions (Huo *et al*. 2014; Mi *et al*. 2016; Ou *et al*. 2017), the share of emissions from construction in Tibet was still astonishingly high.

The consumptions of different sectors are associated with different final demands (Figure 6-2d), namely, rural consumption, urban consumption, government consumption, capital formation and inventory change. The consumptions of construction and electric equipment and machinery were predominantly driven by capital formation and inventory change. As a result, 74% of the consumption-based emissions were related to the demands of capital formation and inventory change. The second highest demand was government consumption, which accounted for 14% of the total consumption-based emissions. Approximately 84% and 42% of the emissions from other services and transport were related to the government's demand, respectively. Urban and rural consumption each accounted for 6% of the total emissions through the demands of food processing, garments and fiber products, and agriculture. Among these final demands, 74%, 44%, 56% and 72% of the demands of capital formation and inventory change, government consumption, urban consumption and rural consumption, respectively, were supported by production in other provinces, as shown in Figure 6-2e.

6.3. Interactions with other provinces

Tibet was interconnected with most provinces in China through interprovincial trade. Figure 6-3 illustrates the CO_2 emissions related to Tibet's demands, i.e., embodied emissions in import to Tibet. In particular, flows of CO_2 emissions were significant for the provinces adjacent to Tibet, e.g., Qinghai, Sichuan and Gansu. Qinghai, Tibet's neighbor to the east, was the region with the largest support of Tibet's demands and consumption-based emissions (20%, 3.8 Mt). Approximately 0.9 and 0.6 Mt CO_2 emissions were embodied in the interprovincial trade from Sichuan and Gansu to Tibet, respectively. Net emission flows from other regions to Tibet were also observed, especially from regions in the north, such as Hebei (1.9 Mt) and Inner Mongolia (0.8 Mt). Some minor flows also originated from the Yangtze River (Shanghai, Zhejiang and Jiangsu) and the Pearl River Delta (Guangdong), which are China's most economically developed areas. These results make Tibet stand out from its western counterparts, which are usually net emission exporters supporting the developed coastal areas, i.e., CO_2 emissions flowed from west to east (Mi *et al*. 2016).

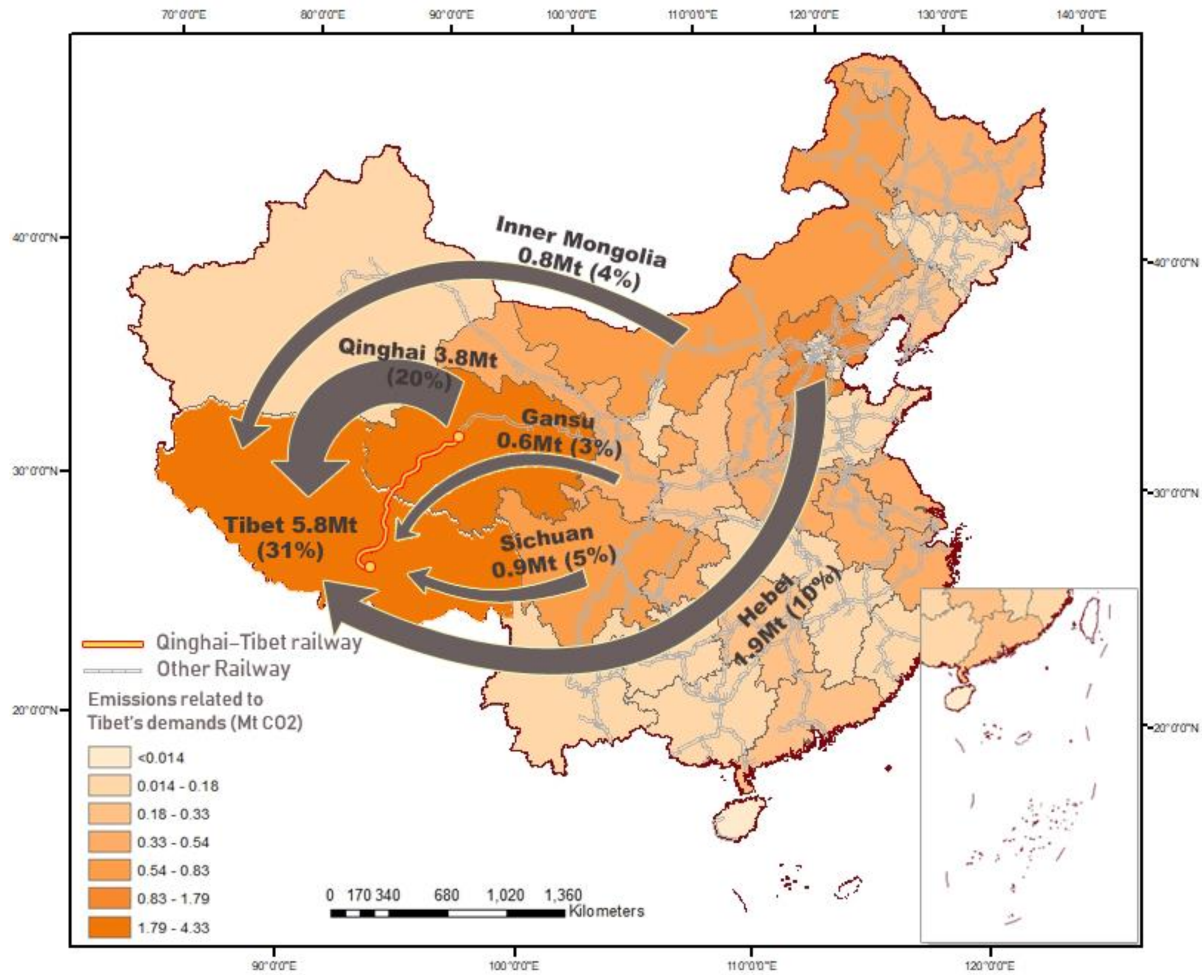

Figure 6-3 CO_2 emissions related to Tibet's demands. Percentage represents the contribution of the inflowing province to the consumption-based emission of Tibet

Some studies have noted that CO_2 emission flows began to reverse in 2012 (Mi *et al*. 2017). Some provinces in southwest China (e.g., Sichuan, Chongqing, Guizhou and Guangxi) have shifted from being net emission exporters to net emission importers. However, the provinces in northwest China (including Xinjiang, Qinghai, Inner Mongolia, Gansu, Shaanxi and Ningxia) are still net emission exporters. The aftermath of the global financial crisis and China's supply- and demand-side reforms might be the reasons leading to this change. Tibet borders provinces in both southwest and northwest China and is not included in previous studies. In this study, the consumption-based emission patterns of Tibet were more similar to those in southwest China. The consumption characteristics of Tibet in this study are additional evidence of the ongoing reversal in emission flows within China.

Such frequent interaction between Tibet and other provinces in China has been enabled by the development of the Qinghai-Tibet railway in recent years. As shown in Figure 6-3, the density of the national railway network becomes sparser from the east to west. After, 2006 Tibet was connected to the national railway network through the Qinghai-Tibet railway stretching from Lhasa in Tibet to Golmud in Qinghai. Prior to this time, only road and air transportation were available. Air transport was expensive and limited in volume. Road transport was unreliable due to the harsh geographical conditions and weather such as frequent mud and rock slides. More stable and cheaper transportation was available after the Qinghhai-Tibet Railway was put into use, which reduced the freight rate from 0.27 (road transport) to 0.12 RMB per ton (price in 2007 RMB). The volume of railway freight surged from 24.9 million tons in 2006 to 40.2 million tons in 2012, and this transportation method is responsible for 75% of the goods transported to/from Tibet.

Tibet's economy is mainly supported by agriculture, animal husbandry, forestry and services. Such an economic structure results in high dependences on a wide range of industrial products, especially those from heavy-industries such as cement, iron, steel, machinery and equipment. Specifically, non-metal mineral products, iron and steel, general and special equipment and machinery, metal products, chemical products, processed food, garments and fiber products, and paper products from other regions in China accounted for 71% of imported goods to Tibet. The supply of such products has inevitably led to more intense production activity in other provinces, especially in the regions that support Tibet the most, including Qinghai, Hebei, Inner Mongolia, Gansu and Sichuan. The production activities related to Tibet's demands were generally in energy-intense sectors. As shown in Figure 6-4, the sectors associated with Tibet's demands were the most diversified in Qinghai and included non-metal mineral products, electricity production, metal pressing and smelting, and the chemical industry. The emissions from these four sectors increased by 1.7, 1.0, 0.6 and 0.5 Mt, respectively. The emissions outsourced to Hebei were mainly related to non-metal mineral products (0.5 Mt), electricity production (0.5 Mt) and metal pressing and smelting (0.5 Mt). For Inner Mongolia, Gansu and Sichuan, electricity production and non-metal mineral products were the dominant sectors. Electricity production made up an important proportion of outsourced production activities, but Tibet did not directly import electricity from other regions. Instead, it was induced by the increased electricity demand from other production activities such as equipment and machinery manufacturing, food processing, and other products when they were produced locally and exported to Tibet afterwards.

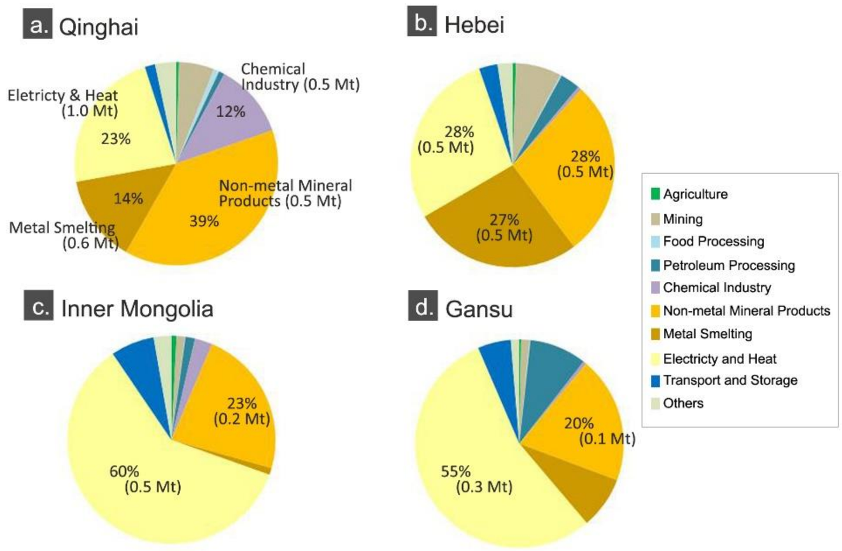

Figure 6-4 Production activity inflows from (a) Qinghai, (b) Hebei, (c) Inner Mongolia and (d) Gansu due to the demands of Tibet. The number next to each sector's name (e.g., 1.0 Mt) indicates the absolute CO_2 emissions, and the percentage represents the sectoral contribution to CO_2 emissions related to Tibet's demand in a given region.)

The outsourced sectors described above are generally the critical supporting sectors in secondary industry, but these sectors are not flourishing in Tibet due to the limitations of the local environment and natural resources. Tibet is a traditionally agriculture-based autonomous region. After the economic development of the past decade, tertiary industry is now the leading economic driver in this region and accounted for 54% of its GDP in 2012 (National Bureau of Statistics of the People's Republic of China, 2013). Industry, including non-metal mineral products, metal processing, chemical industry and others, accounted for only 8% of the annual GDP of Tibet.

6.4. Implications for Tibet's sustainable production and consumption

The ratio of consumption-based to production-based emissions of Tibet was the highest among the 31 Chinese provinces studied here. Nearly 70% of the consumption-based emissions of CO_2 of Tibet were emitted in other regions instead of in Tibet itself. If these off-site emissions were to occur locally, Tibet's local emissions would triple, increasing from 6.2 to 18.8 Mt CO_2 in a year. Considering the less advanced manufacturing technology in Tibet, these emissions would climb to 22.3 Mt, 3.6 times greater than the current emissions. Such a relocation of emissions is not as relevant for greenhouse gases that are long-lived and have environmental impacts that are not sensitive to emission location, such as CO_2. However, for short-lived air pollutants and air toxics, such as sulphur dioxide, nitrogen oxides, VOCs, and heavy metals, the emission location greatly determines the harm to ecosystems and human health (Lin *et al.*, 2014; Jiang *et al.*, 2015; Huo *et al.*, 2017). Given that air pollutants and CO_2 have large overlaps in their emissions sources from fossil fuel combustion (Cifuentes *et al.*, 2001; West *et al.*, 2013; Schmale *et al.*, 2014), the consumption-based characteristics observed in this study are also applicable to air pollutants. If off-site emissions occurred locally in Tibet, the fragile environment would experience catastrophic damage. Further study on how the consumption patterns and virtual transport of emissions affect the local and national environment should be carried out.

As inter-regional interactions are expected to become more frequent under the development of western China, the design of a more sustainable consumption pathway for Tibet is crucial. The inter-regional interactions observed in this study are enabled by the transformation of the transportation system in the northwest China in recent years. The transportation infrastructure is expected to be steadily upgraded in the coming decade under China's plan to develop the northwest and the Belt and Road Initiative. Previous studies have defined two criteria for regions within "Goldemberg's Corner," namely, per capita carbon emissions (consumption-based perspective) of less than one tonne C per year and a life expectancy of over 70 years (Steinberger *et al*., 2012; Steinberger and Roberts 2010; Lamb *et al*., 2014). Regions within Goldemberg's Corner represent a sustainable lifestyle with a good balance of environmental conservation and human welfare. Tibet exhibits the opposite trend with a high carbon footprint and a low life expectancy. The per capita carbon emissions in Tibet were 1.74 tonne C in 2012, and the average life expectancy was 67.8 years. The carbon footprint of Tibet ranked 3rd highest among the 31 Chinese provinces studied here after Tianjin and Shanghai. However, the life expectancies of Tianjin and Shanghai were 75.4 and 72.3 years, respectively (see Figure 6-5). The geographical and meteorological constraints would be one reason for the lower life expectancy in Tibet. Thin oxygen, strong solar radiation and frequent extreme weather are prone to shorten life expectancy. Underdeveloped medical care and other economic factors are also contributing. From the perspective of consumption, the high carbon footprint suggests more can be done to benefit both human welfare and environmental concerns. The high proportion of red meat in Tibet's dietary structure, for example, shortens human life expectancy and leads to high carbon and air pollutant emissions. Under the quickly developing transportation system, opportunities to change the consumption patterns are emerging with easier access of healthier and more environmentally friendly products. In addition, substantial consumption-based emissions are associated with construction, whose emission intensity is generally high. Tibet needs to diversify the local economy towards low carbon development in the long run.

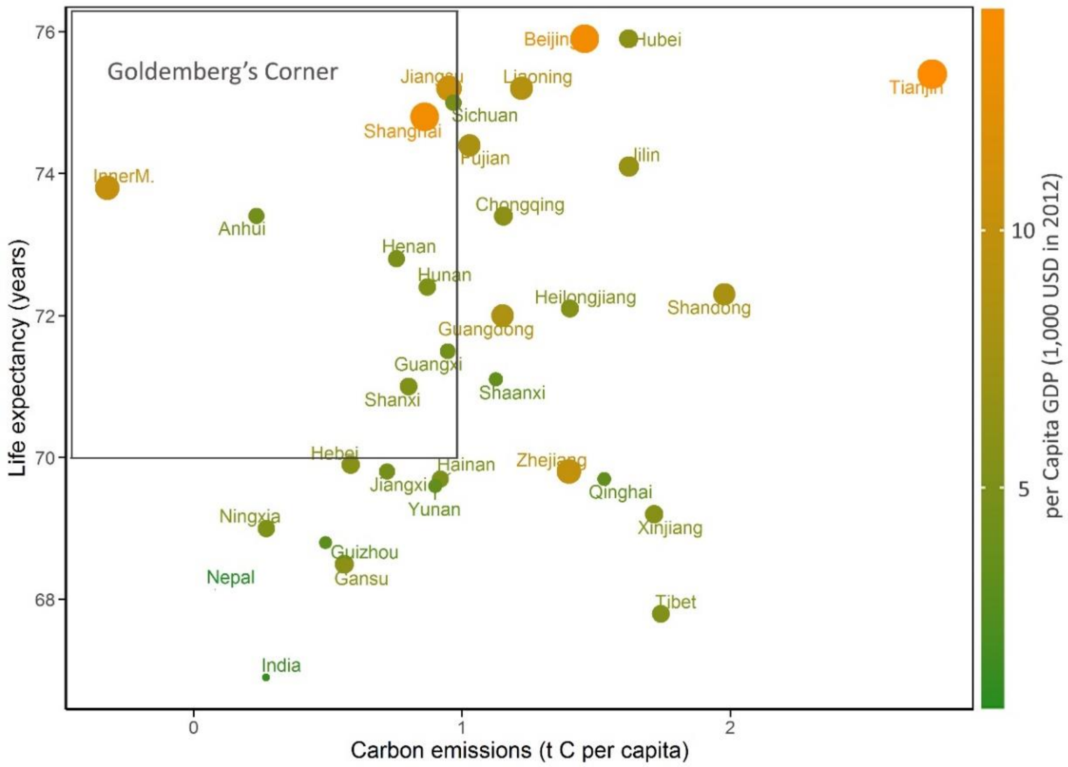

Figure 6-5 Carbon footprint and life expectancy of 31 provinces in China, India and Nepal. The rectangle at the upper left represents the "Goldemberg's Corner", in which per capita carbon emission (consumption-based perspective) is less than one tonne C per year and life expectancy is over 70 years (Steinberger *et al*., 2012; Steinberger and Roberts 2010; Lamb *et al*., 2014). Countries with "Goldemberg's Corner" are generally considered as representations of sustainable lifestyle with a good balance of both environmental conservation (as reflected by per capita carbon emission) and human welfare (as reflected by life expectancy). Tibet was located at the lower right corner, which indicates the opposite representation of "Goldemberg's Corner". In other words, per capita carbon emission in Tibet was high and the life expectancy was low.

6.5. Summary

Located in the most western part of China and as the world's highest plateau known as Qinghai-Tibet Plateau, Tibet plays a unique role in the global ecosystem and climate. Nevertheless, Tibet is usually missing from China's emission accounts, especially from those of consumption-based emissions. This Chapter presents the first consumption-based estimation of Tibet's emissions. Though Tibet's emissions might be low compared to the total emissions of China (0.2% of the national total from the consumption perspective), such knowledge is indispensable in understanding the environmental issues in Tibet. Results show that the consumption-based CO_2 emissions in Tibet (18.8 Mt, similar to Guinea's emissions in 2015) were three times as high as the production-based estimate (6.2 Mt). Tibet displays unique emission patterns with the highest ratio of consumption- to production-based emissions in China, which are more similar to the east developed provinces rather than its counterparts in west China. More than half of Tibet's consumption-based emissions are supported by Qinghai, Hebei, Sichuan and others, enabled by the Qinghai-Tibet railway that connected Tibet to China's national railway system. High carbon footprint but low life expectancy is found in Tibet, suggesting the emerging need of a more sustainable consumption pathway under the intensifying interregional connections.

Due to the limited data source, a quantitative estimation on the uncertainty of Tibet's consumption-based emission is unavailable. Nevertheless, it is expected that the uncertainty of Tibet's consumption-based carbon account would be much higher than China's national metrics. A recent study found that Chinese national data is one of the largest contributors to the uncertainty of global consumption-based carbon account with a coefficient of variation of 9.07% (Rodrigues *et al.*, 2018). Another consensus is that consumption-based emission is associated with higher uncertainty than the production-based metrics since more data transformation are involved (Owen *et al.*, 2014; Sato, 2014). According to the estimation by Shan *et al*. (2018), the uncertainties of China's provincial CO_2 emission were roughly (-15%, 25%) at a 97.5% confidence interval. Given the poorer data quality of activity level data and emission factors, the uncertainty of Tibet's consumption-based emission estimation would be higher than the above mentioned range. More efforts are needed to measure the uncertainty of consumption-based account to prioritize uncertainty reduction efforts.

Chapter 7 Integrated assessment on ground-level ozone pollution in China and its mitigation

This Chapter presents a national case study on energy, pollution and socioeconomic integrated assessment using the proposed framework in Figure 1-9. It tackles the rising ground-level O_3 problem in China with special focus on export industries. The primary energy consumption matrix supports the development of production- and consumption-based emission inventories for O_3 precursors: NMVOCs, NOx and CO. Since the production-based emission characteristics have been studied extensively, the focus of Section 7.1 is on the consumption-based emissions of O_3 precursors. Contributions from final demands, i.e., rural and urban consumption, governmental consumption, capital formation and export, to precursors' emissions are estimated. Given the non-linear relationship between O_3 and its precursors, contributions to precursors' emissions are not necessarily the same as those to the ambient O_3 level. Hence, input-output analysis was combined with an air quality model to quantify the ambient O_3 level associated with different demands. Among these final demands, export represents the exogenous driving force, while the others are domestic. In Section 7.2, scenarios with and without export-driven emissions were constructed to study the contributions from exogenous and domestic driving forces. In Section 7.3, a possible mitigation pathway was explored by comparing the emission intensities in China and 28 European countries (EU28). Mitigation potentials were measured in terms of precursor emissions, footprint, and ambient O_3 level reduction. Section 7.4 discusses the implications for further O_3 pollution mitigation in China, from the perspectives of production and consumption. Section 7.5 closes this Chapter with a summary of key findings and limitations.

7.1. Net emissions by provinces

Contribution patterns to the total emissions can be relatively different from the production- and consumption-based perspectives, as observed in Chapter 5 and 6. One of the key questions after the development of consumption-based emission inventories, therefore, is how the consumption-based contributors vary from those from production-based accounting. In China, environmental polices such as total emission caps are based upon production-based emissions. It is beneficial to understand if the consumption-based contributors are different from those production-based emitters that are targeted in policy formulation.

The net of consumption- and production-based emissions of a province defines its role as a "production-based" or "consumption-based" province (Mi *et al.*, 2016). If its production-based emissions exceed its consumption-based emissions, this province is "production-based" as its local emissions are not only emitted to satisfy its own demands but also to support other provinces. By contrast, for a "consumption-based" province, its consumption-based emissions surpass its production-based emissions, indicating that demand of this province has overflowed and increased the emissions in other provinces. Figure 7-1 shows the net emissions by provinces. Due to the variations in emission sources, the roles of provinces in terms of NMVOCs emissions were different from those of NOx and CO emissions. Regarding NMVOCs, provinces with the highest net consumption-based emissions were Beijing, Jilin, Hunan, Guangdong and Yunnan. The production-based provinces of NMVOCs, on the other hand, were Jiangsu, Zhejiang, Fujian, Hebei and Shandong. These provinces are quintessential light industries hubs in China, which produce and send out huge amount of industrial goods. With respect to NOx and CO, the production-based provinces were typically the energy suppliers such as Hebei, Shanxi, and Inner Mongolia.

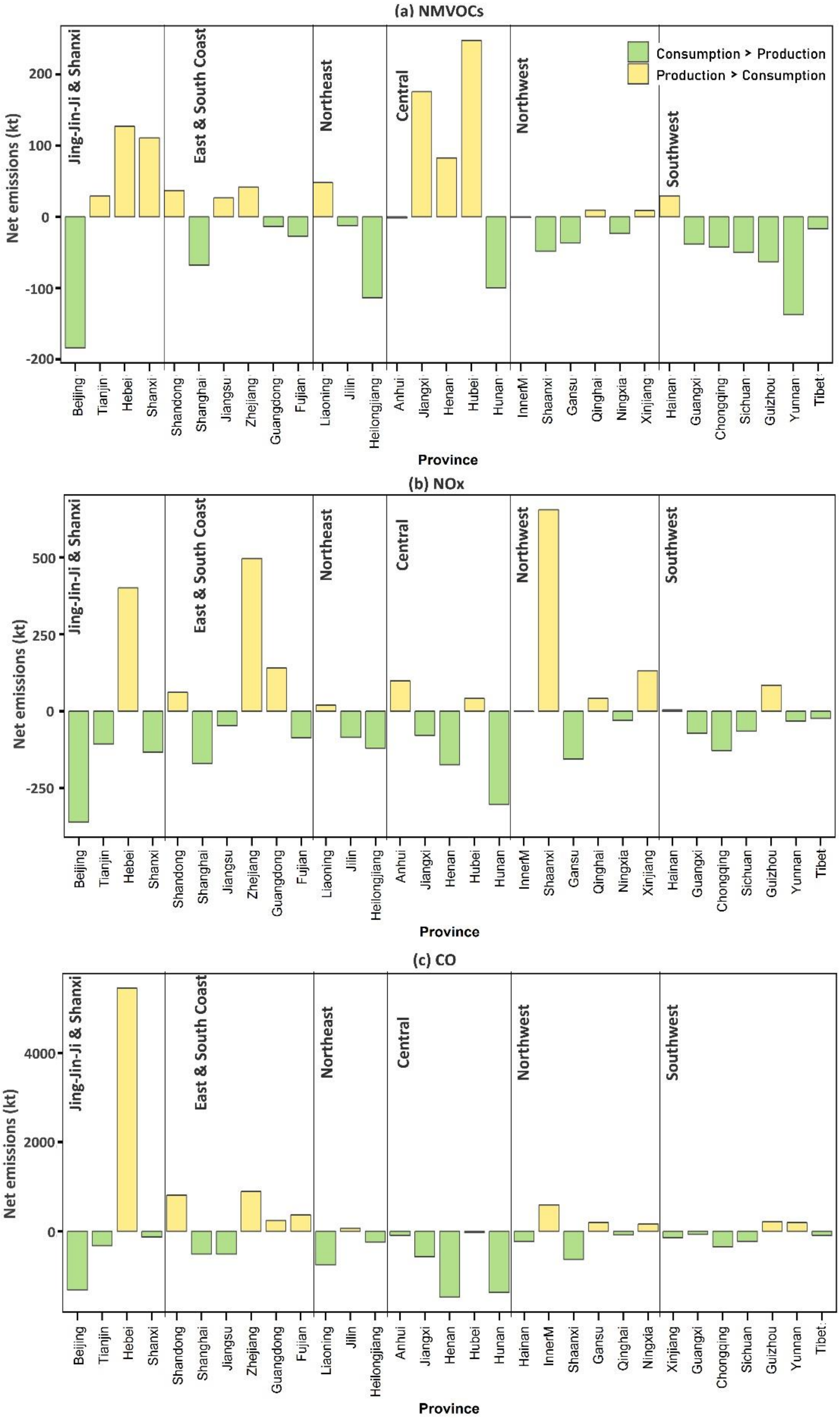

Figure 7-1 NMVOCs, NOx and CO net emissions by province. The net emission shows the difference between production- and consumption-based emissions.

Though provinces had different roles in production and consumption, the provincial contributions did not change significantly from these two perspectives. Table 7-1 displays the production- and consumption-based emissions and relative contributions by provinces. Despite the absolute differences in production- and consumption-based emissions, the relative contributions to total emissions were generally stable. The top 10 contributors to production-based NMVOCs emissions, for example, made up 59% of the total emission budget. They were also the top contributors to the consumption-based emissions, which together accounted for 53% of the consumption-based emissions. Only a few exceptions were found for Beijing and Fujian. In terms of production, Beijing contributed only 1% of the national emissions. From consumption, its demands drove 4% of NMVOCs emissions. By contrast, the contribution from Fujian to production-based emissions (4%) was double its consumption-based contribution (2%). To sum up, the contributors from consumption-based perspective generally overlap with those from production. Current polices do not overlook any major emitters but might need to address not only the local production activities but also demand-side guidance and transitions.

Table 7-1 Production- and consumption-based emissions and relative contributions by provinces

	NMVOCs				NOx				CO			
Province	**Production-based**		**Consumption-based**		**Production-based**		**Consumption-based**		**Production-based**		**Consumption-based**	
Beijing	286	1%	962	4%	226	1%	1610	6%	1079	1%	3574	2%
Tianjin	560	2%	574	2%	520	2%	685	2%	2354	2%	2911	2%
Hebei	1544	6%	1480	6%	2537	9%	2300	8%	18175	12%	14201	9%
Shandong	2515	9%	2207	9%	2590	9%	2647	9%	13442	9%	13002	9%
Liaoning	1135	4%	1063	4%	1472	5%	1846	6%	7475	5%	6803	4%
Jilin	603	2%	675	3%	621	2%	910	3%	4363	3%	5456	4%
Heilongjiang	1125	4%	1096	4%	849	3%	874	3%	6171	4%	6634	4%
Shanxi	747	3%	741	3%	1440	5%	827	3%	6999	5%	5649	4%
Anhui	903	3%	888	4%	984	3%	831	3%	5491	4%	4989	3%
Jiangxi	594	2%	615	2%	552	2%	665	2%	3797	2%	3415	2%
Henan	1591	6%	1592	6%	1751	6%	1648	6%	9578	6%	9947	7%
Hubei	939	4%	900	4%	942	3%	1049	4%	6075	4%	5855	4%
Hunan	826	3%	931	4%	764	3%	990	3%	5670	4%	6036	4%
Shanghai	599	2%	482	2%	788	3%	506	2%	1859	1%	1689	1%
Jiangsu	2047	8%	1509	6%	1827	6%	1802	6%	9175	6%	8948	6%
Zhejiang	1772	7%	1137	5%	1175	4%	1164	4%	3513	2%	4775	3%
Fujian	964	4%	615	2%	614	2%	457	2%	2216	1%	2059	1%
Guangdong	1979	7%	1550	6%	1615	6%	1412	5%	6115	4%	6359	4%
Hainan	132	0%	138	1%	152	1%	214	1%	443	0%	914	1%
Inner Mongolia	708	3%	831	3%	1847	6%	878	3%	6520	4%	5272	3%
Shaanxi	638	2%	647	3%	813	3%	858	3%	3747	2%	4010	3%
Gansu	411	2%	404	2%	450	2%	388	1%	2942	2%	2668	2%
Qinghai	83	0%	107	0%	104	0%	151	1%	654	0%	839	1%

Continued on next page

Table 7-2 Production- and consumption-based emissions and relative contributions by provinces (Continued)

	NMVOCs				NOx				CO			
Province	Production-based		Consumption-based		Production-based		Consumption-based		Production-based		Consumption-based	
Ningxia	145	1%	139	1%	430	1%	282	1%	1058	1%	906	1%
Xinjiang	603	2%	563	2%	815	3%	754	3%	3814	2%	3836	3%
Guangxi	683	3%	705	3%	615	2%	705	2%	3749	2%	3782	2%
Chongqing	436	2%	460	2%	444	2%	592	2%	2477	2%	2888	2%
Sichuan	1019	4%	1043	4%	836	3%	844	3%	6219	4%	6118	4%
Guizhou	307	1%	370	1%	567	2%	487	2%	3286	2%	2983	2%
Yunnan	541	2%	680	3%	714	2%	742	3%	4751	3%	4425	3%
Tibet	63	0%	78	0%	62	0%	85	0%	582	0%	667	0%

7.2. Emissions driven by final demands

This section deconstructs the demands behind production-based emissions. In every province, the demands driven local production activities are shown in Figure 7-2. Capital formation was the single largest demand driving the emissions within China, which accounted for 30%, 43% and 36% of the NMVOCs, NOx and CO emissions, respectively. Urban consumption was the second largest driver, responsible for 27%, 22% and 20% of the emissions. Contributions from rural consumption were 24% for NMVOCs, 11% for NOx and 30% for CO. Contributions from export were 13% and 10% for NMVOCs and CO, respectively, which were around half of those from rural consumption. As for NOx emissions, export made up 15% of the emissions, which was even higher than that from rural consumption. The emissions caused by the demand of international market were indeed comparable to the emissions triggered by 564 million rural population in China.

