High-resolution spatiotemporal patterns of China’s FFCO2 emissions under the impact of LUCC from 2000 to 2015

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Abstract

Fossil fuel carbon dioxide (FFCO2) emissions have become a principal driver behind the increase of atmospheric CO2 concentration and spatiotemporal variations of atmospheric CO2 in the urban surface layer. This study quantifies the 2000–2015 urban high-resolution spatiotemporal patterns of China’s FFCO2 emissions under the impact of the land-use and land-cover change. Multi-source data were used together with various up-to-date geostatistics and spatial analysis methods. FFCO2 emissions were determined to rise over the 15 years in the highest emitting cities in the South and East of China. The high-value clusters inside of all cities expanded outward from their city centers and in some cases transferred to economic development zones or new city centers, while the expansion speeds and variation time were found to differ significantly. We found further that then FFCO2 emissions spatial distribution is interconnected with diverse factors: urbanization, and either croplands (rainfed, irrigated, and post-flooding) or native vegetation, being the two most important. As expected, the increase in urban areas was associated with increased FFCO2 emissions, while the wettability in croplands or the increase in native vegetation have an association with the decrease of FFCO2 emissions. Unlike previous studies, we have found no change associated with changes in water cover. Finally, while the primary source of FFCO2 emissions is still coal, there has been a gradual move to cleaner energy (natural gas in Beijing) or more efficient industrial processes (Wuxi and Dalian), although diverse industrial structures and energy efficiencies exist. Over time, the current spatial patterns of FFCO2 emissions in China will conflict with these trends at the macroscale.

1. Introduction

A major focus of the science of global change is understanding the response of Earth’s climate to the increase in greenhouse gases in the atmosphere associated with anthropogenic emissions. Anthropogenic greenhouse gas emissions (with 95% certainty), especially carbon dioxide (CO2), are the dominant cause of observed warming since the mid-20th century (IPCC 2013, Le Quéré et al 2015). Fossil fuel CO2 (FFCO2) emissions have become a prime driver of the increase in atmospheric CO2 concentration and its spatiotemporal variations in the surface layer in the continental regions (Peylin et al 2011, Liu et al 2017). In China, human-induced CO2 emissions from fossil fuel combustion (energy-related emissions) and cement production (process-related emissions) account for approximately 30% of global annualized present day CO2 emissions (Janssens-Maenhout et al 2017).
The present estimate of anthropogenic CO₂ emissions is primarily based on bottom-up inventories (Reuter et al. 2014, Li et al. 2018b), followed by top-down measurements (Hakkarainen et al. 2016). Bottom-up inventories are estimated on the basis of statistics (Olivier et al. 1999, Park and Schade 2016) at the global and regional scales. 9 existing inventories (the Carbon Dioxide Information Analysis Center (CDIAC), the Emission Database for Global Atmospheric Research (EDGAR), the Fossil Fuel Data Assimilation System (FFDAS), the Open Source Data Inventory for Anthropogenic CO₂ (ODIAC), the Multi-resolution Emission Inventory for China (MEIC), the Regional Emission inventory in Asia (REAS), the Greenhouse Gas–Air Pollution Interactions and Synergies (GAINS), the inventory made at Nanjing University (ZHAO), and the China Emission Accounts and Datasets (CEADs) show significant differences (Hutchins et al. 2017, Saikawa et al. 2017). The uncertainty mainly comes from the difficulties of collecting consumption data (Guan et al. 2012), conflicting estimates of energy consumption and emission factors, few actual measurements representative of the mix of Chinese fuels (Liu et al. 2015a), unreliable statistical methods to confine the spatial resolution of FFCO₂ (Reuter et al. 2014), time delays of the current emission inventories (Wang et al. 2018) and missing or mis-timed sources (Cohen and Prinn 2011, Cohen 2014).

In contrast, the measurements underlying top-down approaches, such as aircraft and satellites, have been used to determine emissions based on the amounts and rates of observed trace gases (Cohen and Wang 2014, Dlugokencky and Tans 2020, Conley et al. 2017). This application of top-down measurements has led to an accuracy of global CO₂ concentrations estimated from space-borne observations better than 1% (less than 4 ppmv) and could decrease the uncertainty in regional estimates of CO₂ sources and sinks (Rayner and O’Brien 2001). However, although Hakkarainen et al. (2018) showed how global and local satellite-based CO₂ anomalies can be used to study anthropogenic CO₂ emission sources, Zhang et al. (2018) concluded the existing discrepancies between inventories and models based on different methods and data sources, result in significant uncertainties and gaps associated with these emission inventories (Guevara et al. 2017, Zhao et al. 2017). Presently, the community has not found a sufficient way to comprehensively monitor and verify anthropogenic CO₂ emissions.