As the world's largest exporter for a lot of NMVOCs-relevant products, the contributions from export industries to domestic emissions were not as high as expected. This is due to the fact that a substantial amount of NMVOCs (~30%) comes from direct emissions (not relevant to trade) such as household solvents and biomass burning. Nevertheless, if such a relative contribution was translated into absolute number, export elevated the anthropogenic emissions of NMVOCs by 3478 kt in 2013. If such emissions were considered from a single country, it can be ranked as the 10th largest NMVOCs emitter in the world (Huang *et al.*, 2017), or be half the emissions of 28 European countries (EU-28) (European Environment Agency, 2019).

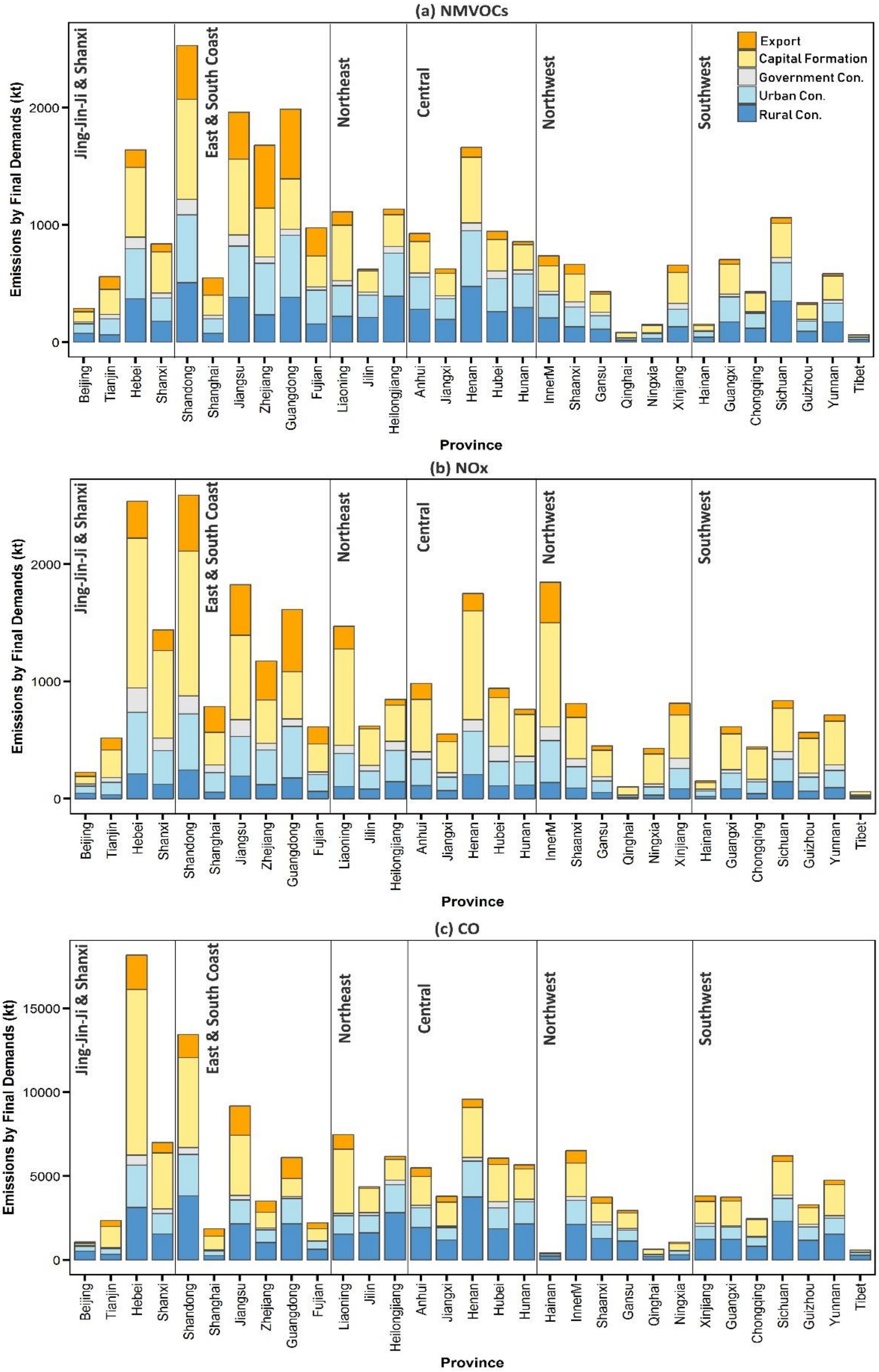

Figure 7-2 NMVOCs, NOx and CO provincial emissions by final demands.

In addition, China's export industries are concentrated along the east and south coast as shown in Figure 7-3. Shandong, Yangtze River Delta (YRD), Guangdong and Fujian together made up 65% of China export-related GDP in 2013 (Figure 7-3). The impacts of export were highlighted in these areas. Around 18~26% NMVOCs emissions from human activities in these areas were indeed associated with demand for export rather than local or domestic demand.

From the perspective of NOx emissions, 15% of the national emissions were related to export. The contributions of export stood out not only in the east and south coastal areas but also some inland provinces such as Inner Mongolia, Hebei and Shanxi. Export-related emission accounted for 18~33% of the NOx emissions in the above four areas. In addition, they were responsible for 19%, 12% and 12% of the NOx budgets in Inner Mongolia, Hebei and Shanxi, respectively. This is due to the NOx emissions from power and other heavy industry sectors to support the production of export commodities.

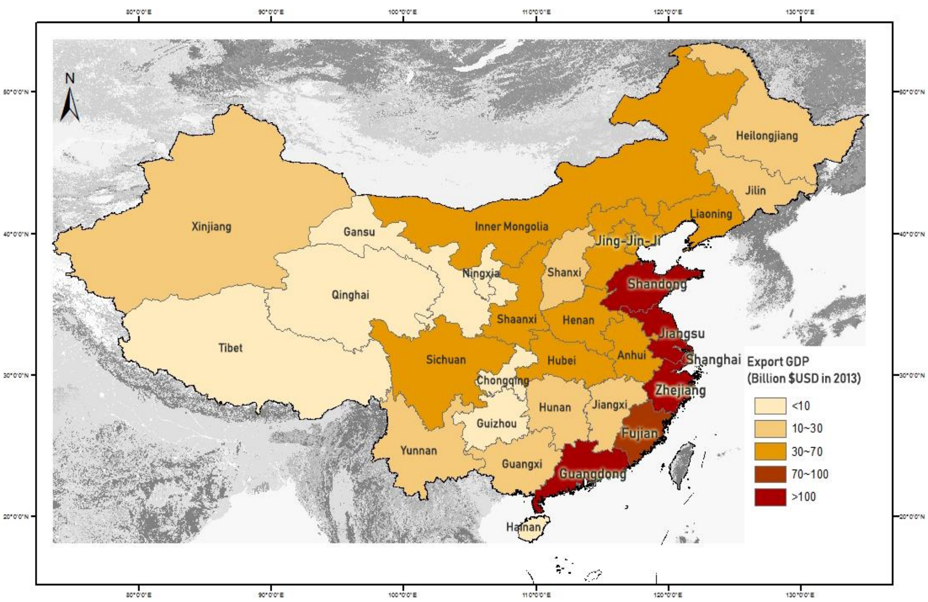

Figure 7-3 GDP of export by provinces in 2013.

The conjunction of China's MRIO table with GTAP enables one to track down destinations of China's export goods. China exports goods to 140 countries but the United States (US) alone accounted for 23% NMVOCs emissions relevant to export (as shown in Figure 7-4). Demand from the US accounted for 20% and 19% of the

NOx and CO emissions embodied in export, respectively. Contributions from Western Europe were neck and neck to those from North America, which explained 22%, 22% and 21% of export-related emissions.

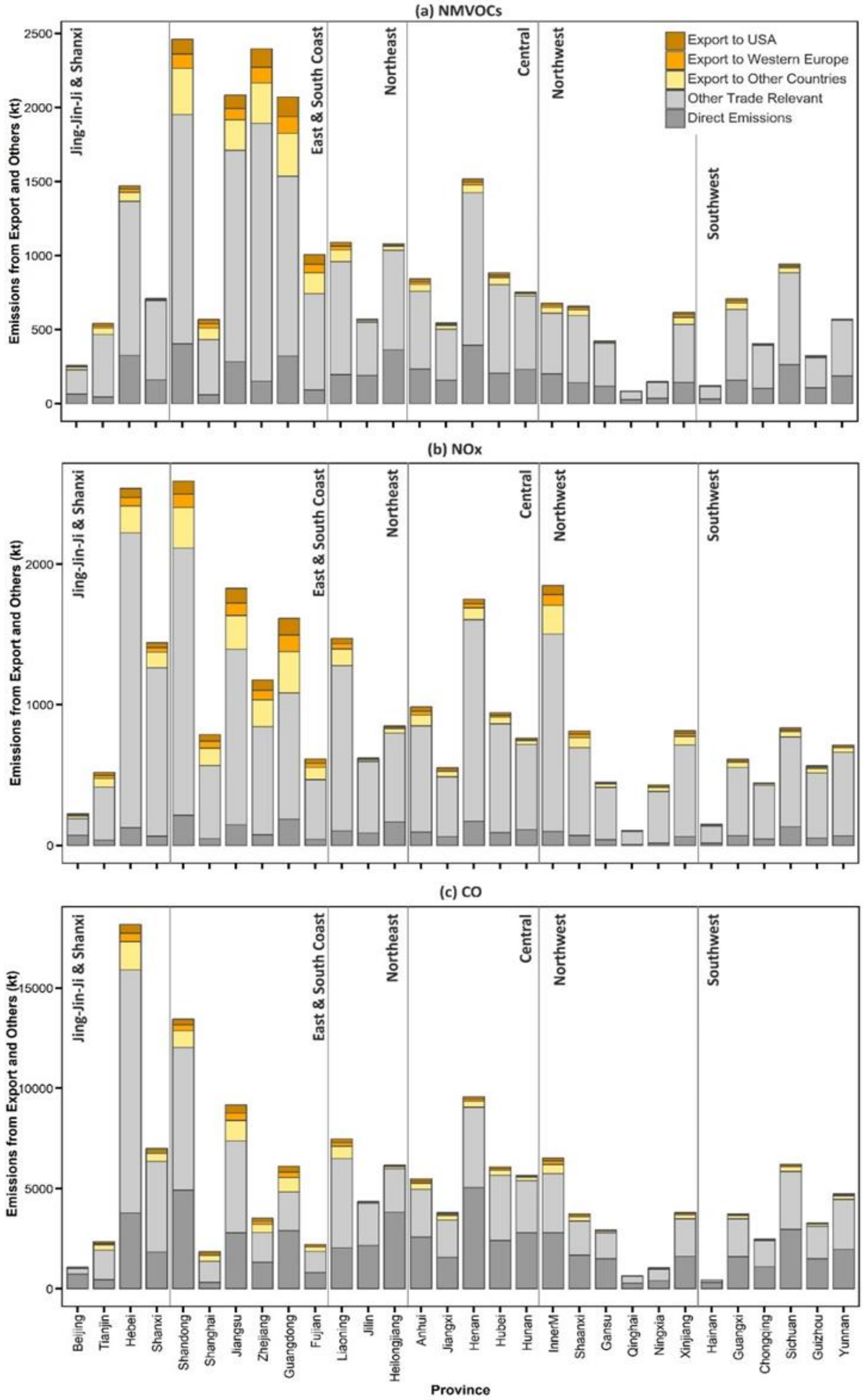

Figure 7-4 Export-driven emissions by destinations. For NMVOCs emissions (a), Export-driven emissions stood out in the east and south coast, e.g., Shandong, Jiangsu, Zhejiang and Guangdong. Demands from the USA and western Europe explained nearly half the export-relevant emissions. As for NOx emissions (b), export contributed to 15% national sum of

NOx emissions. Export embodied emissions were notable in the east and south coast as well as other inland provinces such as Inner Mongolia and Hebei. Regarding CO emissions in (c), about 10% CO emissions in China were driven by export. Impacts of export were highlighted in Hebei, Shandong and Jiangsu.

7.3. Scenario constructions

To understand the exact impact of different demands on O_3 concentrations in China, sscenarios were constructed in an air quality modelling platform. As shown in Figure 7-5, a base case and 4 scenarios were constructed. The differences between different bases were emission inputs. For the base case, air pollutant emissions of NOx, NMVOCs and CO for the year of 2013 were adopted, which represented the 'true' emissions (emissions in reality under the best knowledge) in 2013. Case 1 to 4 used reconstructed emissions under different assumptions. Two months representing the typical high O_3 values in the north China (i.e., July) and the south China (i.e., October) were selected for analysis.

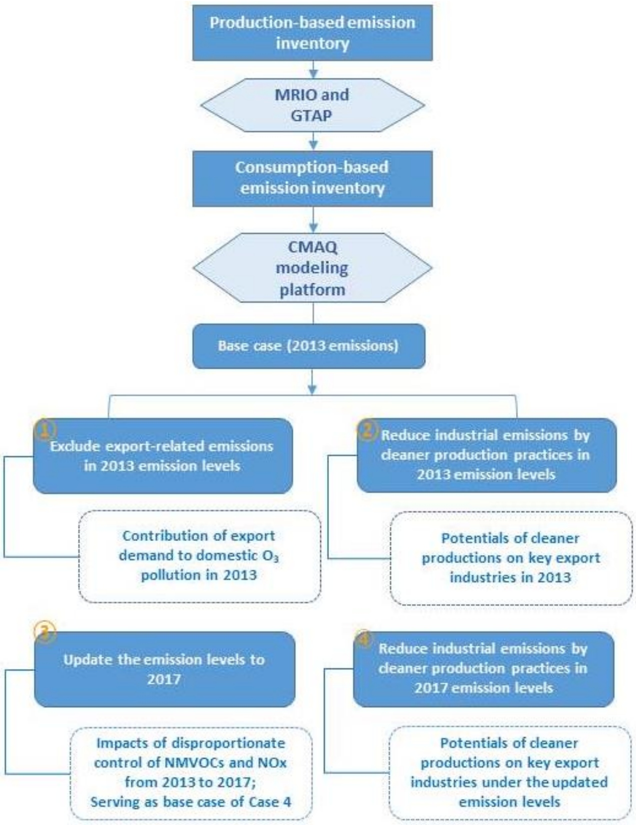

Figure 7-5 Design of scenarios. Emission inputs were the key differences between different cases. Their emissions and reasons for such settings are elaborated in the main text.

For Case 1, NOx, NMVOCs, and CO emissions relevant to export demands were excluded. By comparing the modelling results from base case and Case 1, the contribution of export-driven emissions on O_3 concentration can be revealed.

For Case 2, industrial emissions of NMVOCs were reduced by certain percentages. The percentages were sector-specific, according to the reduction potentials. The sectoral NMVOCs emission intensities in China were compared to those in the EU28 as estimated in the GAINS model (Amann *et al.*, 2011) and determined the reduction percentages by sectors. Results of the comparison were discussed in Section 7.4.1. Emission inputs in Case 2 reflected the NMVOCs emission reduction potentials from industrial sectors under such cleaner production practices. By comparing the results of base case and Case 2, the effectiveness of cleaner production on O_3 pollution control was estimated. It should be noted that only NMVOCs emission reduction potentials were explored here. This is due to the fact that NMVOCs emission control measures are still lacking in China while emissions of other pollutants have seen significant decreased.

Regarding Case 3, it was developed to understand the impacts of disproportional control of NMVOCs and NOx in China from 2013 to 2017 on O_3 concentrations and served as base case of Case 4. As a consequence of China's clear air actions aiming at $PM_{2.5}$ and end-of-pipe treatments in the energy sectors, NOx emissions had decreased by 21% from 2013 to 2017 while NMVOCs still grew persistently (+2%). It is suspected that such uncoordinated control would result in recent increase of O_3. In Case 3, emissions of NMVOCs, NOx and CO had been updated to the levels of 2017.

Case 4 was then constructed to test if the cleaner production measures from the industrial sectors were still effective under the emission levels in 2017. Given the chemistry of O_3 formation, the disproportional control of NMVOCs and NOx from 2013 to 2017 might affect the effectiveness of future control strategies. The effectiveness of cleaner production measures in Case 2 might have been altered. Sectoral reduction percentages in Case 2 were considered under the emission levels in 2017 in Case 4. Results of the above cases are discussed in the following sections.

7.4. Impacts from export: Ozone chemistry, concentration and premature mortality

This section discussed the impact from export demands, which were based upon the results of base case and Case 1. Serving as an entry point to understand the O_3 pollution problem from the consumption-based perspective, the impacts from exogenous and domestic demands were studied. Here, emphasis was placed on the export demand as it was related to the mitigation strategies explored in Section 7.5. It is true that more studies to investigate the mitigation potentials and strategies from capital formation, rural and urban consumption are also needed.

As mentioned above, there exist a non-linear relationship between O_3 concentration and the emissions of NMVOCs, NOx and CO. Such a non-linearity refers to two different regimes: NOx- and NMVOC-limited (Jacob, 2000; Li *et al.*, 2015; Fujita *et al.*, 2016). Under the NOx-limited regime, the NMVOCs/NOx ratio in the atmosphere is generally higher (characteristics of rural areas and of suburbs); and lowering NOx concentrations either at constant NMVOCs concentration or in conjunction with lowering VOCs results in lower peak concentrations of O_3. For the NMVOCs- limited regime, the NMVOCs/NOx ratio in the atmosphere is lower with ample supply of NOx (characteristics of some highly polluted urban and industrial areas); Lowering NMVOCs at constant NOx results in lower peak O_3 concentration, but lowering NOx at constant NMVOCs will result in increased O_3. The NMVOCs/NOx emission ratios are crucial to determine the O_3 regime and consequently, the control strategies on its precursors' emissions.

The demand of export might not only change the magnitude of precursor emissions, but also the ratio between NMVOCs and NOx, and subsequently, the chemistry of O_3 formation. Here, it was found that export did alert the emission ratios between NMVOCs and NOx differently across the country, but the impact was not significant. As shown in Figure 7-6a, the demand of export was generally associated with more NMVOCs emission in the east and south coastal areas but more NOx emissions in the northern and inland provinces. This is due to the emission characteristics of NMVOCs and NOx and the industry layout of China. In addition to common sources such as transportation, NOx emissions are generally from fossil fuel combustion from the energy-intensive and heavy industrial sectors, while NMVOCs emissions are emitted from miscellaneous non-combustion processes of light industries. As light industries thrive in the east and south coast but heavy industries in the northern and inland provinces, the NMVOCs emissions from export in coastal provinces generally outweighed those of NOx emissions, and vice versa for northern and inland provinces. Nevertheless, the export-relevant emissions were still dwarfed by the emissions from domestic demands within China. As a result, the overall NMVOCs to NOx emission ratio did not change significantly. Nationally, export emissions have decreased the NMVOCs to NOx ratio from 0.94 to 0.91. The decrease was more notable in most O_3 hotspots in China such as the Jing-Jin-Ji, Shanxi, Guangdong and Jiangsu (Figure 7-6. It suggests that demand of export have slightly increased the sensitivity of O_3 formation to NMVOCs emissions ('more NMVOCs-limited'). Under such a NMVOCs-intensified chemistry, a rebound[2] of O_3 would be expected if NOx was reduced without conjunct reduction of NMVOCs, which was the case of China's clean air actions from 2010 to 2017 (Zheng *et al.*, 2018a; Li *et al.*, 2018c).

[2] A rebound here indicates the undesirable increase of O_3 under NMVOCs-limited regime (characteristics of some highly polluted urban and industrial areas). Under such a regime, lowering NMVOCs at constant NOx results in lower peak O_3 concentration, but lowering NOx at constant NMVOCs will result in increased O_3. More details on the NMVOCs-NOx-O_3 chemistry can refer to Chapter 1.4.

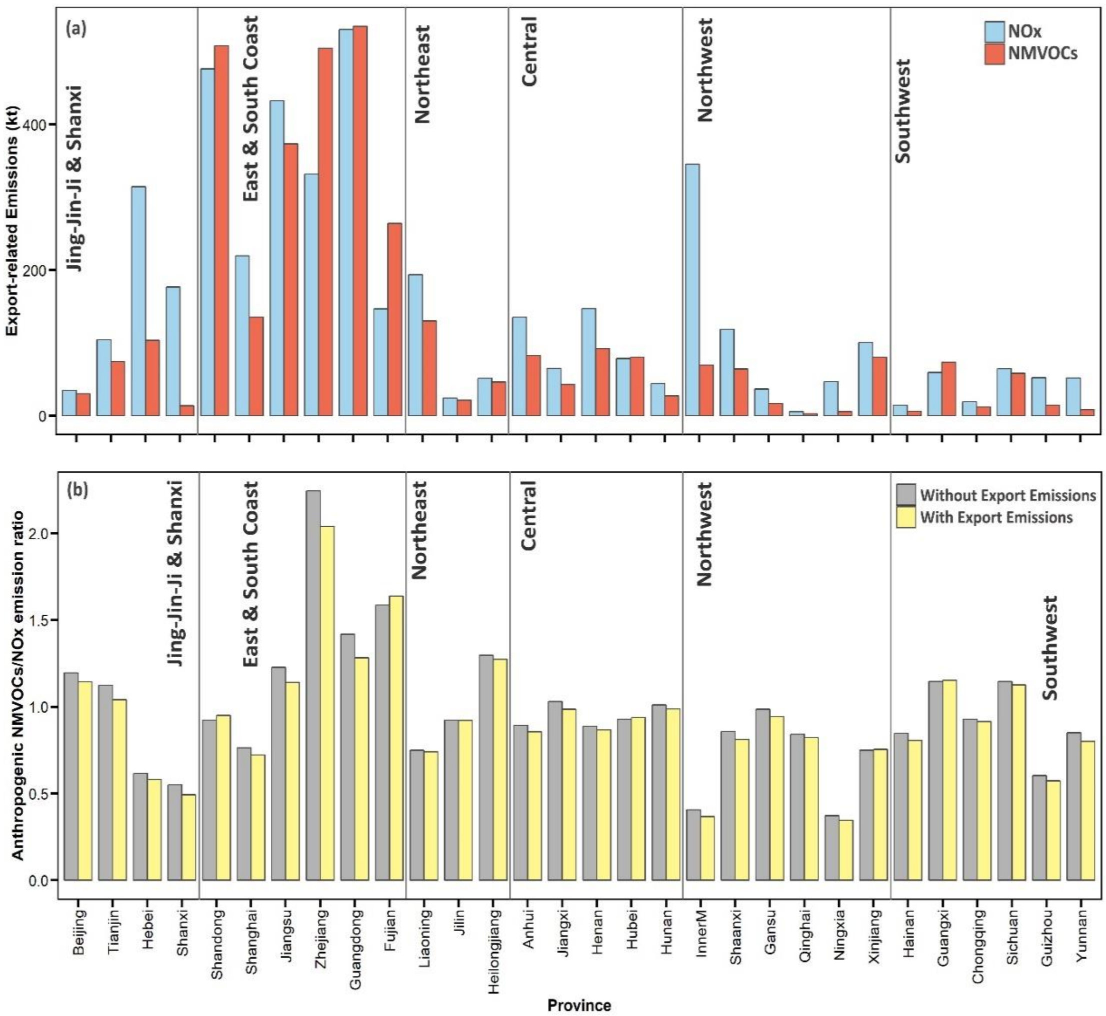

Figure 7-6 Relative emissions of NMVOCs and NOx alerted by export demand. a, Absolute value of NOx (in blue) and NMVOCs (in red) related to export demand by provinces. b, Ratio between anthropogenic NMVOCs to NOx emissions with (in yellow) and without (in grey) export demands. The ratio slightly decreased for the whole nation. Decreases were more notable in most east and southern coastal provinces with intensive export-driven NMVOCs emissions.

Comparing to base case, results of Case 1 indicate that export-related emissions had mixed effects on the O_3 formation due to the varying NMVOCs/NOx emission ratios and change of O_3 chemistry in different seasons. In July, the impact from export was consistent across the country (Figure 7-7a). Demand from export had elevated the peak O_3 level (daily max 1h concentration) in Shandong, YRD, Guangdong and Fujian by 6~10 μg/m^3, accounting for 6~20% of the peak O_3 level by anthropogenic causes. The Jing-Jin-Ji region, although not an export industry hub, also suffered from notable elevation of O_3 (+6 μg/m^3). In October, the impact of export-related emissions varied. Similar increases of O_3 were observed in southern China (Figure 7-7b). In the vast areas north to the Yangtze River Delta, instead of an increase, export-related emissions inhibited the O_3 peak by 1~3 μg/m^3. Inhibition from export emissions were most notable around the Jing-Jin-Ji area (3~5 μg/m^3).

The mixed effect in October is mainly explained by the intensification of NMVOCs-limited chemistry in the northern China due to the changes of biogenic NMVOCs emissions and export emissions. In most urban areas of China such as Jing-Jin-Ji, the formation of O_3 is governed by NMVOCs-limited regime (Wang *et al.*, 2006b, 2010b; Han *et al.*, 2008; Ou *et al.*, 2016; Zhang *et al.*, 2016b; Zheng *et al.*, 2017). Such a regime is characterized by low NMVOCs/NOx emission ratio. As the temperature dropped from July to October, biogenic NMVOCs emissions declined and led to even lower NMVOCs/NOx emission ratio in October. This is especially true for the northern provinces where temperature dropped more significantly than that in the south. On top of this, the demand of exports had pumped more NOx than NMVOCs emissions in the atmosphere (as discussed in the last section). When excluding the export-relevant emissions, O_3 would increase as shown in Figure 7-7b.

In this sense, emissions from export demand helped alleviate the O_3 pollution in October in the vast northern China. Nevertheless, October is not the typical O_3 high season for the north China. Considering the peak O_3 that poses threat to human health (>100 μg/m^3 for 8h mean (WHO, 2005)), the impact of export-relevant emissions is generally negative. It was estimated that an annualized premature death from respiratory disease attributable to export emissions was 4615 (1514 ~ 7600; 95% confidence interval). It accounted to 5% of the national death toll from respiratory disease relevant to ambient O_3 pollution (Liu *et al.*, 2018b).

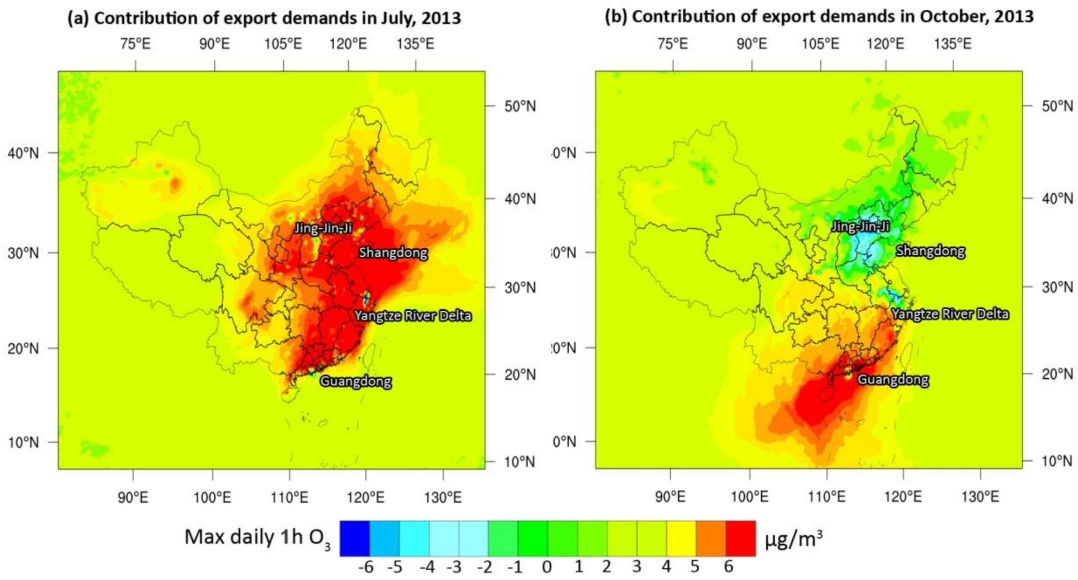

Figure 7-7 Contributions of export demands to O_3 concentrations in (a) July and (b) October, 2013. O_3 concentrations in base case were subtracted from those in Case 1 (O_3 in Case 1 − O_3 in base case). Export demand had mixed effects on the peak O_3 concentration. It contributed to the increases of O_3 concentrations in most areas of China in July. In October, it elevated the O_3 concentration in south China but inhibited O_3 formation in the north China plain. More details refer to discussion in Section 7.4.

7.5. Closing the gap in emission intensity: Mitigation potentials and cost

7.5.1. Mapping the emission intensity in China and EU28

The adverse impact from export activities can be potentially eased by either decreasing the quantity of export goods or cutting down the emissions emitted per unit of goods ('emission intensity'). The on-going US-China trade war overshadows the future of China's export industries. While it is hard to predict how the export industries will develop, effort from the homeland to promote cleaner production is always necessary. Here, the NMVOCs emission levels per unit of goods produced in China were compared with those in the EU28 as estimated in the GAINS model (Amann *et al.*, 2011). For most industrial sectors, the emission intensities in China around 2013 were comparable to the upper bound of the EU28 around 2000, as shown in Figure 7-8 a-e. Following the experience in EU28, NMVOCs levels can be substantially cut down with proven and affordable technologies (Amann *et al.*, 2018). For example, it has been shown that implementation of improved management practices in degreasing sector could lead to 41% lower emissions while more advanced techniques such as the combination of sealed degreasers, hydrofluorocarbon solvents and activated carbon adsorption can reduce emissions by well over 90%. For a few sectors such as petroleum refineries and rubber tyre production, emission levels in China are systematically higher than those in the EU28. This might be attributed to the different compositions of products or poorer management along the production line that leads to higher NMVOCs emissions.

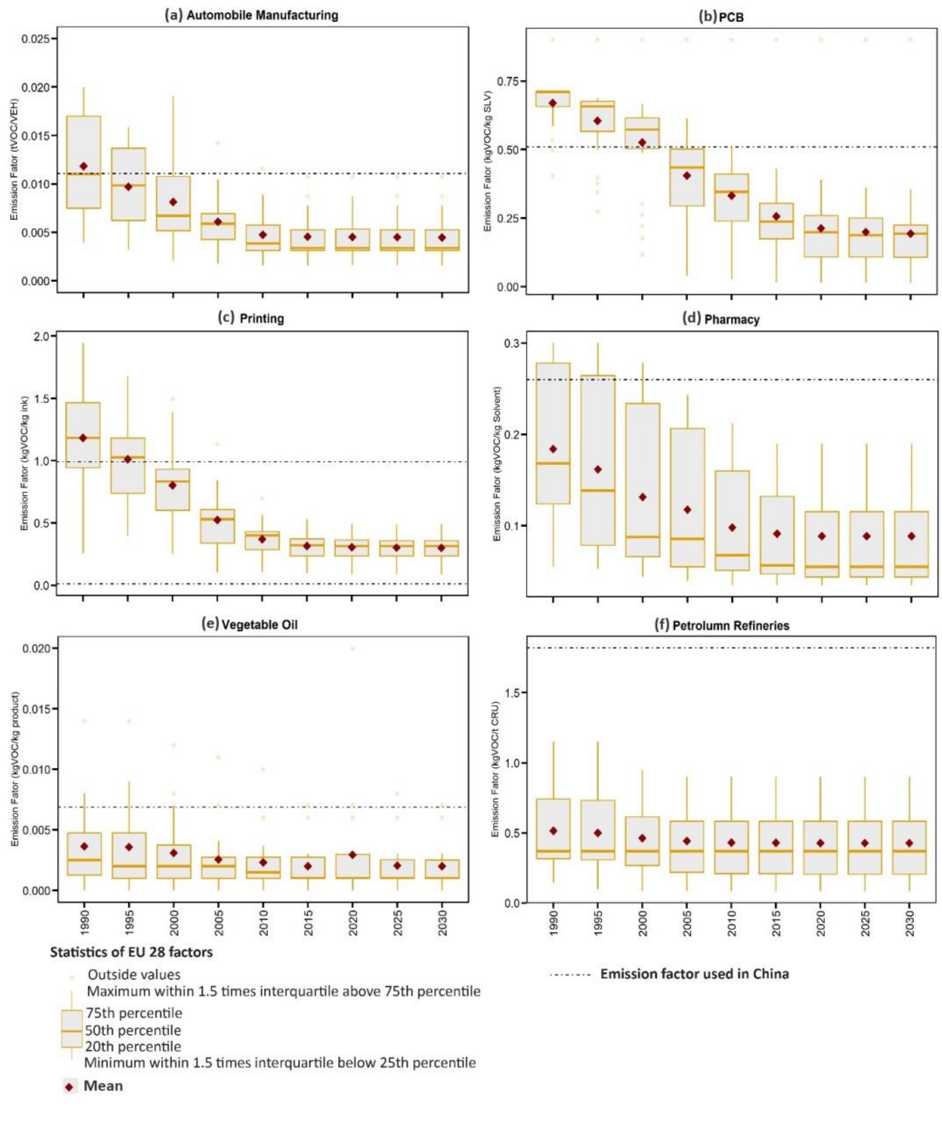

Figure 7-8 NMVOCs emission intensities for China and EU28. Box plots represent the distribution of European levels in every five years from 1990 to 2030. Dotted line denotes the level of China in 2013. Intensities of China fall within the range of EU 28 for most sectors, e.g., a, automobile manufacturing, b, PCB, c, printing, d, pharmacy and e, vegetable oil. For (f), petroleum refineries, intensities in China was systematically higher than in Europe. To evaluate emission reduction potentials, relative change of emission intensities in Europe was adopted.

7.5.2. Potentials of emissions and pollution mitigation

By benchmarking the emission levels in China with those attainable in the EU28 by 2030, the reduction potential for China's export industries were estimated. Here, the reduction potential of emissions is first discussed, followed by the mitigation potentials in terms of ambient O_3 concentration and premature morality.

For those sectors with emission intensities within the EU range, the mean level across the EU countries (instead of the median or the country with the lowest value) was used as a reference for the possible low level that can be achieved. For the few sectors with systematically higher emission levels, a relative change was adopted instead of an absolute value. It is estimated that 57% of production-based NMVOCs emissions from export industries could be reduced (1165 $kt \cdot a^{-1}$). When expanding the above approach to the whole production capacity, a reduction of 4437 $kt \cdot a^{-1}$ of NMVOCs would be expected, i.e., 58% and 17% of industrial and total anthropogenic NMVOCs emissions in China, respectively.

To study the O_3 mitigation potentials, two scenarios were constructed, which were Case 2 and 4 in Figure 7-5. Case 2 and 4 were developed by considering emission reduction potentials from production practices in line with those in the EU28 based upon the emission rates in 2013 (Case2) and in 2017 (Case 4), respectively. The year of 2013 was the reference year in this study. The inclusion of year 2017 was an attempt to reflect the radical change of NMVOCs and NOx emissions between 2013 and 2017 and to investigate the efficacy of industrial emission reduction under the most up-to-date emissions. As mentioned above, the efficacy of precursor emission reduction on O_3 pollution alleviation can vary depending on the O_3 formation chemistry. Since 2011, the air pollution policy in China was heavily focused on reduction of emissions of SO_2, NOx, and primary particulate matter from the energy sector. NOx emission had peaked around 2012 and decreased by 25% in five years from 2012 to 2017. NMVOCs emission, meanwhile, slightly grew by 2%. (Figure 7-9).

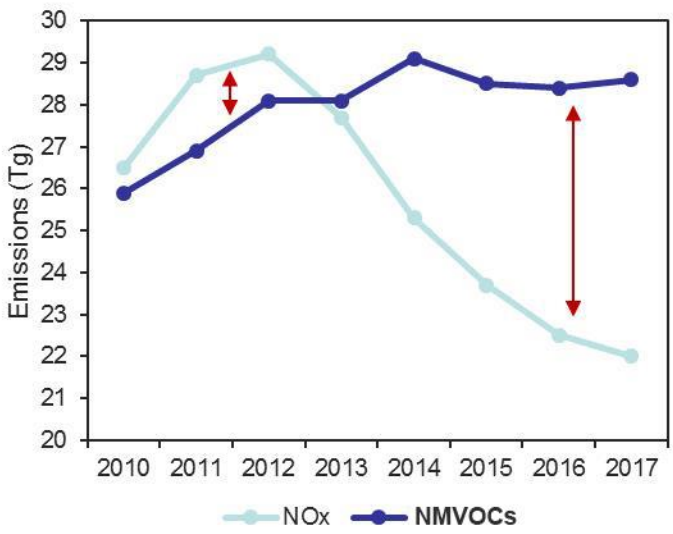

Figure 7-9 China's NMVOCs and NOx emissions from 2010 to 2017 (adapted from Zheng *et al.* (2018a))

When NMVOCs industrial emissions were reduced according to their reduction potentials (NOx and other air pollutant emissions remained constant), a nation-wide O_3 decrease is modelled. As shown in Figure 7-10 a&b, the decrease was significant in the vast coastal areas and some north inland provinces. In July, 2013, the maximum 8 hour O_3 average in Jing-Jin-Ji, Shandong, Yangtze River Delta and Guangdong dropped by 5.0, 3.3, 3.7, and 0.6 μg/m^3, respectively. The O_3 concentration declined more significantly in October. It decreased by 5.6, 5.7, 3.8, and 2.9 μg/m^3 in Jing-Jin-Ji, Shandong, Yangtze River Delta and Guangdong. The intensified NMVOCs-limited chemistry in October made the NMVOCs emission reductions even more effective.

By adopting the same NMVOCs emission reductions for the emission rates of NMVOCs and NOx in 2017, it was found that NMVOCs emission reduction was still effective to lower the peak O_3 level but not as significantly as it for the 2013 emission rates (Figure 7-10 c&d). It suggests that the response of O_3 to the change of NMVOCs emissions is decreasing as NOx emissions keeps going down in China.

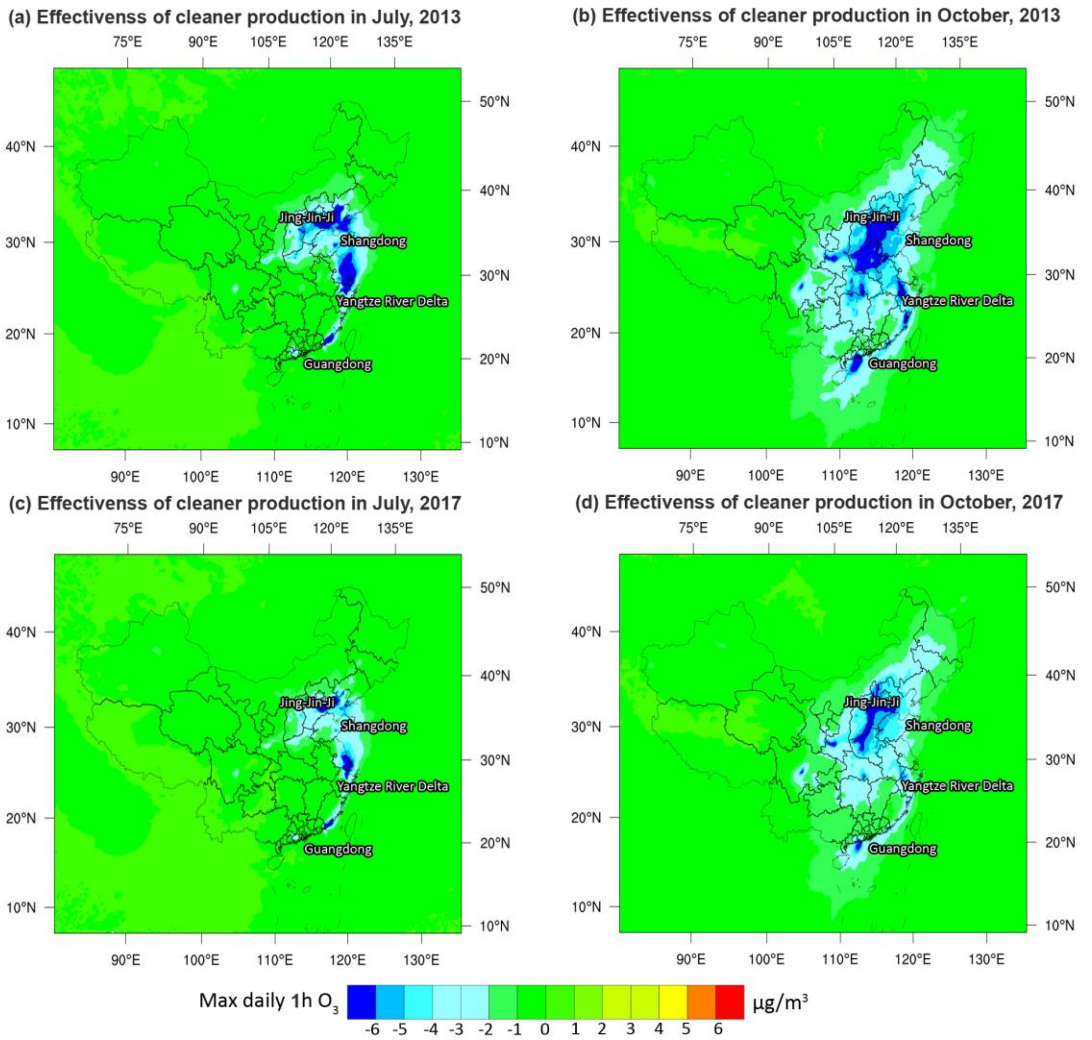

Figure 7-10 Effectiveness of cleaner production practices in 2013 (a&b) and 2017 (c&d). In a&b, O_3 concentrations in base case were subtracted from those in Case 2 (O_3 in Case 2 – O_3 in base case). Nation-wide decreases of O_3 can be observed when emission intensities of NMVOCs from key industrial sectors were lowered to European references under the 2013 emission rates. In c&d, O_3 concentrations in Case 3 were subtracted from those in Case 4 (O_3 in Case 4 – O_3 in Case 3). Considering the reduction of NOx emissions from 2013 to 2017 (-17%), NMVOCs emission reductions from industries were still effective – but not significantly so– on lowering the peak O_3.

7.5.3. Mitigation cost for the industries

The costs of cleaner production in selected industrial sectors and how much they would affect the price competitiveness of China’s goods were estimated. Given that local cost information was not available, this study referred to the cost of such practices in Europe using GAINS model data. Understanding the differences of cost of labour, infrastructure and others between China and Europe, the estimation here has large uncertainty in representing the exact cost in China. Interpretation of the estimated cost will be discussed later in this section by comparison with an existing study.

The costs for introducing such low emission practices were estimated at 0.05% to 0.3% of the annual industrial output, varying across sectors (Table 7-2). For pigment manufacturing and shoe making industries, emissions can be cut down by around 30% with annualized cost of 0.24% and 0.05%, respectively. Regarding printing, PCB, pharmacy and automobile manufacturing, sectoral emission reduction of 50% to 70% can be achieved with annualized cost from 0.13 to 0.3%. Negative unit costs were estimated for few sectors such as tyre manufacturing, wood furniture making and extraction of edible oil. It is because the value of saved or recovered solvent (e.g., hexane in vegetable oil producing process) offsets the investment and additional operating costs of control technologies. The recovery of these NMVOCs does not only reduce the emissions but also increase the output and revenue. Since prices of solvents, pollution discharge fees, labour costs and other input material costs are generally lower in China, the negative costs estimated here might be overstated. Nevertheless, the ‘true’ costs for these sectors should not be excessive and decrease over time. Therefore, it is assumed the costs are relatively low and set them as zero in Table 7-2.

The estimated cost is comparable to a study in the Pearl River Delta region, South China (Streets *et al.*, 2006). Costs for adsorption by activated carbon and switch from low-solvent to solvent-free paints were estimated as $501 and $13317 per ton of abated NMVOCs in that study, respectively. Cost for solvent substitution is much higher. Estimated costs in this paper fall within the above range, varying from $923 to $5992 per ton of NMVOCs; the upper bound is lower than that of previous study (Streets *et al*., 2006) since a mix of technological means is adopted in each sector. For instance, a combination of process modification, solvent substitution, adsorption and incineration techniques are adopted in the automobile manufacturing sector. As a result, the average cost would be lower than a sole measure of solvent substitution.

Table 7-3 Potentials for emission reductions and abatement cost

Sources		NMVOCs Emission Factors			NMVOCs Reduction Potentials (ton) [a]	Annualized Abatement Cost (million $)	Industrial Output in 2013 (million $)
		China in 2013	Possible low level	Unit			
Petroleum Refinery		1.82 [b]	1.08 [c]	kg/t product	353972	0	
Extraction of Edible Oil		6.88 [d]	2.29 [c]	kg/t product	256444	0	
Tyre		0.6 [e]	0.44 [c]	kg/tyre	176464	0	
Wood Furniture Making		0.92 [f]	0.49 [c]	kg/piece	252913	0	
Extraction of Oil		1.42 [b]	0.93 [c]	kg/t	105982	0	
Paint Manufacturing		15 [b]	11 [c]	kg/t product	38170	35	53226 (0.24%)
Ink Manufacturing		50 [b]	36 [c]	kg/t product	9459	9	
Dye Manufacturing		81 [b]	58 [c]	kg/t product	20575	19	
Carbon Black Manufacturing		52 [b]	37 [c]	kg/t product	69036	64	
Glue Manufacturing		11 [g]	8 [c]	kg/t product	15742	15	
Printing		993	301	kg/t ink	396216	501	167718 (0.30%)
Shoe Making		0.028 [m]	0.020 [c]	kg/pair	37087	56	106140 (0.05%)
Printed Circuit Board		0.22 [h]	0.09 [c]	kg/m^2	29019	55	22548 (0.24%)
Metal Coating (Small devices)		0.20 [b]	0.08 [c]	kg/piece	67305	127	
Metal Coating (Large devices)		0.40 [b]	0.15 [c]	kg/piece	216	0.4 [o]	
Pharmacy		260 [i]	125 [c]	kg/t product	354546	977	359629 (0.27%)
Automobile Manufacturing							
	Bikes	0.3 [b]	0.12 [c]	kg/VEH	4290	26	853225 (0.13%)

Small Vehicles	2.43 [b]	0.972 [c]	kg/VEH	19208	115
Other Vehicles	21.2 [b]	8.48 [c]	kg/VEH	152106	911
Motorbikes	1.8 [b]	0.72 [c]	kg/VEH	13470	81
Coking	2.1 [j]	0.427 [k]	kg/t coal charged	1128867	NA
Polymeric Coating	0.182 [b]	0.009 [l]	kg/m^2	818404	NA
Polymers and Resins					
Polyethylene	7.85 [m]	2.00 [k]	kg/t product	68679	NA
Polypropylene	3.00 [b]	0.35 [n]	kg/t product	33019	NA
Polyvinyl chloride	0.7448 [b]	0.1 [k]	kg/t product	9865	NA
Polystyrene	2.92 [b]	0.15 [k]	kg/t product	5817	NA

[a] Reduction potentials estimated based on the activity level in 2013;
[b] Emission factor from Ministry of Ecology and Environment P.R. China (2014);
[c] Value is estimated based on the EU- average emission factor trajectory;
[d] Weighted average of the emission factors of corn oil, cottonseed oil, peanut oil and soybean oil from Ministry of Ecology and Environment P.R. China (2014);
[e] Average factor of Ministry of Ecology and Environment P.R. China (2014) and previous studies (Klimont *et al.*, 2002; Hong Kong-Guangdong Joint Working Group on Sustainable Development and Environmental Protection, 2008; Zheng *et al.*, 2009a&b; Huang *et al.*, 2011);
[f] Weighted average of offset printing, rotogravure printing and letterpress printing (Guangdong Polytechnic of Environmental Protection Engineering and South China University of Technology, 2012);
[g] Local factor unavailable. Factor from European Environment Agency (2016) was adopted;
[h] From a field survey in the Pearl River Delta (Guangdong Polytechnic of Environmental Protection Engineering and South China University of Technology, 2012);
[i] Emission factor from Zheng *et al.* (2018a);
[j] Local factor unavailable. Factor from United States Environmental Protection Agency (2009) was adopted (Wei *et al.*, 2008; Huang *et al.*, 2011; Wang *et al.*, 2018b), which was based on the higher bound of emission level in an earlier study by Economic Commission for Europe (1990);
[k] Based on the lower bound of emission level by Economic Commission for Europe (1990);
[l] By carbon adsorption units using activated carbon, 95% of NMVOCs from this process can be removed United States Environmental Protection Agency (2009);
[m] Average of high- and low-density polyethylene emission factors from Ministry of Ecology and Environment P.R. China (2014);
[n] Factor from United States Environmental Protection Agency (2009);
[o] The value should be underestimated since only the activity level data of cutting machine was available for the national statistics.

7.6. Implications for control strategies

The above analysis revealed a multitude of information on the causes and drivers of O_3 pollution in China. This section critically digests the evidence presented in the above sections and strives to inform policy formulation from production and consumption.

7.6.1. Implications for production-based control strategies

This study provides two key messages to inform production-based control strategies in China. The first one is the necessity of coordinated NMVOCs control along with NOx. It is argued that the aggressive reduction of $PM_{2.5}$ in China has been partly attributed to the rise of O_3 level in recent years. The clean-up of the energy sector has resulted in a radical decrease of NOx emissions. It has shaped the O_3 regime to being even more NMVOCs-limited and gave rise to increased O_3 concentrations.

Recalling the result of Case 1, O_3 in the north China increased due to disproportionate reduction of NOx and NMVOCs (Figure 7-7b). It indicates that, under the NMVOCs-limited regime, aggressive reduction of NOx without joint efforts on NMVOCs could result in the rise of O_3 concentrations. For the vast urban areas in China that suffer from high O_3 levels such as the Jing-Jin-Ji, Yangtze River Delta and Pearl River Delta, studies have found that O_3 formation was governed by NMVOCs-limited regime (Wa*ng et al*., 2006b, 2017; Han *et al*., 2011; Xing *et al*., 2011b; Zhu *et al*., 2016; Lyu *et al*., 2016; Xu *et al*., 2016; Zheng *et al*., 2017; Li *et al*., 2018c; Xing *et al*. 2018; Zeng *et al*., 2018). From 2013 to 2017, the hourly concentration of O_3 in China increased by 16~27% from 2013 to 2017 (Figure 1-8), while the O_3 exposure metrics (cumulative O_3 concentration) increased even more by 57~77% (Lu *et al.*, 2018). Meanwhile, as a consequence of China's clear air actions aiming at $PM_{2.5}$ and end-of-pipe treatments in the energy sectors, NOx emissions had decreased by 21% from 2013 to 2017 while NMVOCs still grew persistently (+2%). It is suspected that such uncoordinated control would result in recent increase of O_3.

To testify such an inference, Case 3 was constructed as shown in Figure 7-6. Emission rates in the Base Case, which were the baseline emissions of NMVOCs, NOx and CO in 2013, had been updated to 2017, considering the reduction of NOx and increase in NMVOCs emissions. Modelling results in Case 3 were compared with the Base Case. The change of O_3 concentrations due to the disproportionate reduction on NOx and NMVOCs is illustrated in Figure 7-10. It is clear that uncoordinated control of precursors' emissions have been partly attributed to the rise of O_3 in the populous city clusters. In particular, peak O_3 levels in the Jing-Jin-Ji and the Yangtze River Delta increased by 10.9 and 2.5 μg/m^3, respectively. A recent study investigated the anthropogenic drivers of 2013-2017 trends of surface O_3 in China (Li *et al.*, 2018c). In addition to the changes of precursors emissions, the decrease (~40%) of $PM_{2.5}$ concentration in the atmosphere also contributed significantly to the increasing O_3 trend due to the slow-down of aerosol sink of hydroperoxy (HO_2) radicals and thus simulation of O_3 production (Li *et al.*, 2018c).

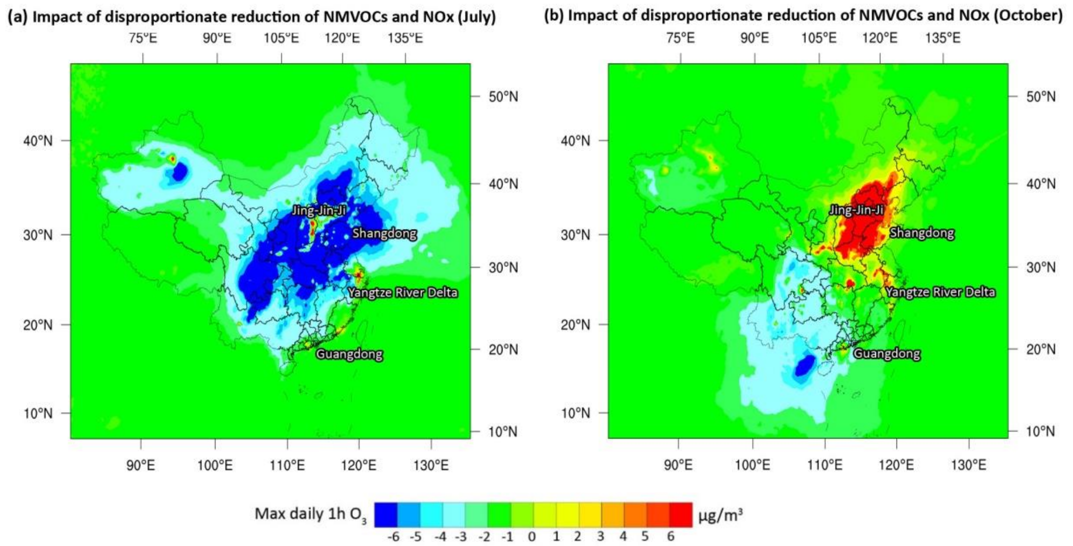

Figure 7-11 Impact of disproportionate reduction of NMVOCs and NOx on O_3 peak concentration in (a) July and (b) October. O_3 concentrations in base case (representing the emissions in 2013) were subtracted from those in Case 3 (representing the missions in 2017) (O_3 in Case 3 – O_3 in base case).

The second implication is on the great reduction potentials from industries at moderate cost. Compared to other criteria pollutants such as SO_2 and NOx, the control of NMVOCs emissions are more challenging due to its complicated sources and varying abatement technologies, especially those from industries (Chan and Yao, 2008; Zheng *et al.*, 2013; Zhong *et al.*, 2013; Ou *et al.*, 2015; Wang *et al.*, 2018b&c). While the transport-related NMVOCs emission had started to decrease since 2010 (Zheng *et al.*, 2018a), NMVOCs emission from industrial processes and solvent use are still increasing. This study estimates a large NMVOCs reduction potential from cleaner industrial production. For the selected 25 industrial sectors, their NMVOCs emission can be cut down by 63% applying end-of-pipe controls or solvent management and low-solvent substitutes. Since these 25 sectors made up 56% of the NMVOCs emissions from all industry, the industrial NMVOC emissions can be reduced by 35%, which is equivalent to 16% of the anthropogenic NMVOCs emissions in China. Such emission reductions would lead to approximately 5, 3 and 2 $\mu g/m^3$ of decrease in max 8h O_3 in Jing-Jin-Ji, Yangtze River Delta and Guangdong, respectively. Compared to the O_3 pollution level that China is confronting, more efforts targeting other industrial sectors as well as the household sector should be carried out.

Cleaner production practices have a positive effect on alleviating the O_3 problem and their cost seem to be bearable for China's industries. Goods produced in China are competitive in both the domestic and international markets since they are cheap, partly due to rather lax emission standards. Requiring introduction of cleaner production technologies resulting in reduction of NMVOCs emissions by 50~70%, the costs for most sectors were less than 3% of the value added of the goods produced. The price competiveness of China's goods would not be seriously undermined. The pharmaceutical industry appears to be an exception with 32% NMVOCs emission reduction at a cost of 4.6% of its value added. Considering the fact that the analysis relies upon the average European costs, the 'real' cost in China might be lower and the mitigation strategy more affordable for the industries.

7.6.2. Implications for consumption-based control strategies

This study mainly explores the potentials of O_3 alleviation from export. The crucial message for policy formulation is that swift actions are needed in order to reap the most benefit. In other words, the efficacy of addressing export industries emissions on O_3 reduction decreases over time.

The nature of export enterprises, i.e., usually large in size and regularly evaluated under the national environment monitoring system, makes them viable for efficient NMVOCs emission control. By closing the gap of emission intensities between China and EU28, the reduced NMVOCs emissions (~4.5 million tons for the whole production capacity) would lead to a nation-wide decrease of peak O_3 in both July and October, 2013, especially for the east and south coast and north China plain (2~8 μg/m^3, Figure 7-7 c&d). It is not a big change compared to the absolute value of O_3 but would slow down the rising trend of O_3 and the number of premature deaths could be reduced by 4708 (1566 ~ 7762; 95% confidence interval). Benefit for local population would be even larger if occupational exposure was also considered. Quite a few NMVOCs species are not only precursors of O_3, but also known or suspected carcinogens. Benzene, for example, is a human carcinogen (Group 1) by the International Agency for Research on Cancer (International Agency for Research on Cancer, 2012). For 3 out of the 20 sectors, i.e., wood furniture making, ink and paint production and shoe making, the number of their employees reached 2.8 million in 2013 (China Light Industry Association, 2014).

By adopting the same NMVOCs emission reduction in the emission rates of NMVOCs and NOx in 2017 (Case 4) showed that that NMVOCs emission reduction was still effective to lower the peak O_3 concentrations but not as significantly as for the 2013 emission rates (Figure 7-7 e&f). It suggests that the response of O_3 to the change of NMVOCs emissions is decreasing as NOx emissions keeps going down in China. Ideally, reductions of NMVOC should precede substantial NOx reduction in order to achieve low ozone concentration in the long term and avoid high peak ozone episodes in the mid-term (Ou *et al.*, 2016). The current policy, however, appears to be the opposite, starting from aggressive NOx reduction followed by tightening NMVOCs standards for both transportation and industrial emissions since 2018 (Ministry of Ecology and Environment of the People's Republic of China, 2019). While reduction of NMVOCs is always beneficiary considering their toxicity or carcinogenic characteristics, its benefit on curbing O_3 rise would be more appreciable if swift actions are taken when O_3 still response significantly to the change of NMVOCs.

China exports goods to 140 countries but the United States (US) alone accounted for 23% NMVOCs emissions relevant to export. A large proportion of industrial products characterized by high NMVOCs emission intensity are subject to recently increased tariffs, such as paints, dyes, glues, adhesives, wood furniture, man-made textiles, machinery, electronics, vehicles and parts, ships and boats. Nevertheless, it is difficult to predict how the demand and structure of export might be affected. In the short term, the reliable supply chain, skilled workers, growing domestic demand still make China highly competitive as the world's factory. The increased tariffs are likely to be borne by the producers assuming decreased profit margins. Even in an extreme case where production for export is heavily distorted, the direct NMVOCs emissions should be only marginally affected. This is because the emissions embodied in US-China trade accounted only for 3% of the anthropogenic national total and 5~7% of export industries hubs.

For substantial reduction of NMVOCs emissions, production for the domestic market (as well as consumption of solvent based products) needs to be addressed. The direct and indirect consumption of urban and rural households in China contributed about 40% of NMVOCs emissions. With increasing household income and consumption, that contribution is expected to grow further. Policies addressing household products and consumer behaviour should be formulated. Long-term attainment of O_3 targets across the country would also call for further NO_x reduction of more than 50% (Ou *et al.*, 2016). As demand from abroad accounted for about 15% of China's NO_x emissions in 2013, strategies targeting domestic demand driving NO_x emissions and end-of-pipe treatment would be the key to halve NOx emission and consequently bring ambient O_3 to a safe level nation-wide.