One approach to quantify and reduce the uncertainties (Janardanan et al. 2016) associated with estimated emissions is homogeneously and optimally integrating all available observations together with prior information. Liu et al. (2017) combined surface measurements with satellite data into a regional high-resolution atmospheric transport model (Kort et al. 2012, Zunkkehr et al. 2017) for central and southern Europe, revealing the spatiotemporal patterns of the FFCO₂ signal and additional changes in the variability in atmospheric CO₂ associated with FFCO₂ emissions. A new airborne method (Wecht et al. 2014, Mitchell et al. 2015) has been applied to quantify localized surface emissions at spatial scales of ~1000 m, with an error less than 10% accounting for smaller-scale turbulent dispersion (Conley et al. 2017).

Efforts to quantify the uncertainties (Guan et al. 2012, Zhao et al. 2017) of the current inventories under different source profile realizations (Cohen and Prinn 2011) and by linking to continuous monitoring of emissions with sampled observations (Oda et al. 2018) is ongoing. Constructing the time-series of CO₂ emissions inventories for nations and provinces (Shan et al. 2018) and other high resolution manifestations (Zhao et al. 2019) also continues. However, attempts to quantify the annual long-term localized high-resolution spatiotemporal patterns of China’s FFCO₂ emission in hotspots (local clusters undergoing unstable natural and/or man-made change) and megacities, is still not settled.

This work develops systematic and intuitive high-resolution spatiotemporal patterns of FFCO₂ emissions in China, and the interconnection between the variations in the spatial structure of the FFCO₂ emissions, land cover (LC) and land-use and land-cover change (LUCC), itself another crucial factor affecting atmospheric carbon concentrations. A comparison of nine LC maps from seven LC datasets (IGBP DISCover, UMD, GLC, MCD12Q1, GLCNMO, Climate Change Initiative (CCI)-LC (Defourny et al. 2016), and GlobalLand30) over China demonstrates that the highest overall accuracy is still less than 68% (Yang et al. 2017), emphasizing that more work still remains to be done.

Therefore, finely classified CCI-LC factors were chosen to simultaneously allow for a more precise determination of the changes in the FFCO₂ emission spatiotemporal patterns as well as the interaction with the land surface. Our integration of high-resolution satellite observations, surface measurements using forward geostatistics and spatial analysis have allowed us to: (i) demonstrate national spatiotemporal variations in FFCO₂ emissions and reveal an initial overall spatiotemporal pattern of China; (ii) analyse local spatial clusters of FFCO₂ emissions and their instabilities; and (iii) determine other positive clusters between 22 LC classes and FFCO₂ emissions. We finally quantify the sources of FFCO₂ emissions and how they change in six unique cities in China.

2. Materials and methods

2.1. ODIAC FFCO₂ emission dataset

The Open-source Data Inventory for Anthropogenic CO₂ (ODIAC) provides globally gridded emissions of fossil fuel CO₂ (Oda and Maksyutov 2011) at
1 km × 1 km over land, by combining nightlight satellite observations and power plant profiles. Data is available from 2000 to 2017 at 10.17595/20170411.001 (Oda et al. 2018). We select ODIAC 2018 because it provides a sufficiently high spatial-temporal resolution compared with other alternatives. Source regions corresponding to human settlements and land transportation are well articulated by the nightlight distribution, which differs in several ways from conventional population-based approaches. The emissions estimates are made on global and national scales with small uncertainties (e.g. 8% for the global scale by Andres et al. (2014) and Oda et al. (2018).

2.2. CCI-LC maps
A time series from 1992 to 2015 of annual global CCI-LC maps at 300 m × 300 m resolution with 22 LC classes were defined based on the UN LC classification system by reprocessing and interpreting 5 different satellite missions, including NOAA-AVHRR HRPT, SPOT-Vegetation, ENVISAT-MERIS FR and RR, ENVISAT-ASAR, and PROBA-V (http://maps.elie. ucl.ac.be/CCI/viewer). Machine learning and unsupervised algorithms were applied to classify the spatial distribution and fractional cover of plant functional types (PFTs), a key uncertainty in land surface models closely linked to uncertainties in global carbon budget. We specifically employ the maps from 2000 to 2015 since they capture the major changes while overlapping with the ODIAC data.