7.7. Summary

China is facing a growing O_3 pollution problem despite its initial success on $PM_{2.5}$ control. With an increase of 16~27% from 2013 to 2017, the O_3 concentrations in China is greater than any other developed country in the world or even the United States in the 1990s. The causes and formation of O_3 pollution in China and possible means for alleviation are investigated in this Chapter.

This study contributes to improved understanding of the consumption-based emissions of O_3 precursors and formation in China. Contribution of 'export-driven' emissions to the O_3 formation within China was estimated. Due to the differences in spatial pattern for various types of industrial production, export industries in the north and inland provinces are more relevant for NOx emissions, while those around the east and south coastal areas have higher NMVOCs emission loadings due to the thriving light industries. As a result, export-related emissions contributed positively to the formation of O_3 in the South China. The export emissions were responsible for 3~6 $\mu g/m^3$ of the max 8h O_3 in light industry hubs such as Guangdong and Zhejiang. For the northern provinces, the high NOx emission loadings driven by export demand inhibit the O_3 formation by 1~2 μg/m^3 under the strong VOCs-limited chemistry regime in October contrasting a 4~6 μg/m^3 increase in July.

Modelling results in this study suggest that aggressive reduction of NOx without coordinated control of NMVOCs could lead to an increase of O_3. This might partly explain the recent rise of O_3 in China and call for a more balanced control of both NMVOCs and NOx. While the transport-related NMVOCs emission have started to decrease, NMVOCs emissions from industries still increase. We found that the selected 25 industrial sectors have large emission reduction potentials; emission density could be reduced by about 63%. If sector-wise reduction was applied (not only for export goods but also for other goods produced in the same plant/facility), such reduction would lead to a decrease of 2~5 μg/m^3 of max 8h O_3 in Jing-Jin-Ji, Yangtze River Delta and Guangdong.

Preliminary cost estimation showed that such cleaner production practices would not seriously undermine the price competiveness of China's goods. With an annualized cost of less than 3% of the value added of goods produced, NMVOCs emissions for most sectors could be reduced by 50~70%. We conclude that NMVOCs reductions from industrial sectors are technically and economically possible.

The 25 industrial sectors, addressed in this study, are estimated to account for about 56% of the industrial emissions, such efforts alone are therefore not enough to combat the O_3 problem in China. Potentials of cleaner production practices for other industrial sectors and greener consumption of household products should be explored in further study.

Chapter 8 Conclusions

This PhD work presents an integrated assessment on the interplay of energy, pollution and socioeconomic demands in China at the time of drastic social and economic transition. Production- and consumption-based accounting approaches are used to connect the environmental and socioeconomic systems and depict the material and emission flows between producers, consumers and environmental receptors. This study has filled in part of the research gaps in integrated assessment and provided policy-relevant implications on China's sustainable production and consumption. Key findings, contributions and limitations of this work are discussed in this Chapter.

8.1. Summary of work and key findings

This study first argues that conventional socioeconomic analysis techniques can be combined with environmental models to understand the full chain of cause and effect of environmental issues. A four-stage research framework is proposed. It starts from the compilation of a primary energy consumption matrix, followed by the establishment of production-based inventories of GHG and air pollutants. Energy and emission accounts are then connected to socioeconomic accounts through EEIO analysis and decomposition techniques. Socioeconomic drivers that are responsible for energy consumption or emissions can be revealed, including entities such as intermediate sectors and final consumers and macroeconomic factors such as population growth, economic growth, industrial structure, energy intensity and energy mix. Meanwhile, production-based emissions marked by different socioeconomic drivers are fed into environmental modelling tools such as CMAQ. Through environmental models, a vast variety of environmental end-points can be evaluated, including but not limited to the ambient air pollutant concentration, air quality attainment rate, pollution formation regimes and death toll. With the corresponding relationship between production- and consumption-based emissions, socioeconomic demands and environmental consequences can be connected in an explicit and quantitative way. This study advocates the idea that the causes and effects of environmental issues should be understood in a socioeconomic context.

This study understands the central roles of energy consumption, emission inventory and IO tables in the integrated assessment framework and tries to overcome some of the limitations in terms of data quality. First, official energy statistics at provincial levels were compared with the national sum. Second, this study evaluated the reliability of NMVOCs emissions with ambient measurements. Third, the MRIO table for 30 provinces in China was extended to 31 provinces covering Tibet.

With the best available data, the proposed assessment framework has been demonstrated in national and subnational studies in China to advance the current understanding of energy consumption and pollution formation. Key findings are summarized as follow:

1) Gaps between national and provincial energy statistics

This study used the latest provincial energy statistics from 2000 to 2016, which was indeed the only available data covering all the mainland provinces in such a time frame. It was found that the gap between national and provincial statistics was closing after China revised its national statistic three times since 2000. The relative differences of total energy consumption between the two were from -6% to 8%.

2) Cross-validation of emission inventory and ambient measurements

Thanks to the ambient measurement record from a gridded sampling campaign, emissions of NMVOCs in this study were validated. Data from the sampling campaign was first analysed by receptor model and then compared with the emission inventory. The key factors leading to the discrepancies between emission inventory and receptor modelling were identified, including the number of NMVOCs species, tempo-spatial resolution, effect of photochemical loss, tracers used in receptor model and potentially missing sources in emission inventory. With respect to the improvement of emission inventory, evaporation emission from vehicles and LPG-related sources were found as the potentially missing sources. Considering the existing evidence from other studies, only evaporation emissions from vehicles were included in the inventories for further assessment.

3) Development of MRIO table for 31 provinces and the regional interactions

A MRIO table for 31 mainland provinces in China was developed. This MRIO table was used for the integrated assessment of ground-level O_3 problem in China. In addition, the production- and consumption-based characteristics of Tibet were investigated. Tibet displays unique emission patterns with the highest ratio of consumption- to production-based emissions in China, which are more similar with the east developed provinces rather than its counterparts in west China. Consumption-based CO_2 emissions in Tibet (18.8 Mt, similar to Guinea's emissions in 2015) were three times as high as the production-based estimate (6.2 Mt). More than half of Tibet's consumption-based emissions are supported by Qinghai, Hebei, Sichuan and others, enabled by the Qinghai-Tibet railway that connected Tibet to China's national railway system. It is also found that Tibet has the third highest carbon footprint (carbon emissions per capita) in China but low life expectancy. It indicates that the current consumption of Tibet is neither climate-friendly nor good for human welfare.

4) Socioeconomic drivers of China's energy consumption from 2003 to 2016

Once the primary energy consumption matrix was developed, this study observed substantial decrease of energy elasticity in China. Such a trend was even more prominent at the provincial level. Eight of the provinces saw declines in their total primary consumption (including coal, petroleum, natural gas and non-fossil fuels) from 2011 to 2016. This work investigated the changes in energy drivers for provinces with observed declines in their primary energy consumption and discussed how their drivers were different from the other provinces. These eight provinces differed from the others since 2011, when the decreasing effect of energy intensity was enhanced and, for the first time, surpassed or approximated the increasing effect of economic growth. The catching-up was more associated with the significant reduction of energy intensity rather than the slowdown of economic growth. New decreasing factors such as the share of coal and industrial structure change were also emerging to curb the growth. In addition, six provinces have levelled off their total primary consumption and decreased the combined consumption of coal and petroleum. Their driver mechanisms were similar but the share of cleaner fuels, e.g., natural gas and non-fossil fuels, increased significantly. Nevertheless, such declines were demonstrated to be initial rather than structural changes. Province-specific pathways should be followed to secure the trend or fasten transition.

5) Socioeconomic drivers of air pollutant emissions in a fast-developing region

The roots of air pollutant emissions in one of the city clusters in China – Guangdong province – were studied from the socioeconomic context. From 2007 to 2012, the

GDP of Guangdong increased dramatically by 80%. Meanwhile, it saw a 28% decrease of SO_2 emissions, accompanied by stabilized NOx emissions and 26, 8.6, 8.5, 31 and 10% increase of CO, PM_{10}, $PM_{2.5}$, NMVOCs and NH_3, respectively. The varying trends of air pollutants from 2007 to 2012 were associated with the production-based control measures and the changes of economic structure and trading patterns. Due to the stringent control of SO_2 in power plants and key industries, the SO_2 emissions from consumption perspective saw substantial declines, while the less-controlled PM_{10}, $PM_{2.5}$, NMVOCs and CO kept growing. Driven by the increasing urban consumption and efforts in industrial transformation, the share of other service industries (excluding transport, storage and post) in Guangdong' GDP grew by 41% in five years, resulting in the increasing proportion of the low-emission-intensity service sector in the emissions of all the 7 pollutants. Meanwhile, export accounted for an astonishingly high share of air pollutant emission (~50%, doubled the national average), but its share started to decrease for most pollutants except NMVOCs and CO.

6) Integrated assessment on the causes and effects of ground-level O_3 in China

While Chinese policies addressing $PM_{2.5}$ pollution resulted in declining concentrations of ambient $PM_{2.5}$, the ground-level O_3 pollution has been on the rise. With an increase of 16~27% from 2013 to 2017, the O_3 level in China is greater than any other developed country in the world or even the United States in the 1990s. With an integrated assessment framework centred by EEIO analysis, this study combined the air quality model, health exposure assessment and a comprehensive set of technical and cost parameters from IIASA-GAINS database to study the causes and effects of rising O_3 in socioeconomic context with a focus on export demand and the related industrial emissions. Goods produced in China for foreign markets lead to an increase of domestic NMVOCs emissions by 3.5 million tons in 2013; about 13% of the national total or, equivalent to half of emissions from EU. Export demand driven emissions have mixed impacts on China's O_3 concentration, but they generally contribute about 6~15% of peak O_3 levels (6~10 $\mu g/m^3$) caused by human activities in the coastal area resulting in an estimated 4615 (1514 ~ 7600) premature deaths.

Past air quality improvement efforts in China have focused on end-of-pipe treatments on energy-related sources such as power plants, industrial boilers and vehicles. Such efforts have not only altered the energy structure in China and also the emission ratios between NMVOCs and NOx, the latter of which has a profound impact on the increase in O_3. It was found that demand for export has slightly increased the sensitivity of O_3 formation to NMVOCs emissions ('more NMVOCs-limited'). In addition to the elevation of peak O_3 level, export demand has shaped the O_3 formation in China in a more hidden way by altering the emission ratios of O_3 precursors.

Differences in the emission intensities between China and the EU 28 were evaluated. Measures from the production-based perspective could significantly lower the consumption footprints of export and other domestic demands at moderate cost. By benchmarking the emission intensity in China to the EU, the export footprint and NMVOCs emissions from the whole production capacity can be reduced by nearly 60%. Such efforts will slow down the upward trend of O_3 with notable health benefits.

For substantial reduction of NMVOCs emissions and ambient O_3 level, demands from domestic market need to be addressed. The direct and indirect consumption of urban and rural households in China contributed about 40% of the NMVOCs emissions. With increasing household income and consumption, that contribution is expected to grow further. Long-term attainment of O_3 across the country would also call for further NO_x reduction of more than 50%. As demand from abroad accounted for about 15% of China's NO_x emissions in 2013, strategies targeting domestic demand driving NO_x emissions and end-of-pipe treatment would be the key to halve NOx emission and consequently bring ambient O_3 to a safe level nation-wide.

8.2. Contributions to scholarship and policy

This study has advanced the current understanding on energy consumption and air pollution in China from an interdisciplinary approach. It advances the methodologies in integrated assessment, provides quantitative evidences on the interlinkages between environmental and socioeconomic systems, and explores the possibilities of cleaner growth from both demand and supply sides.

First, this study has managed to bring together a few powerful tools from the disciplinary of environmental and socioeconomic studies to push the boundaries of application and knowledge. Some of the research gaps in quantitative integrated assessment have been filled. By combining the techniques of production- and consumption-based emission inventory development, a wider range of environmental modelling and socioeconomic analysis tools can be integrated and adjusted in a flexible way according to objectives and research questions. Considering the quick expansion of interdisciplinary studies in recent years, methods and their demonstrations in this study are expected to be influential and contribute to the further development in similar fields. Originality of the methodologies developed in this study has been recognized by the Mikahlevich Award given by the International Institute for Applied Systems Analysis in 2018, which aims to recognize mathematically and methodologically oriented research.

Second, this work has overcome some of the research gaps with respect to the mix of data quality in developing countries. According to the data availability in China, methods to avoid double counting of energy consumption associated with electricity are proposed. Primary sources of electricity used in final consumers are identified by considering the indigenous production of electricity from different sources of energy, electricity moving in from other provinces and electricity sent out to other provinces (Eq. 3-1). Procedures for cross-validation between emission inventories and receptor modelling results are proposed (Section 3.1.3). To make results from these two methods comparable and guide the improvement of both sides, one should ensure consensus of the species used in emission inventory and receptor model, and employ a larger spatial coverage and longer time span to partly cancel out the effect of uneven mixing. Validation in this study exposes the key methodological flaws in both methods. For receptor modelling, chemical losses of reactive species and the overlap of tracers used by different sources are problematic. As for emission inventories, evaporation emissions from vehicles and LPG-related emissions might be underestimated. This study has also contributed to the development of MRIO table in China by extending the table to cover all the 31 mainland provinces. The table has been used in this work and comprised part of the China Emission Accounts and Datasets (CEADS). It is free to download via http://www.ceads.net/data/input-output-tables/ for academic use.

Third, this study provides the first assessment on the driving mechanisms responsible for the declined energy consumption in some of Chinese provinces. This work has captured the catching-up effect of energy intensity and, for the first time, the decreasing effect of energy intensity exceeded or approximated the increasing effect of economic growth. Further analysis showed that the catching-up was more associated with the significant reduction of energy intensity rather than the slowdown of economic growth. New decreasing factors such as the share of coal and industrial structure change were also emerging to curb the growth. Such findings are valuable for the academic discussion of energy transition in China. They are also significant for energy policy. As China caps its total energy consumption at the level of 5000 Mtce and 6000 Mtce by 2020 and 2030, respectively, the annual growth in the coming decade should be no higher than 1.8%. To achieve such a low growth rate, the energy consumption of some provinces should be reduced, or at least, stabilized. The mechanisms identified in this work shed some light on how energy consumption can be reduced at the provincial levels with real-world examples.

Fourth, this work has filled in the knowledge gap in the consumption-based emissions of Tibet, the second largest province in China in terms of area. A consumption-based emission inventory was developed for Tibet and the regional interactions of provincial emissions were studied using the MRIO table for 31 provinces in China. Findings in this study contribute to the research on China's emission accounts, in which emission from Tibet is usually missing. A unique emission pattern is also observed. Tibet is found to have the highest ratio of consumption-based to production-based emissions among 31 mainland provinces in China, exceeding the figures of Beijing, Tianjin and Guangdong. Some studies have noted that CO_2 emission flows began to reverse in 2012 (Mi *et al*. 2017). The consumption characteristics of Tibet in this study are additional evidence of the ongoing reversal in emission flows within China. In terms of policy implications, this study also evaluates the sustainability of Tibet's consumption and production. The unique emission pattern is believed to be explained by the low self-sufficiency of Tibet's economy. It heavily relies on the imported goods of non-metal mineral products, iron and steel, general and special equipment and machinery, metal products, chemical products, processed food, garments and fiber products, and paper products from other regions in China, and thus outsources a significant amount of emissions. Such a virtual transport of emissions might have significant implications on short-lived air pollutants and air toxics, whose negative effects on ecosystems and human health are sensitive to the emission location. Tibet is found to fall out of the "Goldemberg's Corner," indicating an unsustainable lifestyle within the region. As inter-regional interactions are expected to become more frequent under the development of western China, they might serve as potential leverages for a more sustainable consumption pathway in Tibet.

Fifth, this study complements the current production-based knowledge in one of China's most developed city clusters by exploring the drivers of emission growth and pattern changes from the consumption side. Guangdong is one of key economic drivers in China and a microcosm of the fast developing regions that confront the double challenges of sustainable economic development and pollution mitigation. While previous studies have dwelled on the production-based emission characterization for control strategy formulation, the drivers of emission growth and pattern changes from the consumption side are rarely explored. This work presents the first study on the air pollution causes in this region from the perspective of socioeconomic demands. The drivers and demands behind 7 pollutants were examined and how they evolved during the half decade studied. It was found that Guangdong was moving towards a cleaner production and consumption pathway, and transformation of industrial structure and simulating urban demand should benefit further emission reduction while maintain economic development.

Sixth, this study provide timely information on the causes and effects of rising ground-level O_3 problem in China, which is significant in both academia and real-world application. While an integrated assessment has been carried out for some GHG and air pollutants such as $PM_{2.5}$ and BC, studies on O_3 are very limited. For the first time, the socioeconomic driving forces of O_3 in China are revealed. Analysis in this study has shown that the interactions between socioeconomic demands and local O_3 pollution are complicated and different to those of $PM_{2.5}$ and BC. Take the demand from export as an example, its contributions to the observed O_3 level vary with geographic locations and seasons. In addition to the peak O_3 level, export-driven emissions have also altered the emission ratios of O_3 precursors, and thus the chemistry regime and the O_3 response to emission control strategies. It serves as the first piece of evidence on how the relocation of emissions via international trade has shaped the air pollution formation mechanism. Results in this study have real-world significances in a more coordinated control of multi-pollutants. On the one hand, it is arguable that a more balanced control strategy on both NOx and NMVOCs is need for an overall improvement of air quality in China. On the other hand, this study stresses the potentials of air pollution mitigations in developing countries by closing the emission intensities. Thanks to the comprehensive technical and cost parameters embodied in the IIASA-GAINS model, this study compared the NMVOCs emission levels per unit of goods produced in China with those in the EU28. For most industrial sectors, the emission intensities in China around 2013 were comparable to the upper bound of the EU28 around 2000. By closing the gap of emission intensities between China and EU28, the reduced NMVOCs emissions (~4.5 million tons for the whole production capacity) would lead to a nation-wide decrease of peak O_3 in both July and October. It is suggested that export demand could be an entry point to tackle the O_3 precursors' emissions from non-combustion industrial sources.

8.3. Limitations and future research

Despite the efforts to fill in the existing research gaps, this study is subject to some limitations and inherent uncertainties in terms of data and methodologies. Such shortcoming are critically reviewed in this section and suggests for further research are provided.

First, while a great emphasis has been put on environmental modelling and health exposure assessment, analysis from socioeconomics could be enhanced. The author recognizes that the socioeconomic analysis tools incorporated in the research framework are limited. The MRIO and decomposition analysis reflect the activities and demands from economic sectors or in macroeconomic level, which provide decent descriptions on the regional and national socioeconomic systems. However, attentions to the socioeconomic analysis at finer resolutions are rising recently. To enable fundamental transition in consumption patterns, it is argued that analysis should be carried out in granularity level such as individuals. Agent-based models, for example, add decision capabilities to the agents, have more flexibility and could explore more example scenarios in micro levels. In addition, when discussing the demand of final consumers, this study does not incorporate expertise in behaviour studies. Though the key demanders are identified in this study, it is still not clear how their behaviours have resulted in such demands and what are the hurdles to guide a more responsible consumption. The author suggests that the current integrated assessment framework could be improved substantially if analysis tools in granularity level are incorporated.

Second, integrated assessment is inevitably subject to the uncertainties from all the data and models being used. In this study, the major sources of uncertainties include energy statistics, emission factors, activity levels, the input-output table and air quality modelling. Uncertainties in aspects of energy statistics, emission inventory and the air quality model have been discussed and evaluated in this study. However, this study cannot evaluate the uncertainty of MRIO and GTAP data. Moreover, the propagation of uncertainties from different sources in the integrated assessment is not studied. To increase the reliability and robustness, it is urged that quantitative evaluation of uncertainty for the whole work flow of integrated assessment should be carried out in future studies.

Third, the author would like to acknowledge the mismatch of years and study areas in some of the energy consumption and air pollution analysis in this study. While Chapter 4 has investigated the socioeconomic drivers of energy consumption from 2003 to 2016, the integrated assessment on the GHG and air pollution in the following chapters is for one or two years. This is because of the data availability of input-output tables and emission inventories. As a result, this study does not provide a comprehensive analysis on the driving factors and effects of GHG and air pollution in a longer time span. It would be potentially interesting if provincial drivers for GHG and air pollution could be also investigated and compared to the driving mechanisms of just energy consumption. Synergies or trade-offs between energy, climate and pollution can be revealed and serve as important evidences to guide the future development of environmental policies.

Fourth, Chapter 7 mainly addresses the demand of export and industrial emissions. Nevertheless, other domestic demands also make up significant contributions to the O_3 precursors emissions, especially for the inland provinces. For an overall and nation-wide improvement of air quality, emissions driven by the other demands should be analysed to understand the emission reduction potential through emission control or consumer guidance. The author suggests that, after industrial emissions are under control and curbed, which is indeed undergoing in China, relative contributions from urban and rural household could be even higher. Following the framework in this study, contributions of domestic demands and their evolution in the future can be evaluated. Policies from the consumption side could be of vital importance. This also echoes the above-mentioned incorporation of agent-based models and behaviour studies in the integrated assessment.

Appendix 1: Tables

Appendix Table A1 Decomposition results by provinces

		Primary Energy Consumption Changed by Drivers (10^4 tce)							
Province	Period	Population Growth	Economic Growth	Industrial Structure	Energy Intensity	Share of Coal	Share of Petroleum	Share of Natural Gas	Share of Non-fossil Fuels
Chongqing	2011-2016	454	3114	450	-4315	-295	-11	239	54
Chongqing	2007-2011	-26	3053	1029	-1200	337	-21	-74	-229
Chongqing	2003-2007	-243	1782	497	-373	-267	-4	-8	298
Fujian	2011-2016	306	4263	-361	-4482	-897	567	223	100
Fujian	2007-2011	230	3380	510	-754	-405	199	371	-113
Fujian	2003-2007	145	2096	185	500	105	-143	6	45
Hebei	2011-2016	670	9154	-2978	-8742	-399	-14	292	130
Hebei	2007-2011	993	8422	1771	-4148	-84	-51	165	-25
Hebei	2003-2007	395	6847	1866	-605	-140	-49	-9	248
Henan	2011-2016	208	8928	-140	-9681	-590	152	303	133
Henan	2007-2011	57	8161	2274	-6068	-309	-30	158	212
Henan	2003-2007	-396	6629	436	1732	184	-231	30	28
Hubei	2011-2016	222	6070	1276	-8783	-1628	1281	169	170

Hubei	2007-2011	129	6060	1353	-3022	817	-806	158	-116
Hubei	2003-2007	21	3783	1269	-1262	-300	35	44	228
Jilin	2011-2016	13	3509	-698	-4180	-152	-21	52	91
Jilin	2007-2011	59	4328	316	-1995	249	-290	90	-40
Jilin	2003-2007	60	3073	304	-2021	-412	276	20	80
Shanghai	2011-2016	291	3342	-1273	-2455	-690	355	272	60
Shanghai	2007-2011	1148	1983	23	-1360	-238	42	187	11
Shanghai	2003-2007	1077	2229	190	-1429	-378	157	215	15
Yunnan	2011-2016	186	3531	263	-4622	-571	-63	49	577
Yunnan	2007-2011	196	3203	827	-2362	-287	85	-30	238
Yunnan	2003-2007	157	1882	1829	-721	91	-46	-48	9
Beijing	2011-2016	329	1292	-94	-1473	-1030	-135	1072	73
Beijing	2007-2011	786	746	-161	-1261	-488	165	283	40
Beijing	2003-2007	516	1250	138	-934	-172	128	92	-45
Guangdong	2011-2016	759	8347	-721	-7729	-729	-89	702	129
Guangdong	2007-2011	1671	6165	460	-2643	956	-1444	130	382
Guangdong	2003-2007	1034	6032	1267	-2059	170	-373	412	-158
Hunan	2011-2016	307	4665	-230	-4882	383	-126	86	-299
Hunan	2007-2011	390	4671	1427	-3469	-330	-375	58	691

Hunan	2003-2007	-305	3216	863	860	232	-180	59	-74
Liaoning	2011-2016	-5	5214	-3030	-2437	-464	375	63	27
Liaoning	2007-2011	357	8336	2176	-4408	-1815	1724	189	-54
Liaoning	2003-2007	252	5452	1363	-1399	-80	281	-151	-34
Tianjin	2011-2016	954	2784	-318	-3236	-759	97	600	64
Tianjin	2007-2011	1087	2256	421	-989	-717	725	50	-21
Tianjin	2003-2007	346	1521	618	-1035	152	-203	14	51
Zhejiang	2011-2016	232	6163	-858	-5125	-396	-215	437	176
Zhejiang	2007-2011	822	4563	462	-2321	-1097	840	204	72
Zhejiang	2003-2007	553	4199	688	200	210	-288	198	-53

Appendix 2: Jointly-authored publications used in this thesis

Chapter 2, Section 2.5 Research gap

J.M. Ou, Z. J. Huang, Z. Klimont*, G. Jia, S. Zhang, C. Li, J. Meng, Z. Mi, H. Zheng, Y. Shan, J. Zheng*, D. Guan*., 2019. Role of export industries on China's ground-level ozone pollution. Under review by ***Science Advance***.

J.M. Ou, J. Meng, Y. Shan, H. Zheng, Z. Mi, D. Guan*, 2019. Initial Declines in China's Provincial Energy Consumption and Their Drivers. ***Joule***, 3, 5, 1163-1168.

J.M. Ou, J. Meng, J.Y. Zheng*, Z.F. Mi, Y.H. Bian, X. Yu, J.R., Liu, D.B., Guan*, 2017. Demand-driven air pollutant emissions for a fast-developing region in China. ***Applied Energy*** *(IF=7.900)*, 204: 131-124.

J.M. Ou, J. Meng, H. Zheng, Z. Mi, Y. Shan, D. Guan*, 2019. Frequent Interactions of Tibet's CO_2 emissions with those of other regions in China. ***Earth's Future*** *(IF=4.594)*, 7, 491-502.

J.M. Ou, J. Zheng*, Z. Yuan, D. Guan, Z. Huang, F. Yu, M. Shao, PKK Louie, 2018. Reconciling discrepancies in the source characterization of VOCs between emission inventories and receptor modeling. ***Science of the Total Environment*** *(IF=4.900)*, 628, 697-706.

In these jointly-authored publications, this PhD author led the identification of research gaps in existing literature. The identified research gaps are reflected in Section 2.5 of this PhD work. This PhD author contribute over 85% of the methodology, data and knowledge gaps identified.

Chapter 3, Method and data of energy-pollution-socioeconomic integrated assessment

J.M. Ou, Z. J. Huang, Z. Klimont*, G. Jia, et al., 2019. Role of export industries on China's ground-level ozone pollution. Under review by ***Science Advance***.

J.M. Ou, J. Meng, Y. Shan, H. Zheng, Z. Mi, D. Guan*, 2019. Initial Declines in China's Provincial Energy Consumption and Their Drivers. ***Joule***, 3, 5, 1163-1168.

J.M. Ou, J. Meng, J.Y. Zheng*, Z.F. Mi, Y.H. Bian, X. Yu, J.R., Liu, D.B., Guan*, 2017. Demand-driven air pollutant emissions for a fast-developing region in China. ***Applied Energy*** *(IF=7.900)*, 204: 131-124.

J.M. Ou, J. Meng, H. Zheng, Z. Mi, Y. Shan, D. Guan*, 2019. Frequent Interactions of Tibet's CO_2 emissions with those of other regions in China. ***Earth's Future*** *(IF=4.594)*, 7, 491-502.

J.M. Ou, J. Zheng*, Z. Yuan, D. Guan, Z. Huang, F. Yu, M. Shao, PKK Louie, 2018. Reconciling discrepancies in the source characterization of VOCs between emission inventories and receptor modeling. ***Science of the Total Environment*** *(IF=4.900)*, 628, 697-706.

In these jointly-authored publications, this PhD author led the overall research, designed the methodology and conducted quality assurance and quality control of the data. The methods and data sources used in these publications were based upon the methodological framework of this PhD work. This PhD author contribute over 75% of the designed methodologies and data control of the above mentioned publications.

Chapter 4, China's provincial energy consumption and its socioeconomic drivers

J.M. Ou, J. Meng, Y. Shan, H. Zheng, Z. Mi, D. Guan*, 2019. Initial Declines in China's Provincial Energy Consumption and Their Drivers. ***Joule***, 3, 5, 1163-1168.

In this jointly-authored publication, this PhD author led the data analysis and result discussion. J. Meng provided expertise on the applications of decomposition techniques. Y. Shan and H. Zheng helped to collected the raw data of energy statistics. Z. Mi and D. Guan contributed on insights, result discussion and response to reviewers' comments. This PhD author contributed over 80% of the data analysis and result discussion.

Chapter 5, Air pollutant emissions in a fast-developing region and its socioeconomic drivers

J.M. Ou, J. Meng, J.Y. Zheng*, Z.F. Mi, Y.H. Bian, X. Yu, J.R., Liu, D.B., Guan*, 2017. Demand-driven air pollutant emissions for a fast-developing region in China. ***Applied Energy*** *(IF=7.900)*, 204: 131-124.

In this jointly-authored publication, this PhD author contributed over 80% of the data analysis and result discussion. J. Meng provided expertise on the applications of environmentally-extended input-output analysis. J.Y. Zheng, Y.H. Bian helped to compile the production-based emission inventories. Z.F. Mi, X. Yu, J.R, Liu and D.B. Guan contributed on insights, discussion and response to reviewers' comments.

Chapter 6, Emissions from Tibet and its interactions with local and exogenous demands

J.M. Ou, J. Meng, H. Zheng, Z. Mi, Y. Shan, D. Guan*, 2019. Frequent Interactions of Tibet's CO_2 emissions with those of other regions in China. ***Earth's Future*** *(IF=4.594)*, 7, 491-502.

In this jointly-authored publication, this PhD author contributed over 80% of the data analysis and result discussion. J. Meng, H. Zheng, Z. Mi and D. Guan provided support on the development of multi-regional table, and its application. Y. Shan compiled the production-based CO_2 emission inventories. All authors contributed on result discussion and revision.