2.3. 1st City-level CO2 emission inventory
As an accurate and up-to-date inventory of energy, emission and socioeconomic data, we chose inventories provided by the China Emission Accounts and Datasets (CEADs) (www.ceads.net). This database is calculated based on apparent energy consumption from a mass balance of domestic fuel production, international fuelling, international trade, changes in stocks, and subsequent consumption, in connection with revised emission factors (EFs) based on 12 sets of fossil fuel combustion (Liu et al. 2015a, Shan et al. 2017). This study specifically uses the city-level CO2 emission inventory of FFCO2 emissions, which covers 46 socioeconomic sectors, 17 different fossil fuels, and 7 primary industry products, across 182 cities in China, following the IPCC territorial emission accounting approach, and in agreement with national and provincial emission accounts by former studies (Liu 2016). The focus on cities is important, since they contribute up to 85% of the total anthropogenic CO2 emissions in China.

2.4. Methodology
2.4.1. Spatiotemporal visualization
Visualization of the spatial distribution of the CCI-LC covers, the ODIAC FFCO2 emissions, and the 28 highest emitting cities (Moran et al. 2018) in China are shown in figure 1. First, we find that a small number of large and affluent cities drive a significant share of national annualized CO2 emissions, with the 100 most emitting cities producing 18% of the total. Comparing these high FFCO2 emissions cities across time and space demonstrates that human activities and changes of vegetation are the two main factors influencing the spatiotemporal variation of the CO2 in the urban atmosphere.

2.4.2. Local indicators of spatial association (LISA) with empirical Bayes (EB) rate
The current investigation sampled and analysed six representative cities (Beijing, Shanghai, Tianjin, Shenyang, Dalian, and Wuxi) to understand the range of particular spatiotemporal patterns. Beijing, Shanghai and Tianjin remain the top three positions in the overall highest 28 FFCO2 emitting cities from 2000 to 2015, while Shenyang, Dalian, and Wuxi were the 3 cities with maximum change in our FFCO2 emissions ranking. We first collect 10 000 randomly distributed stippled points inside every city and analyse emissions changes over time at each given location, which in turn is statistically related to its respective neighbors. The empirical bayes index EB-smoothed (Assunção and Reis 1999) LISA (Anselin 1995) is used to identify local clusters and spatial outliers of emissions, by indicating significant spatial clustering around each observation. Consider a city divided into m areas and let ni and xi be the number of cases and FFCO2 emissions in area i respectively, with i = 1, …, m, n is the number of analysis areas in the map. The observed rate in the area i is defined as 

\[ p_i = \frac{n_i}{x_i}. \]

However, instead of using the rate \( p_i \), \( z_i \) is an index using a deviation in the estimated marginal mean standardized by an estimate of its standard deviation:

\[ z_i = \frac{p_i - b}{\sqrt{v_i}}, \quad (1) \]

where the marginal expectation and variance of \( p_i \) are estimated by \( b \) and \( v_i = a + b/x_i \), respectively. a and b are proposed by moment estimates, where \( b = n/x, a = s^2 - b/(x/m), \) and \( s^2 = \sum x_i(p_i - b)^2/x. \)

The EBI is defined as

\[ EBI = \frac{m}{\sum w_j z_i z_j} \sum w_j \left( z_i - \overline{z} \right)^2. \quad (2) \]

And the local Moran statistic for observation i is defined as

\[ I_i = (z_i/m_2) \sum w_j z_j, \quad (3) \]

where

\[ m_2 = \frac{\sum z_i^2}{n}. \quad (4) \]

EB-smoothed LISA has been used to analyze the spatial aspects of population density, incidence and crime rate data. High spatial-resolution gridded FFCO2 emissions integrating satellite-observed data with
bottom-up power plant profiles make the applications of this method possible for analysing the local spatiotemporal patterns of emissions. This is the first work to detect long-term local clusters of FFCO$_2$ emissions inside cities and assess the variations in these locations, with previous studies (i.e. Liu 2016, Saikawa et al. 2017, Xu et al. 2018) revealing an overview of the trends in CO$_2$ emissions or a rough distribution with a comparatively low spatial resolution.

2.4.3. Multivariate local Geary

Land-use change factors, as a comprehensive reflection of human activities and one of the key features of these hotspot cities, were used to further explore the changes and uncertainties related to the local high-resolution spatiotemporal patterns of China’s FFCO$_2$ emissions. Here we introduce the local Geary $c_i$, a univariate statistic, but instead apply it to a multivariate context (Anselin 2019). The long-term series 300 m spatial resolution LC images consistent with the 22 IPCC classes benefits data exploration between LC and FFCO$_2$ emissions by using a multivariate statistic.