Chapter 7, Integrated assessment on ground-level ozone pollution in China and its mitigation

J.M. Ou, Z. J. Huang, Z. Klimont*, G. Jia, S. Zhang, C. Li, J. Meng, Z. Mi, H. Zheng, Y. Shan, J. Zheng*, D. Guan*., 2019. Role of export industries on China's ground-level ozone pollution. Under review by ***Science Advance***.

In this jointly-authored publication, this PhD author contributed over 80% of the data analysis and result discussion. This PhD author, Z. Klimont, J. Zheng, S. Zhang and D. Guan designed the studies. Z.J. Huang, G. Jia, and C. Li provided technical support on air quality modelling. Z. Klimont provided data from GAINS database. J. Meng, Z. Mi, Y. Shan and H. Zheng provided support on input-output analysis.

References

Abel, David W., Tracey Holloway, Javier Martínez-Santos, Monica Harkey, Madankui Tao, Cassandra Kubes, and Sara Hayes. 2019. "Air Quality-Related Health Benefits of Energy Efficiency in the United States." *Environmental Science and Technology* 53 (7): 3987–98. doi:10.1021/acs.est.8b06417.

Ackerman, Frank, Stephen J. DeCanio, Richard B. Howarth, and Kristen Sheeran. 2009. "Limitations of Integrated Assessment Models of Climate Change." *Climatic Change* 95 (3–4): 297–315. doi:10.1007/s10584-009-9570-x.

Afroz, Rafia, Mohd Nasir Hassan, and Noor Akma Ibrahim. 2003. "Review of Air Pollution and Health Impacts in Malaysia." *Environmental Research* 92 (2): 71–77. doi:10.1016/S0013-9351(02)00059-2.

Alberini, Anna, and Alan Krupnick. 2000. "Cost-of-Illness and Willingness-to-Pay Estimates of the Benefits of Improved Air Quality: Evidence from Taiwan." *Land Economics* 76 (1): 37–53. doi:10.2307/3147256.

Amann, Markus, Imrich Bertok, Jens Borken-Kleefeld, Janusz Cofala, Chris Heyes, Lena Höglund-Isaksson, Zbigniew Klimont, et al. 2011. "Cost-Effective Control of Air Quality and Greenhouse Gases in Europe: Modeling and Policy Applications." *Environmental Modelling and Software* 26 (12). Elsevier Ltd: 1489–1501. doi:10.1016/j.envsoft.2011.07.012.

Amann, Markus, M Anderl, J Borken-Kleefeld, J Cofala, C Heyes, L Höglund Isaksson, G Kiesewetter, et al. 2018. "Progress towards the Achievement of the EU's Air Quality and Emissions Objectives." Vol. 2018.

Andrés, Lidia, and Emilio Padilla. 2018. "Driving Factors of GHG Emissions in the EU Transport Activity." *Transport Policy* 61 (March 2017): 60–74. doi:10.1016/j.tranpol.2017.10.008.

Ang, BW. 1994. "Decomposition of Industrial Energy Consumption. The Energy Intensity Approach." *Energy Economics* 16 (3): 163–74. doi:10.1016/0140-9883(94)90030-2.

Ang, B. W., and F. Q. Zhang. 2000. "A Survey of Index Decomposition Analysis in Energy and Environmental Studies." *Energy* 25 (12): 1149–76. doi:10.1016/S0360-5442(00)00039-6.

Ang, B W, and F L Liu. 2001. "A New Energy Decomposition Method: Perfect in Decomposition and Consistent in Aggregation" *Energy Economics* 26: 537–48.

Ang, B W. 2005. "The LMDI Approach to Decomposition Analysis : A Practical Guide" *Energy* 33: 867–71. doi:10.1016/j.enpol.2003.10.010.

Ang, B. W., and Na Liu. 2007. "Energy Decomposition Analysis: IEA Model versus Other Methods." *Energy Policy* 35 (3): 1426–32. doi:10.1016/j.enpol.2006.04.020.

Ang, B. W., and X. Y. Xu. 2013. "Tracking Industrial Energy Efficiency Trends Using Index Decomposition Analysis." *Energy Economics* 40: 1014–21. doi:10.1016/j.eneco.2013.05.014.

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and George Filis. 2017. "Energy Consumption, CO2 Emissions, and Economic Growth: An Ethical Dilemma." *Renewable and Sustainable Energy Reviews* 68 (October 2015). Elsevier: 808–24. doi:10.1016/j.rser.2016.09.105.

Arellano, Avelino F., Prasad S. Kasibhatla, Louis Giglio, Guido R. van der Werf, and James T. Randerson. 2004. "Top-down Estimates of Global CO Sources Using MOPITT Measurements." *Geophysical Research Letters* 31 (1): 1–5. doi:10.1029/2003GL018609.

Asdrubali, Francesco, Catia Baldassarri, and Vasilis Fthenakis. 2013. "Life Cycle Analysis in the Construction Sector: Guiding the Optimization of Conventional Italian Buildings." *Energy and Buildings* 64. Elsevier B.V.: 73–89. doi:10.1016/j.enbuild.2013.04.018.

Atkinson, R., 1990. "Gas-phase tropospheric chemistry of organic compounds: a review. " *Atmospheric Environment*, 24A, 1-41.

Atkinson, R., 1994. "Gas-phase tropospheric chemistry of organic compounds. " *Journal of*

Physical Chemistry Reference Data. Monograph 2, 1-216.

Atkinson, Richard W, Dahai Yu, Ben G Armstrong, Sam Pattenden, Paul Wilkinson, Ruth M Doherty, Mathew R Heal, and H Ross Anderson. 2012. "Concentration–Response: Results from Five Urban and Five Rural UK Populations." *Environment Health Perspectives* 120 (10): 1411–17.

Bae, Sanghyuk, Youn Hee Lim, Saori Kashima, Takashi Yorifuji, Yasushi Honda, Ho Kim, and Yun Chul Hong. 2015. "Non-Linear Concentration-Response Relationships between Ambient Ozone and Daily Mortality." *PLoS ONE* 10 (6): 1–11. doi:10.1371/journal.pone.0129423.

Baghersad, Milad, and Christopher W. Zobel. 2015. "Economic Impact of Production Bottlenecks Caused by Disasters Impacting Interdependent Industry Sectors." *International Journal of Production Economics* 168. Elsevier: 71–80. doi:10.1016/j.ijpe.2015.06.011.

Bai, J. 1997. "Estimation of a Change Point in Multiple Regression Models." *Review of Economics and Statistics* 79: 551–63.

Barrett, John, Glen Peters, Thomas Wiedmann, Kate Scott, Manfred Lenzen, Katy Roelich, and Corinne Le Quéré. 2013. "Consumption-Based GHG Emission Accounting: A UK Case Study." *Climate Policy* 13 (4): 451–70. doi:10.1080/14693062.2013.788858.

Baykara, Metin, Ulas Im, and Alper Unal. 2019. "Evaluation of Impact of Residential Heating on Air Quality of Megacity Istanbul by CMAQ." *Science of the Total Environment* 651. Elsevier B.V.: 1688–97. doi:10.1016/j.scitotenv.2018.10.091.

Beevers, Sean D., Nutthida Kitwiroon, Martin L. Williams, Frank J. Kelly, H. Ross Anderson, and David C. Carslaw. 2013. "Air Pollution Dispersion Models for Human Exposure Predictions in London." *Journal of Exposure Science and Environmental Epidemiology* 23 (6). Nature Publishing Group: 647–53. doi:10.1038/jes.2013.6.

Belis, C. A., D. Pernigotti, F. Karagulian, G. Pirovano, B. R. Larsen, M. Gerboles, and P. K. Hopke. 2015. "A New Methodology to Assess the Performance and Uncertainty of Source Apportionment Models in Intercomparison Exercises." *Atmospheric Environment* 119. Elsevier Ltd: 35–44. doi:10.1016/j.atmosenv.2015.08.002.

Bergamaschi, Peter, Christian Frankenberg, Jan Fokke Meirink, Maarten Krol, M. Gabriella Villani, Sander Houweling, Dentener Frank, et al. 2009. "Inverse Modeling of Global and Regional CH4 Emissions Using SCIAMACHY Satellite Retrievals." *Journal of Geophysical Research Atmospheres* 114 (22): 1–28. doi:10.1029/2009JD012287.

Beusen, A. H.W., A. F. Bouwman, P. S.C. Heuberger, G. Van Drecht, and K. W. Van Der Hoek. 2008. "Bottom-up Uncertainty Estimates of Global Ammonia Emissions from Global Agricultural Production Systems." *Atmospheric Environment* 42 (24): 6067–77. doi:10.1016/j.atmosenv.2008.03.044.

Bey, Isabelle, Daniel J. Jacob, Robert M. Yantosca, Jennifer A. Logan, Brendan D. Field, Arlene M. Fiore, Qinbin Li, Honguy Y. Liu, Loretta J. Mickley, and Martin G. Schultz. 2001. "Global Modeling of Tropospheric Chemistry with Assimilated Meteorology: Model Description and Evaluation." *Journal of Geophysical Research Atmospheres* 106 (D19): 23073–95. doi:10.1029/2001JD000807.

Bian, Q., X. H.H. Huang, and J. Z. Yu. 2014. "One-Year Observations of Size Distribution Characteristics of Major Aerosol Constituents at a Coastal Receptor Site in Hong Kong - Part 1: Inorganic Ions and Oxalate." *Atmospheric Chemistry and Physics* 14 (17): 9013–27. doi:10.5194/acp-14-9013-2014.

Bian, Yahui, Jiamin Ou, Zhijiong Huang, Zhuangmin Zhong, Yuanqian Xu, Zhiwei Zhang, Xiao Xiao, et al. 2019. "Evolution of Anthropogenic Air Pollutant Emissions in Guangdong Province, China, from 2006 to 2015." *Atmospheric Chemistry and Physics Discussions*, 1–38. doi:10.5194/acp-2019-235.

Binkowski, Francis S., and Shawn J. Roselle. 2003. "Models-3 Community Multiscale Air Quality (CMAQ) Model Aerosol Component 1. Model Description." *Journal of Geophysical Research D: Atmospheres* 108 (6). doi:10.1029/2001jd001409.

Blake, Donald R., and F. Sherwood Rowland. 1995. "Urban Leakage of Liquefied Petroleum Gas and Its Impact on Mexico City Air Quality." *Science* 269 (5226): 953–56.

doi:10.1126/science.269.5226.953.

Blengini, G. A., E. Brizio, M. Cibrario, and G. Genon. 2011. “LCA of Bioenergy Chains in Piedmont (Italy): A Case Study to Support Public Decision Makers towards Sustainability.” *Resources, Conservation and Recycling* 57. Elsevier B.V.: 36–47. doi:10.1016/j.resconrec.2011.10.003.

Boden, T. A., Marland, G., & Andres, R. J. Global, regional, and national fossil-fuel CO2 emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. 2016. Retrieved from: http://cdiac.ornl.gov/CO2_Emission/timeseries/national

Branger, Frédéric, and Philippe Quirion. 2014. “Climate Policy and the ‘carbon Haven’ Effect.” *Wiley Interdisciplinary Reviews: Climate Change* 5 (1): 53–71. doi:10.1002/wcc.245.

Burtraw, Dallas, Alan Krupnick, Karen Palmer, Anthony Paul, Michael Toman, and Cary Bloyd. 2003. “Ancillary Benefits of Reduced Air Pollution in the US from Moderate Greenhouse Gas Mitigation Policies in the Electricity Sector.” *Journal of Environmental Economics and Management* 45 (3): 650–73. doi:10.1016/S0095-0696(02)00022-0.

Cabeza, Luisa F., Lídia Rincón, Virginia Vilariño, Gabriel Pérez, and Albert Castell. 2014. “Life Cycle Assessment (LCA) and Life Cycle Energy Analysis (LCEA) of Buildings and the Building Sector: A Review.” *Renewable and Sustainable Energy Reviews* 29. Elsevier: 394–416. doi:10.1016/j.rser.2013.08.037.

Camagni, Roberto, Roberta Capello, and Peter Nijkamp. 1998. “Towards Sustainable City Policy: An Economy-Environment Technology Nexus.” *Ecological Economics* 24 (1): 103–18. doi:10.1016/S0921-8009(97)00032-3.

Cansino, José M, Antonio Sánchez-braza, and María L Rodríguez-arévalo. 2018. “How Can Chile Move Away from a High Carbon Economy ?” *Energy Economics* 69. Elsevier B.V.: 350–66. doi:10.1016/j.eneco.2017.12.001.

Cantore, Nicola. 2011. “Distributional Aspects of Emissions in Climate Change Integrated Assessment Models.” *Energy Policy* 39 (5). Elsevier: 2919–24. doi:10.1016/j.enpol.2011.02.070.

Carlsson, Fredrik, and Olof Johansson-Stenman. 2000. “Willingness to Pay for Improved Air Quality in Sweden.” *Applied Economics* 32 (6): 661–69. doi:10.1080/000368400322273.

Chan, Chak K., and Xiaohong Yao. 2008. “Air Pollution in Mega Cities in China.” *Atmospheric Environment* 42 (1): 1–42. doi:10.1016/j.atmosenv.2007.09.003.

Chen, D., Y. Wang, M. B. McElroy, K. He, R. M. Yantosca, and P. Le Sager. 2009. “Regional CO Pollution and Export in China Simulated by the High-Resolution Nested-Grid GEOS-Chem Model.” *Atmospheric Chemistry and Physics* 9 (11): 3825–39. doi:10.5194/acp-9-3825-2009.

Chen, G Q, Shan Guo, Ling Shao, J S Li, and Zhan-ming Chen. 2013. “Three-Scale Input – Output Modeling for Urban Economy : Carbon Emission by Beijing 2007.” *Commun Nonlinear Sci Numer Simulat* 18: 2493–2506. doi:10.1016/j.cnsns.2012.12.029.

Chen, B., J. S. Li, X. F. Wu, M. Y. Han, L. Zeng, Z. Li, and G. Q. Chen. 2018. “Global Energy Flows Embodied in International Trade: A Combination of Environmentally Extended Input–output Analysis and Complex Network Analysis.” *Applied Energy* 210 (July 2017): 98–107. doi:10.1016/j.apenergy.2017.10.113.

Chen, Long, Sai Liang, Maodian Liu, Yujun Yi, Zhifu Mi, Yanxu Zhang, Yumeng Li, et al. 2019. “Trans-Provincial Health Impacts of Atmospheric Mercury Emissions in China.” *Nature Communications*. Springer US, 1–12. doi:10.1038/s41467-019-09080-6.

Cheng, Shuiyuan, Dongsheng Chen, Jianbing Li, Haiyan Wang, and Xiurui Guo. 2007. “The Assessment of Emission-Source Contributions to Air Quality by Using a Coupled MM5-ARPS-CMAQ Modeling System: A Case Study in the Beijing Metropolitan Region, China.” *Environmental Modelling and Software* 22 (11): 1601–16. doi:10.1016/j.envsoft.2006.11.003.

Cherubini, Francesco. 2010. “GHG Balances of Bioenergy Systems - Overview of Key Steps in the Production Chain and Methodological Concerns.” *Renewable Energy* 35 (7). Elsevier

Ltd: 1565–73. doi:10.1016/j.renene.2009.11.035.

China Light Industry Association. 2014. "China Light Industry Yearbook 2014 (in Chinese)."

China National Environmental Monitoring Centre. 2018a. "Monthly/Quarterly Report of Air Quality of 74 Cities."

Chinese State Council. 2013. "Action Plan on Air Pollution Prevention and Control." doi:10.1051/matecconf/201712107005.

Chinhao Chong, Linwei Ma, Zheng Li, Weidou Ni, Shizhong Song. 2015. "Logarithmic Mean Divisia Index (LMDI) Decomposition of Coal Consumption in China Based on the Energy Allocation Diagram of Coal Flows." *Energy* 85: 366–78.

Cifuentes, L., V.H. Borja-Aburto, N. Gouveia, G. Thurston, and D.L. Davis. 2001. "Hidden Health Benefits of Greenhouse Gas Mitigation." *Science* 293 (5533): 1257. doi:10.1126/science.1063357.

Cocks, A. T., I. R. Rodgers, R. A. Skeffington, and A. H. Webb. 1998. "The Limitations of Integrated Assessment Modelling in Developing Air Pollution Control Policies." *Environmental Pollution* 102 (SUPPL. 1): 635–39. doi:10.1016/S0269-7491(98)80092-4.

Coers, Robin, and Mark Sanders. 2013. "The Energy-GDP Nexus; Addressing an Old Question with New Methods." *Energy Economics* 36. Elsevier B.V.: 708–15. doi:10.1016/j.eneco.2012.11.015.

Cogan, A. J., H. Boesch, R. J. Parker, L. Feng, P. I. Palmer, J. F.L. Blavier, N. M. Deutscher, et al. 2012. "Atmospheric Carbon Dioxide Retrieved from the Greenhouse Gases Observing SATellite (GOSAT): Comparison with Ground-Based TCCON Observations and GEOS-Chem Model Calculations." *Journal of Geophysical Research Atmospheres* 117 (21). doi:10.1029/2012JD018087.

Committee on Methods for Estimating Greenhouse Gas Emissions. 2010. "Verifying Greenhouse Gas Emissions: Methods to Support International Climate Agreements."

Coordinating Research Council. 2015. "Projected Ozone Trends and Changes in the Ozone-Precursor Relationship in the South Coast Ari Basin in Responses to Varying Reductions of Precursor Emissions."

Davis, Steven J., and Ken Caldeira. 2010. "Consumption-Based Accounting of CO 2 Emissions." *Proceedings of the National Academy of Sciences of the United States of America* 107 (12): 5687–92. doi:10.1073/pnas.0906974107.

Davis, Jerry, William Cox, Adam Reff, and Pat Dolwick. 2011. "A Comparison of CMAQ-Based and Observation-Based Statistical Models Relating Ozone to Meteorological Parameters." *Atmospheric Environment* 45 (20). Elsevier Ltd: 3481–87. doi:10.1016/j.atmosenv.2010.12.060.

Dios, M., J. A. Souto, J. J. Casares, N. Gallego, A. Sáez, M. L. Macho, D. Cartelle, and J. M. Vellón. 2012. "A Mixed Top-down and Bottom-up Methodology in Spatial Segregation of Emissions Based on GIS Tools." *WIT Transactions on Ecology and the Environment* 157: 225–36. doi:10.2495/AIR120201.

Dodge, M.C. 1977. Combined use of modeling techniques and smog chamber data to derive ozone—precursor relationships in International Conference on Photochemical Oxidant Pollution and its Control: Proceedings, Vol. II., B. Dimitriades, ed. EPA/600/3-77-001b. U.S. Environmental Protection Agency, Environmental Sciences Research Laboratory, Research Triangle Park, N.C.

Du, Huibin, Daniel C. Matisoff, Yangyang Wang, and Xi Liu. 2016. "Understanding Drivers of Energy Efficiency Changes in China." *Applied Energy* 184. Elsevier Ltd: 1196–1206. doi:10.1016/j.apenergy.2016.05.002.

Du, Gang, Chuanwang Sun, Xiaoling Ouyang, and Chi Zhang. 2018. "A Decomposition Analysis of Energy-Related CO 2 Emissions in Chinese Six High-Energy Intensive Industries." *Journal of Cleaner Production* 184. Elsevier Ltd: 1102–12. doi:10.1016/j.jclepro.2018.02.304.

Dudek, Dan, Alexander Golub, and Elena Strukova. 2003. "Ancillary Benefits of Reducing Greenhouse Gas Emissions in Transitional Economies." *World Development* 31 (10):

1759–69. doi:10.1016/S0305-750X(03)00139-6.

Duncan, B.N, LN Lamsal, AM Thompson, Y Yoshida, ZF Lu, DG Streets, MM Hurwitz, and KE Pickering. 2016. "A Space-Based, High-Resolution View of Notable Changes in Urban NOx Pollution around the World (2005–2014)." *Journal of Geophysical Research Atmospheres* 121 (X): 976–96. doi:10.1002/2014JC010564.Received.

Ebi, Kristie L., and Glenn McGregor. 2008. "Climate Change, Tropospheric Ozone and Particulate Matter, and Health Impacts." *Environmental Health Perspectives* 116 (11): 1449–55. doi:10.1289/ehp.11463.

Economic Commission for Europe. 1990. "VOC Tas Force-Emissions for Volatile Organic Compounds from Stationary Sources and Possibilities of Their Control."

Elliott, Robert J R, Puyang Sun, and Tong Zhu. 2017. "The Direct and Indirect Effect of Urbanization on Energy Intensity : A Province-Level Study for China." *Energy* 123. Elsevier Ltd: 677–92. doi:10.1016/j.energy.2017.01.143.

Emery, Christopher, Zhen Liu, Armistead G Russell, M Talat Odman, Naresh Kumar, Christopher Emery, Zhen Liu, Armistead G Russell, and M Talat Odman. 2017. "Recommendations on Statistics and Benchmarks to Assess Photochemical Model Performance." *Journal of the Air & Waste Management Association* 67 (5). Taylor & Francis: 582–98. doi:10.1080/10962247.2016.1265027.

European Environment Agency. Air pollutant emission inventory guidebook 2016. Technical guidance to prepare national emission inventories. Available via https://www.eea.europa.eu/publications/emep-eea-guidebook-2016 (accessed on 21 September, 2018).

European Environment Agency. 2019. "Air Pollutant Emissions Data Viewer (Gothenburg Protocol, LRTAP Convention) 1990-2017." doi:.1037//0033-2909.I26.1.78.

Evans, Annette, Vladimir Strezov, and Tim J. Evans. 2009. "Assessment of Sustainability Indicators for Renewable Energy Technologies." *Renewable and Sustainable Energy Reviews* 13 (5): 1082–88. doi:10.1016/j.rser.2008.03.008.

Ezzati, M., B. H. Singer, and D. M. Kammen. 2001. "Towards an Integrated Framework for Development and Environment Policy: The Dynamics of Environmental Kuznets Curves." *World Development* 29 (8): 1421–34. doi:10.1016/S0305-750X(01)00044-4.

Ezzati, Majid, and Daniel M. Kammen. 2002. "The Health Impacts of Exposure to Indoor Air Pollution from Solid Fuels in Developing Countries: Knowledge, Gaps, and Data Needs." *Environmental Health Perspectives* 110 (11): 1057–68. doi:10.1289/ehp.021101057.

Fan, Jing-li, Yue-jun Zhang, and Bing Wang. 2017. "The Impact of Urbanization on Residential Energy Consumption in China : An Aggregated and Disaggregated Analysis." *Renewable and Sustainable Energy Reviews* 75 (November 2016). Elsevier Ltd: 220–33. doi:10.1016/j.rser.2016.10.066.

Fann, Neal, Charles M. Fulcher, and Bryan J. Hubbell. 2009. "The Influence of Location, Source, and Emission Type in Estimates of the Human Health Benefits of Reducing a Ton of Air Pollution." *Air Quality, Atmosphere and Health* 2 (3): 169–76. doi:10.1007/s11869-009-0044-0.

Feng, Chao, Jian Bai Huang, and Miao Wang. 2018. "The Driving Forces and Potential Mitigation of Energy-Related CO2 Emissions in China's Metal Industry." *Resources Policy* 59 (August). Elsevier Ltd: 487–94. doi:10.1016/j.resourpol.2018.09.003.

Feyen, Luc, Rutger Dankers, Katalin Bódis, Peter Salamon, and José I. Barredo. 2012. "Fluvial Flood Risk in Europe in Present and Future Climates." *Climatic Change* 112 (16): 47–62. doi:10.1029/2008JD011523.

Figueres, Christiana, Corinne Le Quéré, Anand Mahindra, Oliver Bäte, Gail Whiteman, Glen Peters, and Dabo Guan. 2018. "Emissions Are Still Rising: Ramp up the Cuts." *Nature* 564 (Dec): 27–30. doi:10.1038/d41586-018-07585-6.

Foley, K. M., S. J. Roselle, K. W. Appel, P. V. Bhave, J. E. Pleim, T. L. Otte, R. Mathur, et al. 2010. "Incremental Testing of the Community Multiscale Air Quality (CMAQ) Modeling System Version 4.7." *Geoscientific Model Development* 3 (1): 205–26. doi:10.5194/gmd-3-

205-2010.

Franzen, Axel, and Sebastian Mader. 2018. "Consumption-Based versus Production-Based Accounting of CO 2 Emissions: Is There Evidence for Carbon Leakage?" *Environmental Science and Policy* 84 (March). Elsevier: 34–40. doi:10.1016/j.envsci.2018.02.009.

Frey, H Christopher, and Junyu Zheng. 2002. "Quantification of Variability and Uncertainty in Air Pollutant Emission Inventories: Method and Case Study for Utility NOx Emissions." *Journal of the Air & Waste Management Association (1995)* 52 (9): 1083–95. doi:10.1080/10473289.2002.10470837.

Fujita, Eric M, John G Watson, Judith C Chow, and Karen L Magliano. 1995. "Receptor Model and Emissions Inventory Source Apportionments of Nonmethane Organic Gases in California'S San Joaquin Valley and San Francisco Bay Area." *Atmospheric Environment* 29 (21): 3019–35.

Fujita, Eric M., David E. Campbell, William R. Stockwell, Emily Saunders, Rosa Fitzgerald, and Roberto Perea. 2016. "Projected Ozone Trends and Changes in the Ozone-Precursor Relationship in the South Coast Air Basin in Response to Varying Reductions of Precursor Emissions." *Journal of the Air and Waste Management Association* 66 (2). Taylor & Francis: 201–14. doi:10.1080/10962247.2015.1106991.

Fusco, Andrew C., and Jennifer A. Logan. 2003. "Analysis of 1970-1995 Trends in Tropospheric Ozone at Northern Hemisphere Midlatitudes with the GEOS-CHEM Model." *Journal of Geophysical Research D: Atmospheres* 108 (15): 1–25. doi:10.1029/2002jd002742.

Gambhir, Ajay. 2019. "Planning a Low-Carbon Energy Transition: What Can and Can't the Models Tell Us?" *Joule* 3 (8). Elsevier Inc.: 1795–98. doi:10.1016/j.joule.2019.07.016.

Gan, Jianbang, and C. T. Smith. 2011. "Drivers for Renewable Energy: A Comparison among OECD Countries." *Biomass and Bioenergy* 35 (11). Elsevier Ltd: 4497–4503. doi:10.1016/j.biombioe.2011.03.022.

Gégo, Edith, Alice Gilliland, James Godowitch, S. Trivikrama Rao, P. Steven Porter, and Christian Hogrefe. 2008. "Modeling Analyses of the Effects of Changes in Nitrogen Oxides Emissions from the Electric Power Sector on Ozone Levels in the Eastern United States." *Journal of the Air and Waste Management Association* 58 (4): 580–88. doi:10.3155/1047-3289.58.4.580.

Gelzleichter, Thomas R., Hanspeter Witschi, and Jerold A. Last. 1992. "Concentration-Response Relationships of Rat Lungs to Exposure to Oxidant Air Pollutants: A Critical Test of Haber's Law for Ozone and Nitrogen Dioxide." *Toxicology and Applied Pharmacology* 112 (1): 73–80. doi:10.1016/0041-008X(92)90281-V.

Ghoshray, Atanu, Yurena Mendoza, Mercedes Monfort, and Javier Ordoñez. 2018. "Re-Assessing Causality between Energy Consumption and Economic Growth." *PLoS ONE* 13 (11): 1–15. doi:10.1371/journal.pone.0205671.

Ghude, Sachin D., Gabriele G. Pfister, Chinmay Jena, R. J. Van Der A, Louisa K. Emmons, and Rajesh Kumar. 2013. "Satellite Constraints of Nitrogen Oxide (NOx) Emissions from India Based on OMI Observations and WRF-Chem Simulations." *Geophysical Research Letters* 40 (2): 423–28. doi:10.1029/2012GL053926.

Giraud, Gaël. 2014. "How Dependent Is Growth from Primary Energy ? Output Energy Elasticity in 50 Countries," 1–21.

Gleick, Peter H. 2014. "Water, Drought, Climate Change, and Conflict in Syria." *Weather, Climate, and Society* 6 (3): 331–40. doi:10.1175/WCAS-D-13-00059.1.

Glotfelty, Timothy, Jian He, and Yang Zhang. 2017. "Impact of Future Climate Policy Scenarios on Air Quality and Aerosol-Cloud Interactions Using an Advanced Version of CESM/CAM5: Part I. Model Evaluation for the Current Decadal Simulations." *Atmospheric Environment* 152. Elsevier Ltd: 222–39. doi:10.1016/j.atmosenv.2016.12.035.

Goh, Tian, B W Ang, Bin Su, and H Wang. 2018. "Drivers of Stagnating Global Carbon Intensity of Electricity and the Way Forward." *Energy Policy* 113 (July 2017). Elsevier Ltd: 149–56. doi:10.1016/j.enpol.2017.10.058.

Gould, Brian W., and Surendra N. Kulshreshtha. 1986. "An Interindustry Analysis of Structural

Change and Energy Use Linkages in the Saskatchewan Economy." *Energy Economics* 8 (3): 186–96. doi:10.1016/0140-9883(86)90018-6.

Gracceva, Francesco, and Peter Zeniewski. 2013. "Exploring the Uncertainty around Potential Shale Gas Development - A Global Energy System Analysis Based on TIAM (TIMES Integrated Assessment Model)." *Energy* 57. Elsevier Ltd: 443–57. doi:10.1016/j.energy.2013.06.006.

Griggs, David, Mark Stafford Smith, Johan Rockström, Marcus C. Öhman, Owen Gaffney, Gisbert Glaser, Norichika Kanie, Ian Noble, Will Steffen, and Priya Shyamsundar. 2014. "An Integrated Framework for Sustainable Development Goals." *Ecology and Society* 19 (4). doi:10.5751/ES-07082-190449.

Groosman, Britt, Nicholas Z. Muller, and Erin O'Neill-Toy. 2011. "The Ancillary Benefits from Climate Policy in the United States." *Environmental and Resource Economics* 50 (4): 585–603. doi:10.1007/s10640-011-9483-9.

Gu, Y., T. W. Wong, C. K. Law, G. H. Dong, K. F. Ho, Y. Yang, and S. H.L. Yim. 2018. "Impacts of Sectoral Emissions in China and the Implications: Air Quality, Public Health, Crop Production, and Economic Costs." *Environmental Research Letters* 13 (8). doi:10.1088/1748-9326/aad138.