In general, for $k$ attributes, a multivariate Local Geary can be defined as:

$$c_{k,i} = \sum_{i=1}^{k} c_{v,i}$$

which $c_{v,i}$ is the local Geary statistic for the variable $v_i$.

The multivariate local Geary is a new spatial statistic to identify local clusters in multivariate space by formalizing the combination of attribute similarity and location similarity. It indicates an association of the notion of distance in a multi-attribute space (LC and FFCO$_2$ emissions) with that of its geographic neighbours. The combination of distances along the LC classes and FFCO$_2$ dimensions and the relation of their rates of change allow for a quantitative way to determine the respective contributions of these two factors essential to understanding the increase in greenhouse gases in the atmosphere associated with anthropogenic emissions. The weak point of the local indicator of multivariate spatial association is that it is statistical and not physical (Efron and Hastie 2016, Anselin 2019).

3. Results

3.1. Spatiotemporal national variations in FFCO$_2$ emissions

We test the spatiotemporal patterns and trends from 2000 to 2015 of China’s FFCO$_2$ emissions using a gridded 1 km spatial-resolution database of China’s 28 highest emitting cities from ODIAC, in figure 2. This database is derived from individual power plant emissions and location profiles, as well as satellite observations of nighttime data. The FFCO$_2$ emissions from all 28 cities were higher in 2015 than in 2000, and

Figure 1. (a) The 2015 CCI-LC cover distribution. (b) The 2015 FFCO$_2$ emissions distribution from ODIAC. (c) The 28 highest emitting cities in China in the global top 100 from the result of the Gridded Global Model of City Footprints (GGMCF). The CCI-LC maps with a 300 m spatial resolution demonstrate the 22 LC classes (see appendix for details). The ODIAC emissions field was aggregated to a common 1 × 1 km resolution. The value is given in the unit of one log of one thousand tons C cell$^{-1}$.
all 28 cities presented an outward diffusion characteristic, consistent with previous studies (Liu 2016, Shan et al. 2018). We specifically analyze 6 cities in more depth in this work, the first three of which, Beijing, Shanghai, and Tianjin, maintained their top 3 spots in terms of FFCO₂ emissions over the 15 years. The fourth of which, Wuxi, had the largest increase in rank (22nd to 7th). The fifth and sixth of which, Dalian and
Shenyang, had the greatest decline in rank respectively from (11th to 21st) and (10th to 19th).

These results on an individual city basis are not consistent with the latest research from the Norwegian University of Science and Technology, which based on its Gridded Model of City Footprints (GGMCF) ranked Guangzhou, Hong Kong SAR, and Shanghai as the top three cities with the largest footprint. The GGMCF is based on downscaled national carbon footprints (CFs), themselves based on population, purchasing power, and existing subnational CFs studies from the United States (US), China, the European Union (EU), and Japan. These significantly different results are a direct result of the inclusion of power plant profiles and satellite-observed nightlight data, unique to our approach.

The quantitative and visualization analysis to determine an initial spatiotemporal pattern (2000–2015) of national FFCO2 emissions was based on the maximum deviation in the CFs results from Moran et al (2018). However, their study did not consider the variation caused by man-made and natural factors in the spatiotemporal patterns of China’s FFCO2 emissions, which therefore is the focus of our subsequent work.

### 3.2. Local spatial clusters and instability of FFCO2 emissions

Previous studies (Cohen and Prinn 2011, Liu et al 2015a, Liu 2016) about FFCO2 emissions in China have focused almost entirely on the unit city or reflected the spatially dense aggregation of CO2 emissions from the burning of fossil fuels by using a regional high-resolution atmospheric transport model and indicated distinct annual mean structures deep into the troposphere (Liu et al 2017). We compute the local spatial associations inside of the six cities in China using an EB-smoothed LISA with a rook continuity weight. The goal is to focus on two interpretations: indicators of local spatial clusters and diagnostics for local instability.

First, as shown in figure 3, the most significant local cluster distributions in all six megacities were almost constant over the 15 years. However, outward expansion of the most significant clusters in Beijing and Wuxi can be clearly observed. The spatial clustering of these most significant local clusters of high FFCO2 emissions is centred over the respective inner districts in each city. The two exceptions are Tianjin, where there is a second significant local cluster in the Binhai New Area, and Dalian, where the main cluster extends along the coast.