Guan, Dabo, Klaus Hubacek, Christopher L Weber, Glen P Peters, and David M Reiner. 2008. "The Drivers of Chinese CO2 Emissions from 1980 to 2030." *Global Environmental Change* 18: 626–34. doi:10.1016/j.gloenvcha.2008.08.001.

Guan, Dabo, Glen P. Peters, Christopher L. Weber, and Klaus Hubacek. 2009. "Journey to World Top Emitter: An Analysis of the Driving Forces of China's Recent CO2 Emissions Surge." *Geophysical Research Letters* 36 (4): 1–5. doi:10.1029/2008GL036540.

Guan, Dabo, Zhu Liu, Yong Geng, Sören Lindner, and Klaus Hubacek. 2012. "The Gigatonne Gap in China's Carbon Dioxide Inventories." *Nature Climate Change* 2 (9). Nature Publishing Group: 672–75. doi:10.1038/nclimate1560.

Guan, Dabo, Stephan Klasen, Klaus Hubacek, Kuishuang Feng, Zhu Liu, Kebin He, Yong Geng, and Qiang Zhang. 2014. "Determinants of Stagnating Carbon Intensity in China." *Nature Climate Change* 4 (11): 1017–23. doi:10.1038/nclimate2388.

Guan, Dabo, Jing Meng, David M Reiner, Ning Zhang, Yuli Shan, Zhifu Mi, Shuai Shao, Zhu Liu, Qiang Zhang, and Steven J Davis. 2018. "Structural Decline in China's CO2 Emissions through Transitions in Industry and Energy Systems." *Nature Geoscience* 11 (August). Springer US: 551–55. doi:10.1038/s41561-018-0161-1..

Guangdong Polytechnic of Environmental Protection Engineering and South China University of Technology. 2012. "Report on the Field Survey of Key Air Pollution Sources in Foshan-Phase II."

Haagen-Smit, A.J., and M.M. Fox. 1954. "Photochemical ozone formation with hydrocarbons and automobile exhaust". *J. Air Pollut. Control Assoc*. 4:105—109.

Hajime, Akimoto, Ohara Toshimasa, Kurokawa Jun-ichi, and Horii Nobuhiro. 2006. "Verification of Energy Consumption in China during 1996–2003 by Using Satellite Observational Data." *Atmoshperic Environment* 40: 7663–67. doi:10.1029/2005GL022770.

Hallegatte, Stephane. 2015. "The Indirect Cost of Natural Disasters and an Economic Definition of Macroeconomic Resilience." *Policy Research Working Papers*, no. July: 1–40. https://www.gfdrr.org/sites/gfdrr.org/files/documents/Public finance and macroeconomics, Paper 3.pdf.

Hallegatte, Stephane, and Valentin Przyluski. 2010. "The Economics of Natural Disasters." *CESifo Forum* 11 (2): 14–24. doi:10.1146/annurev-resource-073009-104211.

Han, Zhiwei, Tijian Wang, and Renjian Zhang. 2008. "Impacts of Biogenic Emissions of VOC and NO x on Tropospheric Ozone during Summertime in Eastern China." *Science of The Total Environment* 95: 41–49. doi:10.1016/j.scitotenv.2008.01.059.

Han, Suqin, Hai Bian, Yinchang Feng, Aixia Liu, Xiangjin Li, Fang Zeng, and Xiaoling Zhang. 2011. "Analysis of the Relationship between O3, NO and NO2 in Tianjin, China." *Aerosol and Air Quality Research* 11 (2): 128–39. doi:10.4209/aaqr.2010.07.0055.

Harfoot, Michael, Derek P. Tittensor, Tim Newbold, Greg Mcinerny, Matthew J. Smith, and Jörn P.W. Scharlemann. 2014. "Integrated Assessment Models for Ecologists: The Present and the Future." *Global Ecology and Biogeography* 23 (2): 124–43. doi:10.1111/geb.12100.

Harley, Robert a, and Glen R Cass. 1995. "Modeling the Atmospheric Concentrations of Individual Volatile Organic Compounds." *Atmospheric Environment* 29 (8): 905–22.

Hawkins, Jacob, Chunbo Ma, Steven Schilizzi, and Fan Zhang. 2015. "Promises and Pitfalls in Environmentally Extended Input-Output Analysis for China: A Survey of the Literature." *Energy Economics* 48. Elsevier B.V.: 81–88. doi:10.1016/j.eneco.2014.12.002.

Henry, Ronald C., Charles W. Lewis, Philip K. Hopke, and Hugh J. Williamson. 1984. "Review of Receptor Model Fundamentals." *Atmospheric Environment (1967)* 18 (8): 1507–15. doi:10.1016/0004-6981(84)90375-5.

Henze, D. K., J. H. Seinfeld, and D. T. Shindell. 2009. "Inverse Modeling and Mapping US Air Quality Influences of Inorganic PM 2.5 Precursor Emissions Using the Adjoint of GEOS-Chem." *Atmospheric Chemistry and Physics* 9 (16): 5877–5903. doi:10.5194/acp-9-5877-2009.

Hertwich, Edgar G., Thomas Gibon, Evert A. Bouman, Anders Arvesen, Sangwon Suh, Garvin A. Heath, Joseph D. Bergesen, Andrea Ramirez, Mabel I. Vega, and Lei Shi. 2015. "Integrated Life-Cycle Assessment of Electricity-Supply Scenarios Confirms Global Environmental Benefit of Low-Carbon Technologies." *Proceedings of the National Academy of Sciences of the United States of America* 112 (20): 6277–82. doi:10.1073/pnas.1312753111.

Hoesly, Rachel M., Steven J. Smith, Leyang Feng, Zbigniew Klimont, Greet Janssens-Maenhout, Tyler Pitkanen, Jonathan J. Seibert, et al. 2018. "Historical (1750-2014) Anthropogenic Emissions of Reactive Gases and Aerosols from the Community Emissions Data System (CEDS)." *Geoscientific Model Development* 11 (1): 369–408. doi:10.5194/gmd-11-369-2018.

Hogrefe, C., B. Lynn, K. Civerolo, J. Y. Ku, J. Rosenthal, C. Rosenzweig, R. Goldberg, S. Gaffin, K. Knowlton, and P. L. Kinney. 2004. "Simulating Changes in Regional Air Pollution over the Eastern United States Due to Changes in Global and Regional Climate and Emissions." *Journal of Geophysical Research D: Atmospheres* 109 (22): 1–13. doi:10.1029/2004JD004690.

Hong, Chaopeng, Qiang Zhang, Yang Zhang, Youhua Tang, Daniel Tong, and Kebin He. 2017. "Multi-Year Downscaling Application of Two-Way Coupled WRF v3 . 4 and CMAQ v5 . 0 . 2 over East Asia for Regional Climate and Air Quality Modeling : Model Evaluation and Aerosol Direct Effects." *Geoscientific Model Development* 10: 2447–70.

Hong Kong-Guangdong Joint Working Group on Sustainable Development and Environmental Protection. 2008. "Pearl River Delta Regional Air Quality Management Plan Mid-Term Review Report."

Horton, Pascal, Bettina Schaefli, Abdelkader Mezghani, Benoît Hingray, and André Musy. 2006. "Assessment of Climate-Change Impacts on Alpine Discharge Regimes with Climate Model Uncertainty." *Hydrological Processes* 20 (10): 2091–2109. doi:10.1002/hyp.6197.

Houweling, Sander, Peter Bergamaschi, Frederic Chevallier, Martin Heimann, Thomas Kaminski, Maarten Krol, Anna M. Michalak, and Prabir Patra. 2017. "Global Inverse Modeling of CH4 Sources and Sinks: An Overview of Methods." *Atmospheric Chemistry and Physics* 17 (1): 235–56. doi:10.5194/acp-17-235-2017.

Hsu, Ying Kuang, Tony VanCuren, Seong Park, Chris Jakober, Jorn Herner, Michael FitzGibbon, Donald R. Blake, and David D. Parrish. 2010. "Methane Emissions Inventory Verification in Southern California." *Atmospheric Environment* 44 (1). Elsevier Ltd: 1–7. doi:10.1016/j.atmosenv.2009.10.002.

Hu, Jianlin, Jianjun Chen, Qi Ying, and Hongliang Zhang. 2016. "One-Year Simulation of Ozone and Particulate Matter in China Using WRF / CMAQ Modeling System." *Atmospheric Chemistry and Physics* 16: 10333–50. doi:10.5194/acp-16-10333-2016.

Huang, C., C. H. Chen, L. Li, Z. Cheng, H. L. Wang, H. Y. Huang, D. G. Streets, Y. J. Wang, G. F. Zhang, and Y. R. Chen. 2011. "Emission Inventory of Anthropogenic Air Pollutants and VOC Species in the Yangtze River Delta Region, China." *Atmospheric Chemistry and*

Physics 11 (9): 4105–20. doi:10.5194/acp-11-4105-2011.

Huang, Kan, Joshua S. Fu, N. Christina Hsu, Yang Gao, Xinyi Dong, Si Chee Tsay, and Yun Fat Lam. 2013. "Impact Assessment of Biomass Burning on Air Quality in Southeast and East Asia during BASE-ASIA." *Atmospheric Environment* 78. Elsevier: 291–302. doi:10.1016/j.atmosenv.2012.03.048.

Huang, Ganlin, Rosie Brook, Monica Crippa, Greet Janssens-Maenhout, Christian Schieberle, Chris Dore, Diego Guizzardi, Marilena Muntean, Edwin Schaaf, and Rainer Friedrich. 2017. "Speciation of Anthropogenic Emissions of Non-Methane Volatile Organic Compounds: A Global Gridded Data Set for 1970-2012." *Atmospheric Chemistry and Physics* 17 (12): 7683–7701. doi:10.5194/acp-17-7683-2017.

Hui, Mulin, Qingru Wu, Shuxiao Wang, Sai Liang, Lei Zhang, Fengyang Wang, Manfred Lenzen, et al. 2017. "Mercury Flows in China and Global Drivers." *Environmental Science and Technology* 51 (1): 222–31. doi:10.1021/acs.est.6b04094.

Huo, Hong, Qiang Zhang, Dabo Guan, Xin Su, Hongyan Zhao, and Kebin He. 2014. "Examining Air Pollution in China Using Production- and Consumption-Based Emissions Accounting Approaches." *Environmental Science and Technology* 48 (24): 14139–47. doi:10.1021/es503959t.

Huo, Hong, Zhu Liu, Zifeng Lu, David G Streets, Ruijing Ni, Michael Brauer, Aaron Van Donkelaar, and V Randall. 2017. "Transboundary Health Impacts of Transported Global Air Pollution and International Trade." *Nature* 543 (7647). Nature Publishing Group: 705–9. doi:10.1038/nature21712.

Huppmann, Daniel, Matthew Gidden, Oliver Fricko, Peter Kolp, Clara Orthofer, Michael Pimmer, Nikolay Kushin, et al. 2019. "The MESSAGEix Integrated Assessment Model and the Ix Modeling Platform (Ixmp): An Open Framework for Integrated and Cross-Cutting Analysis of Energy, Climate, the Environment, and Sustainable Development." *Environmental Modelling and Software* 112 (November 2018). Elsevier: 143–56. doi:10.1016/j.envsoft.2018.11.012.

International Agency for Research on Cancer. 2012. "2012 IARC Monograph - Benzene." *IARC Monographs - 100F*. Vol. 1987.

International Energy Agency (IEA). 2017. "IEAdata." *Statistics by Country*. https://www.iea.org/statistics/statisticssearch/.

International Monetary Fund, 2018. World Economic Outlook Database-GDP per capita, current prices. Avaialbe via http://www.imf.org/external/datamapper/PPPPC@WEO/THA (Last accessed on 01 April 2020.)

International Institute for Applied System Analysis, 2018. The Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) model. Available via https://iiasa.ac.at/web/home/research/researchPrograms/air/GAINS.html (Last accessed on 01 April 2020)

Intergovernmental Panel on Climate Change 1996. "The IPCC Guidelines for National Greenhouse Gas Inventories 1996."

Intergovernmental Panel on Climate Change. 2014. "Climate Change 2014: Working Group III: Mitigation of Climate Change."

Jackson, Randall, and Alan Murray. 2004. "Alternative Input-Output Matrix Updating Formulations." *Economic Systems Research* 16 (2): 135–48. doi:10.1080/0953531042000219268.

Jackson, J. Elizabeth, Michael G. Yost, Catherine Karr, Cole Fitzpatrick, Brian K. Lamb, Serena H. Chung, Jack Chen, Jeremy Avise, Roger A. Rosenblatt, and Richard A. Fenske. 2010. "Public Health Impacts of Climate Change in Washington State: Projected Mortality Risks Due to Heat Events and Air Pollution." *Climatic Change* 102 (1–2): 159–86. doi:10.1007/s10584-010-9852-3.

Jacob, Daniel J. 2000. "Heterogeneous Chemistry and Tropospheric Ozone." *Atmospheric Environment* 34 (12–14): 2131–59. doi:10.1016/S1352-2310(99)00462-8.

Jakeman, A. J., and R. A. Letcher. 2003. "Integrated Assessment and Modelling: Features, Principles and Examples for Catchment Management.” *Environmental Modelling and Software* 18 (6): 491–501. doi:10.1016/S1364-8152(03)00024-0.

Jenkin, M.E., Clemitshaw, K.C., 2000. “Ozone and other secondary photochemical pollutants: chemical process governing their formation in the planetary boundary layer.” *Atmospheric Environment*, 34(16): 2499-2527.

Jerrett, Michael, Richard T. Burnett, C. Arden Pope, Kazuhiko Ito, George Thurston, Daniel Krewski, Yuanli Shi, Eugenia Calle, and Michael Thun. 2009. “Long-Term Ozone Exposure and Mortality.” *New England Journal of Medicine* 360 (11): 1085–95. doi:10.1056/NEJMoa0803894.

Jiang, Lei, Henk Folmer, and Minhe Ji. 2014. “The Drivers of Energy Intensity in China: A Spatial Panel Data Approach.” *China Economic Review* 31. Elsevier Inc.: 351–60. doi:10.1016/j.chieco.2014.10.003.

Jiang, Xujia, Qiang Zhang, Hongyan Zhao, Guannan Geng, Liqun Peng, Dabo Guan, Haidong Kan, et al. 2015. “Revealing the Hidden Health Costs Embodied in Chinese Exports.” *Enviromental Science and Technology* 49: 4381–88. doi:10.1021/es506121s.

Jiang, Jingjing, Bin Ye, Dejun Xie, and Jie Tang. 2017. “Provincial-Level Carbon Emission Drivers and Emission Reduction Strategies in China : Combining Multi-Layer LMDI Decomposition with Hierarchical Clustering.” *Journal of Cleaner Production* 169. Elsevier Ltd: 178–90. doi:10.1016/j.jclepro.2017.03.189.

Junguo, Liu, and Yang Hong. 2009. “China Fights Against Statistical Corruption.” *Science* 325 (1): 675–76.

Kakosimos, Konstantinos E., Ole Hertel, Matthias Ketzel, and Ruwim Berkowicz. 2010. “Operational Street Pollution Model (OSPM) - A Review of Performed Application and Validation Studies, and Future Prospects.” *Environmental Chemistry* 7 (6): 485–503. doi:10.1071/EN10070.

Kalaugher, Electra, Janet F. Bornman, Anthony Clark, and Pierre Beukes. 2013. “An Integrated Biophysical and Socio-Economic Framework for Analysis of Climate Change Adaptation Strategies: The Case of a New Zealand Dairy Farming System.” *Environmental Modelling and Software* 39. Elsevier Ltd: 176–87. doi:10.1016/j.envsoft.2012.03.018.

Kan, Haidong, and Bingheng Chen. 2004. “Particulate Air Pollution in Urban Areas of Shanghai, China: Health-Based Economic Assessment.” *Science of the Total Environment* 322 (1–3): 71–79. doi:10.1016/j.scitotenv.2003.09.010.

Kannari, Akiyoshi, Yutaka Tonooka, Tsuyoshi Baba, and Kentaro Murano. 2007. “Development of Multiple-Species 1 Km × 1 Km Resolution Hourly Basis Emissions Inventory for Japan.” *Atmospheric Environment* 41 (16): 3428–39. doi:10.1016/j.atmosenv.2006.12.015.

Karagulian, Federico, and Claudio A. Belis. 2012. “Enhancing Source Apportionment with Receptor Models to Foster the Air Quality Directive Implementation.” *International Journal of Environment and Pollution* 50 (1–4): 190–99. doi:10.1504/IJEP.2012.051192.

Kay, Jennifer E., Casey Wall, Vineel Yettella, Brian Medeiros, Cecile Hannay, Peter Caldwell, and Cecilia Bitz. 2016. “No Access Global Climate Impacts of Fixing the Southern Ocean Shortwave Radiation Bias in the Community Earth System Model (CESM).” *Journal of Climate* 29 (12): 4617–36. doi:10.1175/JCLI-D-15-0358.1.

Kennedy, Christopher, Julia Steinberger, Barrie Gasson, Yvonne Hansen, Timothy Hillman, Miroslav Havránek, Diane Pataki, Aumnad Phdungsilp, Anu Ramaswami, and Gara Villalba Mendez. 2009. “Greenhouse Gas Emissions from Global Cities.” *Environmental Science and Technology* 43 (19): 7297–7302. doi:10.1021/es900213p.

Kennedy, Christopher, Julia Steinberger, Barrie Gasson, Yvonne Hansen, Timothy Hillman, Miroslav Havranek, Diane Pataki, Aumnad Phdungsilp, Anu Ramaswami, and Gara Villalba Mendez. 2010. “Methodology for Inventorying Greenhouse Gas Emissions from Global Cities.” *Energy Policy* 38 (9): 4828–37. doi:10.1016/j.enpol.2009.08.050.

Kim, P. S., D. J. Jacob, J. A. Fisher, K. Travis, K. Yu, L. Zhu, R. M. Yantosca, et al. 2015. “Sources, Seasonality, and Trends of Southeast US Aerosol: An Integrated Analysis of Surface, Aircraft, and Satellite Observations with the GEOS-Chem Chemical Transport Model.” *Atmospheric Chemistry and Physics* 15 (18): 10411–33. doi:10.5194/acp-15-

10411-2015.

Kim, Youngseob, You Wu, Christian Seigneur, and Yelva Roustan. 2018. "Multi-Scale Modeling of Urban Air Pollution: Development and Application of a Street-in-Grid Model (v1.0) by Coupling MUNICH (v1.0) and Polair3D (v1.8.1)." *Geoscientific Model Development* 11 (2): 611–29. doi:10.5194/gmd-11-611-2018.

Kitzes, Justin. 2013. "An Introduction to Environmentally-Extended Input-Output Analysis." *Resources* 2 (4): 489–503. doi:10.3390/resources2040489.

Klaassen, Ger, and Keywan Riahi. 2007. "Internalizing Externalities of Electricity Generation: An Analysis with MESSAGE-MACRO." *Energy Policy* 35 (2): 815–27. doi:10.1016/j.enpol.2006.03.007.

Klimont, Zbigniew, David G. Streets, Shalini Gupta, Janusz Cofala, Fu Lixin, and Yoichi Ichikawa. 2002. "Anthropogenic Emissions of Non-Methane Volatile Organic Compounds in China." *Atmospheric Environment* 36: 1309–22. doi:10.1016/S1352-2310(01)00529-5.

Knutti, Reto, and Jan Sedláček. 2013. "Robustness and Uncertainties in the New CMIP5 Climate Model Projections." *Nature Climate Change* 3 (4). Nature Publishing Group: 369–73. doi:10.1038/nclimate1716.

Kondo, Y., Y. Moriguchi, and H. Shimizu. 1998. "CO2 Emissions in Japan: Influences of Imports and Exports." *Applied Energy* 59 (2–3): 163–74. doi:10.1016/S0306-2619(98)00011-7.

Kuan, C.M., Hornik, K. 1995. "The Generalized Fluctuation Test: A Unifying View." *Econometric Reviews* 14: 135–61.

Kuenen, J. J.P., A. J.H. Visschedijk, M. Jozwicka, and H. A.C. Denier Van Der Gon. 2014. "TNO-MACC-II Emission Inventory; A Multi-Year (2003-2009) Consistent High-Resolution European Emission Inventory for Air Quality Modelling." *Atmospheric Chemistry and Physics* 14 (20): 10963–76. doi:10.5194/acp-14-10963-2014.

Kumar, Prashant, and Devendra P. Saroj. 2014. "Water-Energy-Pollution Nexus for Growing Cities." *Urban Climate* 10 (P5). Elsevier B.V.: 846–53. doi:10.1016/j.uclim.2014.07.004.

Kypreos, Socrates, and Antti Lehtila. 2015. "Decomposing TIAM-MACRO to Assess Climatic Change Mitigation." *Environmental Modeling and Assessment* 20 (6): 571–81. doi:10.1007/s10666-015-9451-9.

Kyselý, Jan. 2002. "Comparison of Extremes in GCM-Simulated, Downscaled and Observed Central-European Temperature Series." *Climate Research* 20 (3): 211–22. doi:10.3354/cr020211.

Lee, Chulkyu, Randall V. Martin, Aaron Van Donkelaar, Hanlim Lee, Russell R. Dickerson, Jennifer C. Hains, Nickolay Krotkov, Andreas Richter, Konstantine Vinnikov, and James J. Schwab. 2011. "SO2 Emissions and Lifetimes: Estimates from Inverse Modeling Using in Situ and Global, Space-Based (SCIAMACHY and OMI) Observations." *Journal of Geophysical Research Atmospheres* 116 (6): 1–13. doi:10.1029/2010JD014758.

Le Quéré, C., Andrew, R. M., Canadell, J. G., Sitch, S., Korsbakken, J. I., Peters, G. P., Manning, A. C., Boden, T. A., Tans, P. P., & Houghton, R. A. (2016). Global carbon budget 2016. Earth System Science Data, 8(2), 605.

Lenzen, Manfred, Joy Murray, Fabian Sack, and Thomas Wiedmann. 2007. "Shared Producer and Consumer Responsibility - Theory and Practice." *Ecological Economics* 61 (1): 27–42. doi:10.1016/j.ecolecon.2006.05.018.

Lenzen, Manfred, Lise Lotte Pade, and Jesper Munksgaard. 2004. "CO2 Multipliers in Multi-Region Input-Output Models." *Economic Systems Research* 16 (4): 389–412. doi:10.1080/0953531042000304272.

Leontief, Wassily. 1970. "Environmental Repercussions and the Economic Structure : An Input-Output Approach Author (s): Wassily Leontief Source : The Review of Economics and Statistics , Vol . 52 , No . 3 (Aug ., 1970), Pp . 262-271 Published by : The MIT Press Stable URL : Ht." *The Review of Economics and Statistics* 52 (3): 262–71.

Levelt, Pieternel F., Gijsbertus H.J. Van Den Oord, Marcel R. Dobber, Anssi Mälkki, Huib Visser, Johan De Vries, Piet Stammes, Jens O.V. Lundell, and Heikki Saari. 2006. "The

Ozone Monitoring Instrument.” *IEEE Transactions on Geoscience and Remote Sensing* 44 (5): 1093–1100. doi:10.1109/TGRS.2006.872333.

Li, Lingyu, Shaodong Xie, Limin Zeng, Rongrong Wu, and Jing Li. 2015. “Characteristics of Volatile Organic Compounds and Their Role in Ground-Level Ozone Formation in the Beijing-Tianjin-Hebei Region, China.” *Atmospheric Environment* 113. Elsevier Ltd: 247–54. doi:10.1016/j.atmosenv.2015.05.021.

Li, Cheng, Zibing Yuan, Jiamin Ou, Xiaoli Fan, Siqi Ye, Teng Xiao, Yuqi Shi, et al. 2016. “An AIS-Based High-Resolution Ship Emission Inventory and Its Uncertainty in Pearl River Delta Region, China.” *Science of the Total Environment* 573. Elsevier B.V.: 1–10. doi:10.1016/j.scitotenv.2016.07.219.

Li, Meng, Huan Liu, Guannan Geng, Chaopeng Hong, Fei Liu, Yu Song, Dan Tong, et al. 2017a. “Anthropogenic Emission Inventories in China: A Review.” *National Science Review* 4 (6): 834–66. doi:10.1093/nsr/nwx150.

Li, Feng, Xusheng Liu, Xiaoling Zhang, Dan Zhao, Hongxiao Liu, Chuanbin Zhou, and Rusong Wang. 2017b. “Urban Ecological Infrastructure: An Integrated Network for Ecosystem Services and Sustainable Urban Systems.” *Journal of Cleaner Production* 163. Elsevier: S12–18. doi:10.1016/j.jclepro.2016.02.079.

Li, J. S., B. Chen, G. Q. Chen, W. D. Wei, X. B. Wang, J. P. Ge, K. Q. Dong, H. H. Xia, and X. H. Xia. 2017c. “Tracking Mercury Emission Flows in the Global Supply Chains: A Multi-Regional Input-Output Analysis.” *Journal of Cleaner Production* 140: 1470–92. doi:10.1016/j.jclepro.2016.10.002.

Li, Donghuan, Tianjun Zhou, Liwei Zou, Wenxia Zhang, and Lixia Zhang. 2018a. “Extreme High-Temperature Events Over East Asia in 1.5°C and 2°C Warmer Futures: Analysis of NCAR CESM Low-Warming Experiments.” *Geophysical Research Letters* 45 (3): 1541–50. doi:10.1002/2017GL076753.

Li, Cheng, B.K. Jens, J.Y. Zheng, Z.B. Yuan, J.M. Ou, Y. Li, Y.L. Wang. 2018b. Decadal evolution of ship emissions in China from 2004 to 2013 by using an integrated AIS-based approach and projection to 2040. *Atmospheric Chemistry and Physics* 18 (8):6075-6093.

Li, Ke, Daniel J Jacob, Hong Liao, Lu Shen, Qiang Zhang, and Kelvin H Bates. 2018c. “Anthropogenic Drivers of 2013 – 2017 Trends in Summer Surface Ozone in China.” *Proc. Natl. Acad. Sci. USA* 116 (2): 1–6. doi:10.1073/pnas.1812168116.

Liao, K. J., E. Tagaris, K. Manomaiphiboon, C. Wang, J. H. Woo, P. Amar, S. He, and A. G. Russell. 2009. “Quantification of the Impact of Climate Uncertainty on Regional Air Quality.” *Atmospheric Chemistry and Physics* 9 (3): 865–78. doi:10.5194/acp-9-865-2009.

Limaye, Vijay S., Wolfgang Schöpp, and Markus Amann. 2019. “Applying Integrated Exposure-Response Functions to PM 2.5 Pollution in India.” *International Journal of Environmental Research and Public Health* 16 (1). doi:10.3390/ijerph16010060.

Lin, Ching Ho, Yee Lin Wu, Chin Hsing Lai, John G. Watson, and Judith C. Chow. 2008. “Air Quality Measurements from the Southern Particulate Matter Super Site in Taiwan.” *Aerosol and Air Quality Research* 8 (3): 233–64. doi:10.4209/aaqr.2008.04.0012.

Lin, Jintai, Da Pan, Steven J. Davis, Qiang Zhang, Kebin He, Can Wang, David G. Streets, Donald J. Wuebbles, and Dabo Guan. 2014. “China’s International Trade and Air Pollution in the United States.” *Proceedings of the National Academy of Sciences of the United States of America* 111 (5): 1736–41. doi:10.1073/pnas.1312860111.

Liu, Na, and B. W. Ang. 2007. “Factors Shaping Aggregate Energy Intensity Trend for Industry: Energy Intensity versus Product Mix.” *Energy Economics* 29 (4): 609–35. doi:10.1016/j.eneco.2006.12.004.

Liu, Ying, Min Shao, Sihua Lu, Chih-Chung Chang, Jia-Lin Wang, and Linlin Fu. 2008. “Source Apportionment of Ambient Volatile Organic Compounds in the Pearl River Delta, China: Part II.” *Atmospheric Environment* 42 (25): 6261–74. doi:10.1016/j.atmosenv.2008.02.027.

Liu, Xiao-huan, Yang Zhang, Shu-hui Cheng, Jia Xing, Qiang Zhang, David G Streets, Carey Jang, Wen-xing Wang, and Ji-ming Hao. 2010. “Understanding of Regional Air Pollution over China Using CMAQ , Part I Performance Evaluation and Seasonal Variation.” *Atmospheric Environment* 44: 2415–26. doi:10.1016/j.atmosenv.2010.03.035.

Liu, Zhu, Yong Geng, Soeren Lindner, and Dabo Guan. 2012. "Uncovering China ' s Greenhouse Gas Emission from Regional and Sectoral Perspectives." *Energy* 45 (1). Elsevier: 1059–68. doi:10.1016/j.energy.2012.06.007.

Liu, Zhu, Dabo Guan, Wei Wei, Steven J. Davis, Philippe Ciais, Jin Bai, Shushi Peng, et al. 2015a. "Reduced Carbon Emission Estimates from Fossil Fuel Combustion and Cement Production in China." *Nature* 524 (7565): 335–38. doi:10.1038/nature14677.

Liu, Huan, Hanyang Man, Michael Tschantz, Ye Wu, Kebin He, and Jiming Hao. 2015b. "VOC from Vehicular Evaporation Emissions: Status and Control Strategy." *Environmental Science and Technology* 49 (24): 14424–31. doi:10.1021/acs.est.5b04064.

Liu, Jun, Denise L. Mauzerall, Qi Chen, Qiang Zhang, Yu Song, Wei Peng, Zbigniew Klimont, et al. 2016. "Air Pollutant Emissions from Chinese Households: A Major and Underappreciated Ambient Pollution Source." *Proceedings of the National Academy of Sciences of the United States of America* 113 (28): 7756–61. doi:10.1073/pnas.1604537113.

Liu, Fei, Steffen Beirle, Qiang Zhang, Ronald J. Van Der A, Bo Zheng, Dan Tong, and Kebin He. 2017. "NOx Emission Trends over Chinese Cities Estimated from OMI Observations during 2005 to 2015." *Atmospheric Chemistry and Physics* 17 (15): 9261–75. doi:10.5194/acp-17-9261-2017.

Liu, Huanjia, Bobo Wu, Shuhan Liu, Panyang Shao, Xiangyang Liu, Chuanyong Zhu, Yong Wang, et al. 2018a. "A Regional High-Resolution Emission Inventory of Primary Air Pollutants in 2012 for Beijing and the Surrounding Five Provinces of North China." *Atmospheric Environment* 181 (July 2017). Elsevier: 20–33. doi:10.1016/j.atmosenv.2018.03.013.

Liu, Huan, Shuai Liu, Boru Xue, Zhaofeng Lv, Zhihang Meng, Xiaofan Yang, Tao Xue, Qiao Yu, and Kebin He. 2018b. "Ground-Level Ozone Pollution and Its Health Impacts in China." *Atmospheric Environment* 173 (November 2017). Elsevier: 223–30. doi:10.1016/j.atmosenv.2017.11.014.

Liu, Xiao, Dequn Zhou, Peng Zhou, and Qunwei Wang. 2018c. "Factors Driving Energy Consumption in China : A Joint Decomposition Approach." *Journal of Cleaner Production* 172. Elsevier Ltd: 724–34. doi:10.1016/j.jclepro.2017.10.238.

López-Aparicio, Susana, Marc Guevara, Philippe Thunis, Kees Cuvelier, and Leonor Tarrasón. 2017. "Assessment of Discrepancies between Bottom-up and Regional Emission Inventories in Norwegian Urban Areas." *Atmospheric Environment* 154: 285–96. doi:10.1016/j.atmosenv.2017.02.004.

Louie, Peter K.K., Josephine W.K. Ho, Roy C.W. Tsang, Donald R. Blake, Alexis K.H. Lau, Jian Zhen Yu, Zibing Yuan, Xinming Wang, Min Shao, and Liuju Zhong. 2013. "VOCs and OVOCs Distribution and Control Policy Implications in Pearl River Delta Region, China." *Atmospheric Environment* 76. Elsevier Ltd: 125–35. doi:10.1016/j.atmosenv.2012.08.058.

Loulou, Richard, and Maryse Labriet. 2008. "ETSAP-TIAM: The TIMES Integrated Assessment Model Part I: Model Structure." *Computational Management Science* 5 (1–2): 7–40. doi:10.1007/s10287-007-0046-z.

Lu, Qing, Junyu Zheng, Siqi Ye, Xingling Shen, Zibing Yuan, and Shasha Yin. 2013. "Emission Trends and Source Characteristics of SO2, NOx, PM10 and VOCs in the Pearl River Delta Region from 2000 to 2009." *Atmospheric Environment* 76: 11–20. doi:10.1016/j.atmosenv.2012.10.062.

Lu, Xiao, Jiayun Hong, Lin Zhang, Owen R Cooper, Martin G Schultz, Xiaobin Xu, Tao Wang, Meng Gao, Yuanhong Zhao, and Yuanhang Zhang. 2018. "Severe Surface Ozone Pollution in China : A Global Perspective." Rapid-communication. *Environmental Science & Technology Letters* 5 (2). American Chemical Society: 487–94. doi:10.1021/acs.estlett.8b00366.

Lucena, André F.P., Mohamad Hejazi, Eveline Vasquez-Arroyo, Sean Turner, Alexandre C. Köberle, Kathryn Daenzer, Pedro R.R. Rochedo, et al. 2018. "Interactions between Climate Change Mitigation and Adaptation: The Case of Hydropower in Brazil." *Energy* 164: 1161–77. doi:10.1016/j.energy.2018.09.005.

Lutsey, Nicholas, and Daniel Sperling. 2008. "America's Bottom-up Climate Change Mitigation

Policy." *Energy Policy* 36 (2): 673–85. doi:10.1016/j.enpol.2007.10.018.

Lyu, X. P., M. Liu, H. Guo, Z. H. Ling, Y. Wang, P. K.K. Louie, and C. W.Y. Luk. 2016. "Spatiotemporal Variation of Ozone Precursors and Ozone Formation in Hong Kong: Grid Field Measurement and Modelling Study." *Science of the Total Environment* 569–570. Elsevier B.V.: 1341–49. doi:10.1016/j.scitotenv.2016.06.214.

Ma, Ben, Guojun Song, Lei Zhang, and David A. Sonnenfeld. 2014. "Explaining Sectoral Discrepancies between National and Provincial Statistics in China." *China Economic Review* 30. Elsevier Inc.: 353–69. doi:10.1016/j.chieco.2014.07.004.

Mac Kinnon, Michael, Brendan Shaffer, Marc Carreras-Sospedra, Donald Dabdub, G. S. Samuelsen, and Jacob Brouwer. 2016. "Air Quality Impacts of Fuel Cell Electric Hydrogen Vehicles with High Levels of Renewable Power Generation." *International Journal of Hydrogen Energy* 41 (38). Elsevier Ltd: 16592–603. doi:10.1016/j.ijhydene.2016.07.054.

Maragatham, K, and P Rafaj. 2012. "Assessment of Air Pollution and GHG Mitigation Strategies in Malaysia Using the GAINS Model."

Marland, Gregg. 2008. "Uncertainties in Accounting for CO2 from Fossil Fuels." *Journal of Industrial Ecology* 12 (2): 136–39. doi:10.1111/j.1530-9290.2008.00014.x.

Marques, António C., José A. Fuinhas, and J. R. Pires Manso. 2010. "Motivations Driving Renewable Energy in European Countries: A Panel Data Approach." *Energy Policy* 38 (11): 6877–85. doi:10.1016/j.enpol.2010.07.003.

Marquis, Melinda, and Pieter Tans. 2008. "Climate Change: Carbon Crucible." *Science* 320 (5875): 460–61. doi:10.1126/science.1156451.

Matus, Kira, Kyung Min Nam, Noelle E. Selin, Lok N. Lamsal, John M. Reilly, and Sergey Paltsev. 2012. "Health Damages from Air Pollution in China." *Global Environmental Change* 22 (1). Elsevier Ltd: 55–66. doi:10.1016/j.gloenvcha.2011.08.006.

McCollum, David L., Volker Krey, and Keywan Riahi. 2011. "An Integrated Approach to Energy Sustainability." *Nature Climate Change* 1 (9). Nature Publishing Group: 428–29. doi:10.1038/nclimate1297.

McMichael, A. J. 1997. "Integrated Assessment of Potential Health Impact of Global Environmental Change: Prospects and Limitations." *Environmental Modeling and Assessment* 2 (3): 129–37. doi:10.1023/A:1019061311283.

Meier, H. E.Markus, Helén C. Andersson, Berit Arheimer, Thorsten Blenckner, Boris Chubarenko, Chantal Donnelly, Kari Eilola, et al. 2012. "Comparing Reconstructed Past Variations and Future Projections of the Baltic Sea Ecosystem - First Results from Multi-Model Ensemble Simulations." *Environmental Research Letters* 7 (3). doi:10.1088/1748-9326/7/3/034005.

Meng, Jing, Junfeng Liu, Yuan Xu, and Shu Tao. 2015. "Tracing Primary $PM_{2.5}$ Emissions via Chinese Supply Chains." *Environmental Research Letters* 10 (5). IOP Publishing: 054005. doi:10.1088/1748-9326/10/5/054005.

Meng, Jing, Junfeng Liu, Songmiao Fan, Chuyun Kang, Kan Yi, Yanli Cheng, Xing Shen, and Shu Tao. 2016a. "Potential Health Benefits of Controlling Dust Emissions in Beijing." *Environmental Pollution* 213. Elsevier Ltd: 850–59. doi:10.1016/j.envpol.2016.03.021.

Meng, Jing, Junfeng Liu, Yuan Xu, and Dabo Guan. 2016b. "Globalization and Pollution : Tele-Connecting Local Primary $PM_{2.5}$ Emissions to Global Consumption." *Pro. R. Soc. A* 472 (20160380).

Meng, Jing, Zhifu Mi, Haozhe Yang, Yuli Shan, Dabo Guan, and Junfeng Liu. 2017. "The Consumption-Based Black Carbon Emissions of China's Megacities." *Journal of Cleaner Production*. Elsevier Ltd. doi:10.1016/j.jclepro.2017.02.185.

Meng, Jing, Junfeng Liu, Kan Yi, Haozhe Yang, Dabo Guan, Zhu Liu, Jiachen Zhang, et al. 2018. "Origin and Radiative Forcing of Black Carbon Aerosol: Production and Consumption Perspectives." Research-article. *Environmental Science and Technology* 52 (11). American Chemical Society: 6380–89. doi:10.1021/acs.est.8b01873.

Meng, Jing, Haozhe Yang, Kan Yi, Junfeng Liu, Dabo Guan, Zhu Liu, Zhifu Mi, et al. 2019. "The Slowdown in Global Air-Pollutant Emission Growth and Driving Factors." *One Earth*

1 (1). Elsevier Inc.: 138–48. doi:10.1016/j.oneear.2019.08.013.

Messner, Sabine, and Leo Schrattenholzer. 2000. "MESSAGE-MACRO: Linking an Energy Supply Model with a Macroeconomic Module and Solving It Iteratively." *Energy* 25 (3): 267–82. doi:10.1016/S0360-5442(99)00063-8.

Mi, Zhifu, Yunkun Zhang, Dabo Guan, Yuli Shan, Zhu Liu, Ronggang Cong, Xiao-Chen Yuan, and Yi-Ming Wei. 2016. "Consumption-Based Emission Accounting for Chinese Cities." *Applied Energy* 184. Elsevier Ltd: 1073–81. doi:10.1016/j.apenergy.2016.06.094.

Mi, Zhifu, Jing Meng, Dabo Guan, and Klaus Hubacek. 2017. "Chinese CO2 Emission Flows Have Reversed since the Global Financial Crisis." *Nature Comminications* 8: 1712. doi:10.1038/s41467-017-01820-w.

Mi, Z., J. Meng, F. Green, D.M. Coffman, and D. Guan. 2018. "China's 'Exported Carbon' Peak: Patterns, Drivers, and Implications." *Geophysical Research Letters*, 4309–18. doi:10.1029/2018GL077915.

Miller, R. E., and P. D Blair. 2009. *Input-Output Analysis: Foundations and Extensions*. Second Edi. Cambridge: Cambridge University Press.

Ministry of Ecology and Environment of the People's Republic of China. 2019. *Regulations on NMVOCs Emissions from Key Industries (in Chinese).*

Ministry of Ecology and Environment P.R. China. 2014. "Emission Inventory Guidebook on Volatile Organic Compounds (Trial) (in Chinese)."

Miraglia, Simone Georges El Khouri, Paulo Hilário Nascimento Saldiva, and György Miklós Böhm. 2005. "An Evaluation of Air Pollution Health Impacts and Costs in São Paulo, Brazil." *Environmental Management* 35 (5): 667–76. doi:10.1007/s00267-004-0042-9.

Molina, L. T., C. E. Kolb, B. De Foy, B. K. Lamb, W. H. Brune, J. L. Jimenez, R. Ramos-Villegas, et al. 2007. "Air Quality in North America's Most Populous City - Overview of the MCMA-2003 Campaign." *Atmospheric Chemistry and Physics* 7 (10): 2447–73. doi:10.5194/acp-7-2447-2007.

Morino, Y., T. Ohara, Y. Yokouchi, and a. Ooki. 2011. "Comprehensive Source Apportionment of Volatile Organic Compounds Using Observational Data, Two Receptor Models, and an Emission Inventory in Tokyo Metropolitan Area." *Journal of Geophysical Research* 116 (D2): D02311. doi:10.1029/2010JD014762.

Munksgaard, Jesper, and Klaus Alsted Pedersen. 2001. "CO2 Accounts for Open Economies: Producer or Consumer Responsibility?" *Energy Policy* 29 (4): 327–34. doi:10.1016/S0301-4215(00)00120-8.

Na, Kwangsam, and Yong Pyo Kim. 2007. "Chemical Mass Balance Receptor Model Applied to Ambient C2-C9 VOC Concentration in Seoul, Korea: Effect of Chemical Reaction Losses." *Atmospheric Environment* 41 (32): 6715–28. doi:10.1016/j.atmosenv.2007.04.054.

Nair, Sudeep, Biju George, Hector M. Malano, Meenakshi Arora, and Bandara Nawarathna. 2014. "Water-Energy-Greenhouse Gas Nexus of Urban Water Systems: Review of Concepts, State-of-Art and Methods." *Resources, Conservation and Recycling* 89. Elsevier B.V.: 1–10. doi:10.1016/j.resconrec.2014.05.007.

Nam, Kyung Min, Noelle E. Selin, John M. Reilly, and Sergey Paltsev. 2010. "Measuring Welfare Loss Caused by Air Pollution in Europe: A CGE Analysis." *Energy Policy* 38 (9). Elsevier: 5059–71. doi:10.1016/j.enpol.2010.04.034.

National Bureau of Statistics of the People's Republic of China. 2013. *Statistic Yearbook of China-2013*.

National Statistics Bureau of China. 2013. *Input-Output Tables for Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Sh*. China Stat. Press, Beijing, China.

National Bureau of Statistics, P.R.China, 2018a. *China statistical yearbook 2018[Chinese Document]*. Beijing, China: China Statistics Press.

National Bureau of Statistics, P.R.China, 2018b. *China energy statistical yearbook 2018[Chinese*

Document]. Beijing, China: China Statistics Press.

National Bureau of Statistics, P.R.China, 2018c. *China industry economy statistical yearbook 2018[Chinese Document]*. Beijing, China: China Statistics Press.

National Bureau of Statistics, P.R.China, 2018d. *The transport yearbook of China 2018[Chinese Document]*. Beijing, China: China Statistics Press.

Nisbet, Euan, and Ray Weiss. 2010. "Top-Down Versus Bottom-Up" 328 (June): 1241–44.

Nopmongcol, Uarporn, Bonyoung Koo, Edward Tai, Jaegun Jung, Piti Piyachaturawat, Chris Emery, Greg Yarwood, Guido Pirovano, Christina Mitsakou, and George Kallos. 2012. "Modeling Europe with CAMx for the Air Quality Model Evaluation International Initiative (AQMEII)." *Atmospheric Environment* 53. Elsevier Ltd: 177–85. doi:10.1016/j.atmosenv.2011.11.023.

Organisation for Economic Co-operation and Development (OECD)/International Energy Agency (IEA)/Eurostat. 2004. "Energy Statistics Manual." *Paris*. doi:10.1038/254284b0.

Oglesby, Robert J, and Barry Saltzman. 1990. "Of Semtner with Other GCM Studies." *Changes* 17 (8): 1089–92.

Olivier, J. G. J., Janssens-Maenhout, G., Muntean, M., & Peters, J. A. H. W. 2016. *Trends in global CO_2 emissions: 2016 report*. Hague, Netherlands: PBL Publishers.http://edgar.jrc.ec.europa.eu/news_docs/jrc-2016-trends-in-global-co2-emissions-2016-report-103425.pdf

Orru, H., K. L. Ebi, and B. Forsberg. 2017. "The Interplay of Climate Change and Air Pollution on Health." *Current Environmental Health Reports* 4 (4). Current Environmental Health Reports: 504–13. doi:10.1007/s40572-017-0168-6.

Ou, Jiamin, Junyu Zheng, Rongrong Li, Xiaobo Huang, Zhuangmin Zhong, Liuju Zhong, and Hui Lin. 2015. "Speciated OVOC and VOC Emission Inventories and Their Implications for Reactivity-Based Ozone Control Strategy in the Pearl River Delta Region, China." *Science of the Total Environment* 530–531 (2). Elsevier B.V.: 393–402. doi:10.1016/j.scitotenv.2015.05.062.

Ou, Jiamin, Zibing Yuan, Junyu Zheng, Zhijiong Huang, Min Shao, Zekun Li, Xiaobo Huang, Hai Guo, and Peter K.K. Louie. 2016. "Ambient Ozone Control in a Photochemically Active Region: Short-Term Despiking or Long-Term Attainment?" *Environmental Science and Technology* 50 (11): 5720–28. doi:10.1021/acs.est.6b00345.

Ou, Jiamin, Jing Meng, Junyu Zheng, Zhifu Mi, Yahui Bian, Xiang Yu, Jingru Liu, and Dabo Guan. 2017. "Demand-Driven Air Pollutant Emissions for a Fast-Developing Region in China." *Applied Energy* 204. The Authors: 131–42. doi:10.1016/j.apenergy.2017.06.112.

Øvergaard, Sara. 2008. "Definition of Primary and Secondary Energy." *Standard International Energy Classification (SIEC) in the International Recommendation on Energy Statistics (IRES)*, no. Energy Statistics: 1–7.

Owen, Anne, Kjartan Steen-olsen, John Barrett, Thomas Wiedmann, Anne Owen, Kjartan Steen-olsen, John Barrett, and Thomas Wiedmann. 2014. "A STRUCTURAL DECOMPOSITION APPROACH TO COMPARING MRIO DATABASES." *Economic Systems Research* 26 (3): 262–83. doi:10.1080/09535314.2014.935299.

Owen, Anne. 2017. *Techniques for Evaluating the Differences in Multiregional Input-Output Databases: A Comparative Evaluation of CO2 Consumption-Based Accounts Calculated Using Eora, GTAP and WIOD*. Springer US. doi:10.1002/ejsp.2570.

Ozturk, Ilhan. 2010. "A Literature Survey on Energy-Growth Nexus." *Energy Policy* 38 (1). Elsevier: 340–49. doi:10.1016/j.enpol.2009.09.024.

Pallav, Purohit, Amann Markus, Mathur Ritu, Gupta Ila, Marwah Sakshi, Verma Vishal, Bertok Imrich, et al. 2010. "GAINS-Asia: SCENARIOS FOR COST-EFFECTIVE CONTROL OF AIR POLLUTION AND GREENHOUSE GASES IN INDIA."

Pao, Hsiao Tien, and Chun Chih Chen. 2019. "Decoupling Strategies: CO2 Emissions, Energy Resources, and Economic Growth in the Group of Twenty." *Journal of Cleaner Production* 206. Elsevier Ltd: 907–19. doi:10.1016/j.jclepro.2018.09.190.

Park, Seung Shik, Sun A. Jung, Bu Joo Gong, Seog Yeon Cho, and Suk Jo Lee. 2013. "Characteristics of PM2.5 Haze Episodes Revealed by Highly Time-Resolved Measurements at an Air Pollution Monitoring Supersite in Korea." *Aerosol and Air Quality Research* 13 (3): 957–76. doi:10.4209/aaqr.2012.07.0184.

Pehnt, Martin. 2006. "Dynamic Life Cycle Assessment (LCA) of Renewable Energy Technologies." *Renewable Energy* 31 (1): 55–71. doi:10.1016/j.renene.2005.03.002.

Peters, G.P., and E.G. Hertwich. 2007. *The Application Ofmulti-Regional Input–output Analysis to Industrialecology: Evaluating Trans-Boundary Environmental Impacts. Springer, Dordrecht.*

Peters, Glen P. 2008. "From Production-Based to Consumption-Based National Emission Inventories." *Ecological Economics* 65 (1): 13–23. doi:10.1016/j.ecolecon.2007.10.014.

Peters, Glen P., and Edgar G. Hertwich. 2008. "Post-Kyoto Greenhouse Gas Inventories: Production versus Consumption." *Climatic Change* 86 (1–2): 51–66. doi:10.1007/s10584-007-9280-1.

Peters, G. P., S. J. Davis, and R. Andrew. 2012. "A Synthesis of Carbon in International Trade." *Biogeosciences* 9 (8): 3247–76. doi:10.5194/bg-9-3247-2012.

Ploberger, W., Krämer, W. 1992. "The CUSUM Test with OLS Residuals." *Econometrica* 60 (2).

Qi, Ye, Nicholas Stern, Tong Wu, Jiaqi Lu, and Fergus Green. 2016. "China's Post-Coal Growth." *Nature Geoscience* 9 (8): 564–66. doi:10.1038/ngeo2777.

Rademaker, Jelle H., Rene Kleijn, and Yongxiang Yang. 2013. "Recycling as a Strategy against Rare Earth Element Criticality: A Systemic Evaluation of the Potential Yield of NdFeB Magnet Recycling." *Environmental Science and Technology* 47 (18): 10129–36. doi:10.1021/es305007w.

Ramesh, T., Ravi Prakash, and K. K. Shukla. 2010. "Life Cycle Energy Analysis of Buildings: An Overview." *Energy and Buildings* 42 (10): 1592–1600. doi:10.1016/j.enbuild.2010.05.007.

Rodrigues, F D, Daniel Moran, Richard Wood, and Paul Behrens. 2018. "Uncertainty of Consumption-Based Carbon Accounts." *Enviromental Science and Technology* 52: 7577–86. doi:10.1021/acs.est.8b00632.

Rogner, Mathis, and Keywan Riahi. 2013. "Future Nuclear Perspectives Based on MESSAGE Integrated Assessment Modeling." *Energy Strategy Reviews* 1 (4). Elsevier Ltd: 223–32. doi:10.1016/j.esr.2013.02.006.

Román, Rocío, José M. Cansino, and Camilo Botia. 2018. "How Far Is Colombia from Decoupling? Two-Level Decomposition Analysis of Energy Consumption Changes." *Energy* In Press. doi:10.1016/j.energy.2018.01.141.

Rose, Adam. 1984. "Technological Change and Input-Output Analysis: An Appraisal." *Socio-Economic Planning Sciences* 18 (5): 305–18. doi:10.1016/0038-0121(84)90039-9.

Rose, A., and S. Casler. 1996. "Input-Output Structural Decomposition Analysis: A Critical Appraisal." *Economic Systems Research* 8 (1): 33–62. doi:10.1080/09535319600000003.

Royal Astronomical Society. 2009. "Verification of Greenhouse Gas Emissions by Atmospheric Measurement."

Ruosteenoja, Kimmo, Heikki Tuomenvirta, and Kirsti Jylhä. 2007. "GCM-Based Regional Temperature and Precipitation Change Estimates for Europe under Four SRES Scenarios Applying a Super-Ensemble Pattern-Scaling Method." *Climatic Change* 81 (SUPPL. 1): 193–208. doi:10.1007/s10584-006-9222-3.

Rutger, Hoekstra, and Jeroen J.C.J.M. van der Bergh. 2003. "Comparing Structural and Index Decomposition Analysis." *Energy Eco* 25: 39–64.

Rypdal, Kristin, Frode Stordal, Jan Fuglestvedt, and Terje Berntsen. 2005. "Introducing Top-down Methods in Assessing Compliance with the Kyoto Protocol." *Climate Policy* 5 (4): 393–405. doi:10.1080/14693062.2005.9685565.

San José, R., J. L. Pérez, and R. M. González. 2007. "An Operational Real-Time Air Quality Modelling System for Industrial Plants." *Environmental Modelling and Software* 22 (3):

297–307. doi:10.1016/j.envsoft.2005.07.030.

Sanderson, Benjamin M., Keith W. Oleson, Warren G. Strand, Flavio Lehner, and Brian C. O'Neill. 2018. "A New Ensemble of GCM Simulations to Assess Avoided Impacts in a Climate Mitigation Scenario." *Climatic Change* 146 (3–4): 303–18. doi:10.1007/s10584-015-1567-z.

Sargento, Ana L.M., Pedro Nogueira Ramos, and Geoffrey J.D. Hewings. 2012. "Inter-Regional Trade Flow Estimation Through Non-Survey Models: An Empirical Assessment." *Economic Systems Research* 24 (2): 173–93. doi:10.1080/09535314.2011.574609.

Sato, Misato. 2014. "EMBODIED CARBON IN TRADE : A SURVEY OF THE EMPIRICAL LITERATURE." *Journal of Economic Surveys* 28 (5): 831–61. doi:10.1111/joes.12027.

Schmale, Julia, Drew Shindell, Erika von Schneidemesser, Ilan Chabay, and Mark Lawrence. 2014. "Clean up Our Skies." *Nature* 515: 335–37. doi:10.1038/515335a.

Schwartz, Joel, Francine Laden, and Antonella Zanobetti. 2002. "The Concentration – Response Relation between PM 2 . 5 and Daily Deaths" 110 (10): 1025–29.

Selosse, Sandrine, and Olivia Ricci. 2014. "Achieving Negative Emissions with BECCS (Bioenergy with Carbon Capture and Storage) in the Power Sector: New Insights from the TIAM-FR (TIMES Integrated Assessment Model France) Model." *Energy* 76. Elsevier Ltd: 967–75. doi:10.1016/j.energy.2014.09.014.

Sesana, Marta Maria, and Graziano Salvalai. 2013. "Overview on Life Cycle Methodologies and Economic Feasibility FornZEBs." *Building and Environment* 67. Elsevier Ltd: 211–16. doi:10.1016/j.buildenv.2013.05.022.

Shan, Yuli, Jianghua Liu, Zhu Liu, Xinwanghao Xu, Shuai Shao, Peng Wang, and Dabo Guan. 2016a. "New Provincial CO2 Emission Inventories in China Based on Apparent Energy Consumption Data and Updated Emission Factors." *Applied Energy* 184. Elsevier Ltd: 742–50. doi:10.1016/j.apenergy.2016.03.073.

Shan, Yuli, Zhu Liu, and Dabo Guan. 2016b. "CO2 Emissions from China's Lime Industry." *Applied Energy* 166: 245–52. doi:10.1016/j.apenergy.2015.04.091.

Shan, Yuli, Dabo Guan, Heran Zheng, Jiamin Ou, Yuan Li, Jing Meng, and Zhifu Mi. 2017. "China CO2 Emission Accounts 1997 – 2015." *Scientific Data* 5 (170201): 1–14.

Sherwani, A. F., J. A. Usmani, and Varun. 2010. "Life Cycle Assessment of Solar PV Based Electricity Generation Systems: A Review." *Renewable and Sustainable Energy Reviews* 14 (1): 540–44. doi:10.1016/j.rser.2009.08.003.

Xu, Shi-chuan, Zheng-xia He, Ru-Yin Long. 2014. "Factors That Influence Carbon Emissions Due to Energy Consumption in China: Decomposition Analysis Using LMDI." *Applied Energy* 127: 182–93.

Xu, Y., Z.Huang, G. Jia, M. Fan, L. Cheng, L. Chen. 2019. "Regional discrepancies in spatiotemporal variations and driving forces of open crop residue burning emissions in China. " *Science of the total Environment*, 671, 536-547.

Shi, Yun, Yin Feng Xia, Bi Hong Lu, Nan Liu, Lei Zhang, Su Jing Li, and Wei Li. 2014. "Emission Inventory and Trends of NO x for China, 2000-2020." *Journal of Zhejiang University: Science A* 15 (6): 454–64. doi:10.1631/jzus.A1300379.

Shimi, S L, and B Reji. 2013. "Elasticity of Energy Consumption in India" 1 (2): 19–24.

Song, Feng, and Xinye Zheng. 2012. "What Drives the Change in China ' s Energy Intensity : Combining Decomposition Analysis and Econometric Analysis at the Provincial Level." *Energy Policy* 51. Elsevier: 445–53. doi:10.1016/j.enpol.2012.08.044.

Steinberger, Julia K, and J Timmons Roberts. 2010. "From Constraint to Suf Fi Ciency : The Decoupling of Energy and Carbon from Human Needs , 1975 – 2005." *Ecological Economics* 70 (2). Elsevier B.V.: 425–33. doi:10.1016/j.ecolecon.2010.09.014.

Steinberger, Julia K, J Timmons Roberts, Glen P Peters, and Giovanni Baiocchi. 2012. "Pathways of Human Development and Carbon Emissions Embodied in Trade." *Nature Climate Change* 2 (2). Nature Publishing Group: 81–85. doi:10.1038/nclimate1371.

Stowell, Jennifer D., Young min Kim, Yang Gao, Joshua S. Fu, Howard H. Chang, and Yang Liu.

2017. “The Impact of Climate Change and Emissions Control on Future Ozone Levels: Implications for Human Health.” *Environment International* 108 (August). Elsevier: 41–50. doi:10.1016/j.envint.2017.08.001.

Streets, David G., Carolyne Yu, Michael H. Bergin, Xuemei Wang, and Gregory R. Carmichael. 2006. “Modeling Study of Air Pollution Due to the Manufacture of Export Goods in China’s Pearl River Delta.” *Environmental Science and Technology* 40 (7): 2099–2107. doi:10.1021/es051275n.

Su, Bin, and B. W. Ang. 2012. “Structural Decomposition Analysis Applied to Energy and Emissions: Some Methodological Developments.” *Energy Economics* 34 (1). Elsevier B.V.: 177–88. doi:10.1016/j.eneco.2011.10.009.

Sullivan, Patrick, Volker Krey, and Keywan Riahi. 2013. “Impacts of Considering Electric Sector Variability and Reliability in the MESSAGE Model.” *Energy Strategy Reviews* 1 (3). Elsevier Ltd: 157–63. doi:10.1016/j.esr.2013.01.001.

Tan, Zhongfu, Li Li, Jianjun Wang, and Jianhui Wang. 2011. “Examining the Driving Forces for Improving China’s CO2emission Intensity Using the Decomposing Method.” *Applied Energy* 88 (12): 4496–4504. doi:10.1016/j.apenergy.2011.05.042.

Tang, W., D. S. Cohan, L. N. Lamsal, X. Xiao, and W. Zhou. 2013. “Inverse Modeling of Texas NOx Emissions Using Space-Based and Ground-Based NO2 Observations.” *Atmospheric Chemistry and Physics* 13 (21): 11005–18. doi:10.5194/acp-13-11005-2013.

Tang, Chor Foon, Bee Wah Tan, and Ilhan Ozturk. 2016. “Energy Consumption and Economic Growth in Vietnam.” *Renewable and Sustainable Energy Reviews* 54. Elsevier: 1506–14. doi:10.1016/j.rser.2015.10.083.

Tang, Xu, Benjamin C. McLellan, Baosheng Zhang, Simon Snowden, and Mikael Höök. 2016. “Trade-off Analysis between Embodied Energy Exports and Employment Creation in China.” *Journal of Cleaner Production* 134: 310–19. doi:10.1016/j.jclepro.2015.08.122.

Tang, Xu, Yi Jin, Benjamin C. McLellan, Jianliang Wang, and Shiqun Li. 2018. “China’s Coal Consumption Declining—Impermanent or Permanent?” *Resources, Conservation and Recycling* 129 (2018). Elsevier B.V.: 307–13. doi:10.1016/j.resconrec.2016.07.018.

Tebaldi, Claudia, and Reto Knutti. 2007. “The Use of the Multi-Model Ensemble in Probabilistic Climate Projections.” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365 (1857): 2053–75. doi:10.1098/rsta.2007.2076.

Tesche, T. W., Ralph Morris, Gail Tonnesen, Dennis McNally, James Boylan, and Patricia Brewer. 2006. “CMAQ/CAMx Annual 2002 Performance Evaluation over the Eastern US.” *Atmospheric Environment* 40 (26): 4906–19. doi:10.1016/j.atmosenv.2005.08.046.

Thaxton, C.; Sherman, J. P.; Krintz, I. A.; Scher, A.; Ross, D.; Schlesselman, D. 2017. “Optimizing Weather Research and Forecasting Model Parameterizations for Boundary-Layer Turbulence Production and Dissipation over the Southern Appalachians.” In *American Geophysical Union, Fall Meeting 2017*.

Tilmes, S., B. M. Sanderson, and B. C. O’Neill. 2016. “Climate Impacts of Geoengineering in a Delayed Mitigation Scenario.” *Geophysical Research Letters* 43 (15): 8222–29. doi:10.1002/2016GL070122.

Toth, Ferenc L. 1998. “Integrated Environmental Assessment Methods: Evolution and Applications.” *Environmental Modeling and Assessment* 3 (3): 193–207. doi:10.1023/A:1019071008074.

Tsinghua University, 2018. Multi-resolution emission inventory for China (MEIC). Available via http://www.meicmodel.org/about.html (Last accessed on 01 April 2020)

Tukker, Arnold. 2000. “Life Cycle Assessment as a Tool in Environmental Impact Assessment.” *Environmental Impact Assessment Review* 20 (4): 435–56. doi:10.1016/S0195-9255(99)00045-1.

Tukker, Arnold, Evgueni Poliakov, Reinout Heijungs, Troy Hawkins, Frederik Neuwahl, José M. Rueda-Cantuche, Stefan Giljum, Stephan Moll, Jan Oosterhaven, and Maaike Bouwmeester. 2009. “Towards a Global Multi-Regional Environmentally Extended Input-Output Database.” *Ecological Economics* 68 (7). Elsevier B.V.: 1928–37.

doi:10.1016/j.ecolecon.2008.11.010.

Turconi, Roberto, Alessio Boldrin, and Thomas Astrup. 2013. “Life Cycle Assessment (LCA) of Electricity Generation Technologies: Overview, Comparability and Limitations.” *Renewable and Sustainable Energy Reviews* 28. Elsevier: 555–65. doi:10.1016/j.rser.2013.08.013.

United Nations. 1982. “Concepts and Methods in Energy Statistics, with Special Reference to Energy Accounts and Balances.”

United States Environmental Protection Agency. 2009. “AP-42: Compilation of Air Emissions Factors.”

US Environmental Protection Agency. 2010. “Life-Cycle GHG Accounting Versus GHG Emission Inventories.” www.epa.gov/sites/production/files/2016-03/documents/life-cycle-ghg-accounting-versus-ghg-emission-inventories10-28-10.pdf.

Van Delden, H., R. Seppelt, R. White, and A. J. Jakeman. 2011. “A Methodology for the Design and Development of Integrated Models for Policy Support.” *Environmental Modelling and Software* 26 (3). Elsevier Ltd: 266–79. doi:10.1016/j.envsoft.2010.03.021.

van Vuuren, Detlef P., Jason Lowe, Elke Stehfest, Laila Gohar, Andries F. Hof, Chris Hope, Rachel Warren, Malte Meinshausen, and Gian Kasper Plattner. 2011. “How Well Do Integrated Assessment Models Simulate Climate Change?” *Climatic Change* 104 (2): 255–85. doi:10.1007/s10584-009-9764-2.

Vázquez-Rowe, Ian, Antonino Marvuglia, Sameer Rege, and Enrico Benetto. 2014. “Applying Consequential LCA to Support Energy Policy: Land Use Change Effects of Bioenergy Production.” *Science of the Total Environment* 472. Elsevier B.V.: 78–89. doi:10.1016/j.scitotenv.2013.10.097.

Venners, Scott A., Binyan Wang, Zhonggui Peng, Yu Xu, Lihua Wang, and Xiping Xu. 2003. “Particulate Matter, Sulfur Dioxide, and Daily Mortality in Chongqing, China.” *Environmental Health Perspectives* 111 (4): 562–67. doi:10.1289/ehp.5664.

Vidale, Pier Luigi, Daniel Lüthi, Christoph Frei, Sonia I. Seneviratne, and Christoph Schär. 2003. “Predictability and Uncertainty in a Regional Climate Model.” *Journal of Geophysical Research D: Atmospheres* 108 (18): 1–23. doi:10.1029/2002jd002810.

Voinov, Alexey, and Herman H. Shugart. 2013. “‘Integronsters’, Integral and Integrated Modeling.” *Environmental Modelling and Software* 39. Elsevier Ltd: 149–58. doi:10.1016/j.envsoft.2012.05.014.

Voita, Thibaud. 2018. *The Power of China’s Energy Efficiency Policies*. *Études de l’Ifri*.

von Deimling, Thomas Schneider, Hermann Held, Andrey Ganopolski, and Stefan Rahmstorf. 2006. “Climate Sensitivity Estimated from Ensemble Simulations of Glacial Climate.” *Climate Dynamics* 27 (2–3): 149–63. doi:10.1007/s00382-006-0126-8.

Vukovich, Jeffrey M., Donald T. Olerud, John N. McHenry, Carlie J. Coats, and William T. Smith. 2006. “Supporting Real-Time Air Quality Forecasting Using the Smoke Modeling System.” *86th AMS Annual Meeting*.

Wagner, Liam, Ian Ross, John Foster, and Ben Hankamer. 2016. “Trading off Global Fuel Supply, CO2 Emissions and Sustainable Development.” *PLoS ONE* 11 (3): 1–17. doi:10.1371/journal.pone.0149406.

Wang, Hong, and John Mullahy. 2006. “Willingness to Pay for Reducing Fatal Risk by Improving Air Quality: A Contingent Valuation Study in Chongqing, China.” *Science of the Total Environment* 367 (1): 50–57. doi:10.1016/j.scitotenv.2006.02.049.

Wang, Jun, Sundar A. Christopher, U. S. Nair, Jeffrey S. Reid, Elaine M. Prins, James Szykman, and Jenny L. Hand. 2006a. “Mesoscale Modeling of Central American Smoke Transport to the United States: 1. ‘Top-down’ Assessment of Emission Strength and Diurnal Variation Impacts.” *Journal of Geophysical Research Atmospheres* 111 (5): 1–21. doi:10.1029/2005JD006416.

Wang, Tao, Aijun Ding, Jian Gao, and Wai Shing Wu. 2006b. “Strong Ozone Production in Urban Plumes from Beijing, China.” *Geophysical Research Letters* 33 (21): 1–5. doi:10.1029/2006GL027689.

Wang, Litao, Carey Jang, Yang Zhang, Kai Wang, Qiang Zhang, David Streets, Joshua Fu, et al. 2010a. "Assessment of Air Quality Benefits from National Air Pollution Control Policies in China. Part I: Background, Emission Scenarios and Evaluation of Meteorological Predictions." *Atmospheric Environment* 44 (28). Elsevier Ltd: 3442–48. doi:10.1016/j.atmosenv.2010.05.051.

Wang, X., Y. Zhang, Y. Hu, W. Zhou, K. Lu, L. Zhong, L. Zeng, M. Shao, M. Hu, and a. G. Russell. 2010b. "Process Analysis and Sensitivity Study of Regional Ozone Formation over the Pearl River Delta, China, during the PRIDE-PRD2004 Campaign Using the Community Multiscale Air Quality Modeling System." *Atmospheric Chemistry and Physics* 10 (9): 4423–37. doi:10.5194/acp-10-4423-2010.

Wang, Jun, Xiaoguang Xu, Daven K. Henze, Jing Zeng, Qiang Ji, Si Chee Tsay, and Jianping Huang. 2012. "Top-down Estimate of Dust Emissions through Integration of MODIS and MISR Aerosol Retrievals with the GEOS-Chem Adjoint Model." *Geophysical Research Letters* 39 (8): 1–6. doi:10.1029/2012GL051136.

Wang, M., M. Shao, W. Chen, B. Yuan, S. Lu, Q. Zhang, L. Zeng, and Q. Wang. 2014a. "A Temporally and Spatially Resolved Validation of Emission Inventories by Measurements of Ambient Volatile Organic Compounds in Beijing, China." *Atmospheric Chemistry and Physics* 14 (12): 5871–91. doi:10.5194/acp-14-5871-2014.

Wang, Long, Shuxiao Wang, Lei Zhang, Yuxuan Wang, Yanxu Zhang, Chris Nielsen, Michael B. McElroy, and Jiming Hao. 2014b. "Source Apportionment of Atmospheric Mercury Pollution in China Using the GEOS-Chem Model." *Environmental Pollution* 190. Elsevier Ltd: 166–75. doi:10.1016/j.envpol.2014.03.011.

Wang, Miao, and Chao Feng. 2017. "Decomposition of Energy-Related CO2emissions in China: An Empirical Analysis Based on Provincial Panel Data of Three Sectors." *Applied Energy* 190. Elsevier Ltd: 772–87. doi:10.1016/j.apenergy.2017.01.007.

Wang, Tao, Likun Xue, Peter Brimblecombe, Yun Fat, Li Li, and Li Zhang. 2017. "Ozone Pollution in China : A Review of Concentrations , Meteorological in Fl Uences , Chemical Precursors , and Effects" 575: 1582–96. doi:10.1016/j.scitotenv.2016.10.081.

Wang, Qiaoli, Sujing Li, Minli Dong, Wei Li, Xiang Gao, Rongmin Ye, and Dongxiao Zhang. 2018. "VOCs Emission Characteristics and Priority Control Analysis Based on VOCs Emission Inventories and Ozone Formation Potentials in Zhoushan." *Atmospheric Environment* 182 (September 2017). Elsevier: 234–41. doi:10.1016/j.atmosenv.2018.03.034.

Wang, Qunwei, Ye Hang, Bin Su, and Peng Zhou. 2018. "Contributions to Sector-Level Carbon Intensity Change : An Integrated Decomposition Analysis." *Energy Economics* 70. Elsevier B.V.: 12–25. doi:10.1016/j.eneco.2017.12.014.

Wang, Yan, Ke Cheng, He Zhong Tian, Peng Yi, and Zhi Gang Xue. 2018. "Analysis of Reduction Potential of Primary Air Pollutant Emissions from Coking Industry in China." *Aerosol and Air Quality Research*, no. 18: 533–41. doi:10.4209/aaqr.2017.04.0139.

Wang, Saige, Brian Fath, and Bin Chen. 2019. "Energy–water Nexus under Energy Mix Scenarios Using Input–output and Ecological Network Analyses." *Applied Energy* 233–234 (19). Elsevier: 827–39. doi:10.1016/j.apenergy.2018.10.056.

Watson, John G., Judith C. Chow, and Eric M. Fujita. 2001. "Review of Volatile Organic Compound Source Apportionment by Chemical Mass Balance." *Atmospheric Environment*. doi:10.1016/S1352-2310(00)00461-1.

Wei, Wei, Shuxiao Wang, Satoru Chatani, Zbigniew Klimont, Janusz Cofala, and Jiming Hao. 2008. "Emission and Speciation of Non-Methane Volatile Organic Compounds from Anthropogenic Sources in China." *Atmospheric Environment* 42 (20): 4976–88. doi:10.1016/j.atmosenv.2008.02.044.

Welsh, Wendy D., Jai Vaze, Dushmanta Dutta, David Rassam, Joel M. Rahman, Ian D. Jolly, Peter Wallbrink, et al. 2013. "An Integrated Modelling Framework for Regulated River Systems." *Environmental Modelling and Software* 39. Elsevier Ltd: 81–102. doi:10.1016/j.envsoft.2012.02.022.

West, J Jason, Steven J Smith, Raquel A Silva, Vaishali Naik, Yuqiang Zhang, Zachariah

Adelman, Meridith M Fry, Susan Anenberg, Larry W Horowitz, and Jean-Francois Lamarque. 2013. "Co-Benefits of Mitigating Global Greenhouse Gas Emissions for Future Air Quality and Human Health." *Nature Climate Change* 3 (10). Nature Publishing Group: 885–89. doi:10.1038/NCLIMATE2009.

WF Lamb, J K Steinberger, A Bows-Larkin, G P Peters, J T Roberts and F RWood. 2014. "Transitions in Pathways of Human Development and Carbon Emissions." *Environmental Research* 9: 014011. doi:10.1088/1748-9326/9/1/014011.

Whetton, PH, AM Fowler, MR Haylock, and AB Pittock. 1993. "Implications of Climate Change Due to the Enhanced Greenhouse Effect on Floods and Droughts in Australia." *Climatic Change* 25: 289–317.

WHO. 2005. "WHO Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide." *World Health Organization* WHO/SDE/PH (Global update 2005): 5–18. https://apps.who.int/iris/bitstream/handle/10665/69477/WHO_SDE_PHE_OEH_06.02_eng.pdf;jsessionid=D984E0D32F3FA3C11D9E13E9E8C69736?sequence=1.

Wiedmann, Thomas. 2009. "A Review of Recent Multi-Region Input-Output Models Used for Consumption-Based Emission and Resource Accounting." *Ecological Economics* 69 (2). Elsevier B.V.: 211–22. doi:10.1016/j.ecolecon.2009.08.026.

Wiedmann, Thomas, Manfred Lenzen, Karen Turner, and John Barrett. 2007. "Examining the Global Environmental Impact of Regional Consumption Activities - Part 2: Review of Input-Output Models for the Assessment of Environmental Impacts Embodied in Trade." *Ecological Economics* 61 (1): 15–26. doi:10.1016/j.ecolecon.2006.12.003.

Wong, Chit Ming, Richard W. Atkinson, H. Ross Anderson, Anthony Johnson Hedley, Ma Stefan, Patsy Yuen Kwan Chau, and Tai Hing Lam. 2002. "A Tale of Two Cities: Effects of Air Pollution on Hospital Admissions in Hong Kong and London Compared." *Environmental Health Perspectives* 110 (1): 67–77. doi:10.1289/ehp.0211067.

World Health Organization. 2018. "9 out of 10 People Worldwide Breathe Polluted Air, but More Countries Are Taking Action." doi:10.1051/matecconf/201712107005.

Wyzga, R. E., and A. C. Rohr. 2015. "Long-Term Particulate Matter Exposure: Attributing Health Effects to Individual PM Components." *Journal of the Air and Waste Management Association* 65 (5). Taylor & Francis: 523–43. doi:10.1080/10962247.2015.1020396.

Xia, Yang, Dabo Guan, Xujia Jiang, Liqun Peng, Heike Schroeder, and Qiang Zhang. 2016. "Assessment of Socioeconomic Costs to China's Air Pollution." *Atmospheric Environment* 139. Elsevier Ltd: 147–56. doi:10.1016/j.atmosenv.2016.05.036.

Xia, Yang, Dabo Guan, Jing Meng, Yuan Li, and Yuli Shan. 2018. "Assessment of the Pollution – Health – Economics Nexus in China," 14433–43.

Xing, Jia, Yang Zhang, Shuxiao Wang, Xiaohuan Liu, Shuhui Cheng, Qiang Zhang, Yaosheng Chen, et al. 2011a. "Modeling Study on the Air Quality Impacts from Emission Reductions and Atypical Meteorological Conditions during the 2008 Beijing Olympics." *Atmospheric Environment* 45 (10). Elsevier Ltd: 1786–98. doi:10.1016/j.atmosenv.2011.01.025.

Xing, J., S. X. Wang, C. Jang, Y. Zhu, and J. M. Hao. 2011b. "Nonlinear Response of Ozone to Precursor Emission Changes in China: A Modeling Study Using Response Surface Methodology." *Atmospheric Chemistry and Physics* 11 (10): 5027–44. doi:10.5194/acp-11-5027-2011.

Xing, Jia, Dian Ding, Shuxiao Wang, Bin Zhao, Carey Jang, Wenjing Wu, Fenfen Zhang, and Yun Zhu. 2018. "Quantification of the Enhanced Effectiveness of NO x Control from Simultaneous Reductions of VOC and NH3 for Reducing Air Pollution in the Beijing – Tianjin – Hebei Region , China." *Atmospheric Chemistry and Physics* 18: 7799–7814.

Xu, X. Y., and B. W. Ang. 2013. "Index Decomposition Analysis Applied to CO2 Emission Studies." *Ecological Economics* 93: 313–29. doi:10.1016/j.ecolecon.2013.06.007.

Xu, Shi Chun, Zheng Xia He, and Ru Yin Long. 2014. "Factors That Influence Carbon Emissions Due to Energy Consumption in China: Decomposition Analysis Using LMDI." *Applied Energy* 127. Elsevier Ltd: 182–93. doi:10.1016/j.apenergy.2014.03.093.

Xu, Ruiguang, Guiqian Tang, Yuesi Wang, and Xuexi Tie. 2016. "Analysis of a Long-Term

Measurement of Air Pollutants (2007–2011) in North China Plain (NCP); Impact of Emission Reduction during the Beijing Olympic Games.” *Chemosphere* 159. Elsevier Ltd: 647–58. doi:10.1016/j.chemosphere.2016.06.025.

Xue, Likun, Tao Wang, Peter K K Louie, Connie W Y Luk, Donald R Blake, and Zheng Xu. 2014. “Increasing External E Ff Ects Negate Local E Ff Orts to Control Ozone Air Pollution : A Case Study of Hong Kong and Implications for Other Chinese Cities.”

Xuesong, Wang, L I Jinlong, Zhang Yuanhang, X I E Shaodong, and Tang Xiaoyan. 2009. “Ozone Source Attribution during a Severe Photochemical Smog Episode in Beijing , China.” *Science in China Series B: Chemistry* 52 (2006): 1270–80. doi:10.1007/s11426-009-0137-5.

Yang, Chuanguo, Zhongbo Yu, Zhenchun Hao, Jiangyun Zhang, and Jianting Zhu. 2012. “Impact of Climate Change on Flood and Drought Events in Huaihe River Basin, China.” *Hydrology Research* 43 (1–2): 14–22. doi:10.2166/nh.2011.112.

Ye, Bin, Jingjing Jiang, Changsheng Li, Lixin Miao, and Jie Tang. 2017. “Quantification and Driving Force Analysis of Provincial-Level Carbon Emissions in China.” *Applied Energy* 198. Elsevier Ltd: 223–38. doi:10.1016/j.apenergy.2017.04.063.

Yin, Shasha, Junyu Zheng, Qing Lu, Zibing Yuan, Zhijiong Huang, Liuju Zhong, and Hui Lin. 2015. “A Refined 2010-Based VOC Emission Inventory and Its Improvement on Modeling Regional Ozone in the Pearl River Delta Region, China.” *Science of The Total Environment* 514. Elsevier B.V.: 426–38. doi:10.1016/j.scitotenv.2015.01.088.

Yoon, Young, Minyoung Yang, and Jinsoo Kim. 2018. “An Analysis of CO2 Emissions from International Transport and the Driving Forces of Emissions Change.” *Sustainability* 10 (5). doi:10.3390/su10051677.

Yuan, Bin, Min Shao, Joost De Gouw, David D. Parrish, Sihua Lu, Ming Wang, Limin Zeng, et al. 2012. “Volatile Organic Compounds (VOCs) in Urban Air: How Chemistry Affects the Interpretation of Positive Matrix Factorization (PMF) Analysis.” *Journal of Geophysical Research Atmospheres* 117 (24). doi:10.1029/2012JD018236.

Yuan, Zibing, Liuju Zhong, Alexis Kai Hon Lau, Jian Zhen Yu, and Peter K.K. Louie. 2013. “Volatile Organic Compounds in the Pearl River Delta: Identification of Source Regions and Recommendations for Emission-Oriented Monitoring Strategies.” *Atmospheric Environment* 76 (x). Elsevier Ltd: 162–72. doi:10.1016/j.atmosenv.2012.11.034.

Yurganov, L. N., V. Rakitin, A. Dzhola, T. August, E. Fokeeva, M. George, G. Gorchakov, et al. 2011. “Satellite- and Ground-Based CO Total Column Observations over 2010 Russian Fires: Accuracy of Top-down Estimates Based on Thermal IR Satellite Data.” *Atmospheric Chemistry and Physics* 11 (15): 7925–42. doi:10.5194/acp-11-7925-2011.

Zeileis, Achim. 2002. “Testing and Dating of Structural Changes in Practice.” *Computational Statistics & Data Analysis* 44: 109–23.

Zeng, X. T., Y. F. Tong, L. Cui, X. M. Kong, Y. N. Sheng, L. Chen, and Y. P. Li. 2017. “Population-Production-Pollution Nexus Based Air Pollution Management Model for Alleviating the Atmospheric Crisis in Beijing, China.” *Journal of Environmental Management* 197: 507–21. doi:10.1016/j.jenvman.2017.04.022.

Zeng, P., X. P. Lyu, H. Guo, H. R. Cheng, F. Jiang, W. Z. Pan, Z. W. Wang, S. W. Liang, and Y. Q. Hu. 2018. “Causes of Ozone Pollution in Summer in Wuhan, Central China.” *Environmental Pollution* 241 (x): 852–61. doi:10.1016/j.envpol.2018.05.042.

Zhang, Meigen, Itsushi Uno, Renjian Zhang, Zhiwei Han, Zifa Wang, and Yifen Pu. 2006. “Evaluation of the Models-3 Community Multi-Scale Air Quality (CMAQ) Modeling System with Observations Obtained during the TRACE-P Experiment: Comparison of Ozone and Its Related Species.” *Atmospheric Environment* 40 (26): 4874–82. doi:10.1016/j.atmosenv.2005.06.063.

Zhang, Junfeng, and Kirk R. Smith. 2007. “Household Air Pollution from Coal and Biomass Fuels in China: Measurements, Health Impacts, and Interventions.” *Environmental Health Perspectives* 115 (6): 848–55. doi:10.1289/ehp.9479.

Zhang, Xing-ping, and Xiao-mei Cheng. 2009. “Energy Consumption , Carbon Emissions , and Economic Growth in China.” *Ecological Economics* 68 (10). Elsevier B.V.: 2706–12.

doi:10.1016/j.ecolecon.2009.05.011.

Zhang, Jungang, Yuesi Wang, Fangkun Wu, Hong Lin, and Weidong Wang. 2009. "Nonmethane Hydrocarbon Measurements at a Suburban Site in Changsha City, China." *Science of the Total Environment* 408 (2). Elsevier B.V.: 312–17. doi:10.1016/j.scitotenv.2009.07.010.

Zhang, Lin, Daniel J. Jacob, Nicole V. Downey, Dana A. Wood, Doug Blewitt, Claire C. Carouge, Aaron van Donkelaar, Dylan B.A. Jones, Lee T. Murray, and Yuxuan Wang. 2011. "Improved Estimate of the Policy-Relevant Background Ozone in the United States Using the GEOS-Chem Global Model with 1/2° × 2/3° Horizontal Resolution over North America." *Atmospheric Environment* 45 (37). Elsevier Ltd: 6769–76. doi:10.1016/j.atmosenv.2011.07.054.

Zhang, Yue-jun, and Ya-bin Da. 2015. "The Decomposition of Energy-Related Carbon Emission and Its Decoupling with Economic Growth in China." *Renewable and Sustainable Energy Reviews* 41. Elsevier: 1255–66. doi:10.1016/j.rser.2014.09.021.

Zhang, Wei, Ke Li, Dequn Zhou, Wenrui Zhang, and Hui Gao. 2016a. "Decomposition of Intensity of Energy-Related CO2emission in Chinese Provinces Using the LMDI Method." *Energy Policy* 92: 369–81. doi:10.1016/j.enpol.2016.02.026.

Zhang, Yang, Xin Zhang, Litao Wang, Qiang Zhang, and Fengkui Duan. 2016b. "Application of WRF / Chem over East Asia : Part I . Model Evaluation and Intercomparison with MM5 / CMAQ." *Atmospheric Environment* 124. Elsevier Ltd: 285–300. doi:10.1016/j.atmosenv.2015.07.022.

Zhang, Qiang, Xujia Jiang, Dan Tong, Davis Steven J, Hongyang Zhao, Guannan Geng, Tong Feng, Bo Zheng, Zifeng Lu, and David G Streets. 2017. "Transboundary Health Impacts of Transported Global Air Pollution and International Trade." *Nature* 543 (7647). Nature Publishing Group: 705–9. doi:10.1038/nature21712.

Zhao, Y., C. P. Nielsen, Y. Lei, M. B. McElroy, and J. Hao. 2011. "Quantifying the Uncertainties of a Bottom-up Emission Inventory of Anthropogenic Atmospheric Pollutants in China." *Atmospheric Chemistry and Physics* 11 (5): 2295–2308. doi:10.5194/acp-11-2295-2011.

Zhao, Yu, Chris P. Nielsen, and Michael B. McElroy. 2012a. "China's CO2 Emissions Estimated from the Bottom up: Recent Trends, Spatial Distributions, and Quantification of Uncertainties." *Atmospheric Environment* 59. Elsevier Ltd: 214–23. doi:10.1016/j.atmosenv.2012.05.027.

Zhao, B., P. Wang, J. Z. Ma, S. Zhu, A. Pozzer, and W. Li. 2012b. "A High-Resolution Emission Inventory of Primary Pollutants for the Huabei Region, China." *Atmospheric Chemistry and Physics* 12 (1): 481–501. doi:10.5194/acp-12-481-2012.

Zhao, Xingrong, Xi Zhang, Ning Li, Shuai Shao, and Yong Geng. 2017. "Decoupling Economic Growth from Carbon Dioxide Emissions in China: A Sectoral Factor Decomposition Analysis." *Journal of Cleaner Production* 142. Elsevier Ltd: 3500–3516. doi:10.1016/j.jclepro.2016.10.117.

Zhao, Bin, Haotian Zheng, Shuxiao Wang, Kirk R. Smith, Xi Lu, Kristin Aunan, Yu Gu, et al. 2018. "Change in Household Fuels Dominates the Decrease in PM2.5 Exposure and Premature Mortality in China in 2005–2015." *Proceedings of the National Academy of Sciences of the United States of America* 115 (49): 12401–6. doi:10.1073/pnas.1812955115.

Zheng, Junyu, and H. Christopher Frey. 2005. "Quantitative Analysis of Variability and Uncertainty with Known Measurement Error: Methodology and Case Study." *Risk Analysis* 25 (3): 663–75. doi:10.1111/j.1539-6924.2005.00620.x.

Zheng, Junyu, Lijun Zhang, Wenwei Che, Zhuoyun Zheng, and Shasha Yin. 2009a. "A Highly Resolved Temporal and Spatial Air Pollutant Emission Inventory for the Pearl River Delta Region, China and Its Uncertainty Assessment." *Atmospheric Environment* 43: 5112–22. doi:10.1016/j.atmosenv.2009.04.060.

Zheng, Junyu, Min Shao, Wenwei Che, Lijun Zhang, Liuju Zhong, Yuanhang Zhang, and David Streets. 2009b. "Speciated VOC Emission Inventory and Spatial Patterns of Ozone Formation Potential in the Pearl River Delta, China." *Environmental Science and Technology* 43 (22): 8580–86. doi:10.1021/es901688e.

Zheng, Junyu, Wenwei Che, Xuemei Wang, Peter Louie, and Liuju Zhong. 2009c. “Road-Network-Based Spatial Allocation of on-Road Mobile Source Emissions in the Pearl River Delta Region, China, and Comparisons with Population-Based Approach.” *Journal of the Air & Waste Management Association (1995)* 59 (12): 1405–16. doi:10.3155/1047-3289.59.12.1405.

Zheng, Junyu, Yufan Yu, Ziwei Mo, Zhou Zhang, Xinming Wang, Shasha Yin, and Kang Peng. 2013. “Industrial Sector-Based Volatile Organic Compound (VOC) Source profiles Measured in Manufacturing Facilities in the Pearl River Delta , China.” *Science of the Total Environment, The* 456–457. Elsevier B.V.: 127–36. doi:10.1016/j.scitotenv.2013.03.055.

Zheng, Chenghang, Jiali Shen, Yongxin Zhang, Xinbo Zhu, Xuecheng Wu, Linghong Chen, and Xiang Gao. 2017. “Atmospheric Emission Characteristics and Control Policies of Anthropogenic VOCs from Industrial Sources in Yangtze River Delta Region, China.” *Aerosol and Air Quality Research* 17 (9): 2263–75. doi:10.4209/aaqr.2016.06.0234.

Zheng, Bo, Dan Tong, Meng Li, Fei Liu, Chaopeng Hong, Guannan Geng, Haiyan Li, et al. 2018a. “Trends in China’s Anthropogenic Emissions since 2010 as the Consequence of Clean Air Actions.” *Atmospheric Chemistry and Physics* 18 (19): 14095–111. doi:10.5194/acp-18-14095-2018.

Zheng, Heran, Yuli Shan, Zhifu Mi, Jing Meng, Jiamin Ou, Heike Schroeder, and Dabo Guan. 2018b. “How Modifications of China’s Energy Data Affect Carbon Mitigation Targets.” *Energy Policy* 116 (June 2017): 337–43. doi:10.1016/j.enpol.2018.02.031.

Zheng, Junyu, Yuanjing Xu, Zhijing Huang, Shasha Yin, and Kang Peng. 2020. “A national emission inventories of ammonia in China and its impliations on aerosol formation.” In preperation.

Zhong, Liuju, Peter K K Louie, Junyu Zheng, Zibing Yuan, Dingli Yue, Josephine W K Ho, and Alexis K H Lau. 2013. “Science-Policy Interplay: Air Quality Management in the Pearl River Delta Region and Hong Kong.” *Atmospheric Environment* 76. Elsevier Ltd: 3–10. doi:10.1016/j.atmosenv.2013.03.012.

Zhou, Baolu, Zhongxue Li, and Congcong Chen. 2017. “Global Potential of Rare Earth Resources and Rare Earth Demand from Clean Technologies.” *Minerals* 7 (11). doi:10.3390/min7110203.

Zhu, Yanhong, Lingxiao Yang, Jianmin Chen, Xinfeng Wang, Likun Xue, Xiao Sui, Liang Wen, et al. 2016. “Characteristics of Ambient Volatile Organic Compounds and the Influence of Biomass Burning at a Rural Site in Northern China during Summer 2013.” *Atmospheric Environment* 124. Elsevier Ltd: 156–65. doi:10.1016/j.atmosenv.2015.08.097.

Zveryaev I.. 2015. “Journal of Geophysical Research : Oceans.” *Journal of Geophysical Research: Oceans*, 2813–25. doi:10.1002/2014JC010387.Received.