From the number of high-value clusters (high–high) in figure 3 and their respective temporal changes in the six cities in figure 4, we clearly determine that the high FFCO2 emissions cluster in Shanghai was the most variable. It increased from 2003 to 2005, and later declined from 2009 to 2010 to a similar magnitude as the 3 year increase, finally maintaining the subsequent value through 2015. 5 city-clusters (Beijing, Tianjin, Dalian, Wuxi, and Shenyang) all expanded during the 15 years, but showed different processes. Unlike the slight expansions found in Dalian (461–623) and Shenyang (402–502), dramatic expansions happened in Beijing (508–952), Tianjin (598–819) and Wuxi (515–997), although Tianjin ebbed during the first 5 years before taking off. ODIAC emissions have used the time invariant nighttime light data and fuel statistics, rather than linearly interpolating missing gaps. These issues are why the data from 2006 through 2009 and 2011 through 2015 does not change, as shown in figure 4. Given these constraints, the computed high-value clusters are reasonable. It is hoped that future versions of emissions will lead to even higher resolution results.

Local Moran’s I of the cities constructed maps of ‘hot spots’ and ‘cold spots’ of FFCO2 emissions. In Beijing and Shenyang, values approaching approximately 0.95 indicate strong positive spatial autocorrelation, presenting extremely stable and compact local spatial clusters. In Tianjin and Wuxi, values around 0.35 suggest the presence of spatial heterogeneity in the strength of the spatial autocorrelation, in the sense that there are observed clusters, but that these are not very stable. But other two cities’ local Moran’s I values were very small (approaching 0), indicating no spatial autocorrelation with an intense local instability. This demonstrates itself in terms of the high-value clusters distributed outside of the centre city.

Therefore, the major FFCO2 point sources were often located within the centre city, and the long-term unstable and various high-value clusters in different cities depend on the different development states and respective geographies of these cities. This shows that there is a significant opportunity for focusing strategies to shift FFCO2 from the cluster-change perspective. The LISA with EB rate shows that the null distribution of the local Moran cannot be effectively approximated by the normal, inferring that the 10 000 randomly distributing samples used in this study should achieve a reliable result.

### 3.3. Multivariate local Geary statistic of FFCO2 emissions and LC

Here we use multivariate local Geary maps of FFCO2 emissions in the six cities, as shown in figure 5, with positive local spatial correlation depicted in dark blue. These results were obtained using a local indicator of multivariate spatial association, which indicates interesting locations that cannot be found in the univariate analyses. The corresponding clusters are shown using a p-value of 0.05 based on 9999 permutations.

First, inner cities and economic development zones were identified as positive clusters, consistent
with the results of section 3.2. Second, other positive clusters are observed, specifically in the areas with vegetation and water cover. For example, 4821 positive locations are identified in Beijing in 2000, while only 3716 cluster (High–High and Low–Low) locations are determined in figure 3. Figure 5 displays more significant locations for LC classes and FFCO$_2$ emissions at the same time, including some positive correlation over ocean/water bodies.

Third, Multivariate measures provide additional insight into local patterns due to the use of a different criterion for attribute similarity.

In 2000, the highest number of significant locations was in Wuxi, and the lowest number was in Dalian. In 2015, the highest number was in Shenyang, and the lowest was still in Dalian. The number of significant locations in five cities showed a decreasing trend, while only those in Dalian increased.
The multivariate statistical results strongly confirm the diversity of factors impacting the FFCO$_2$ emission distribution. However, the approach suffers from multiple comparisons and an additional complication of correlated tests. More precise assessment inferences and testing power, including computational issues when scaling the size of the data sets encountered, will contribute to improved results.

4. Discussion

4.1. Impact of variation in the spatial structure of 22 classes LC on FFCO$_2$ emissions

Prior work has documented factors influencing carbon emissions, such as gross domestic product (GDP) (Xu et al 2018), differences in technology (Li et al 2010, Liu et al 2012), industrial structure and energy efficiency (Su et al 2014). Studies have hinted at the ‘rectification effect’ of fossil-fuel emissions arises from the covariation between the spatiotemporal patterning of the fossil-fuel emissions sources, the variability of their concentrations resulting from atmospheric transport (Zhang et al 2016, Liu et al 2017), and the impact of the biosphere (Denning et al 1996, Larson and Volkmer 2008). However, these studies were almost entirely devoted to the anthropogenic effects on carbon emissions using statistical data or forward models, and did not include integration of surface measurements and satellite data, as has been done in this work. Our approach also aims to detect the simultaneous impact of the variation in the spatial structure of LC on the FFCO$_2$ emissions.
First, we found that FFCO$_2$ emissions at the six chosen cities presented a hot spot distribution (such as in inner city and economic development zones), which supports the recent finding by Liu et al (2017) who demonstrated similar findings in London, Paris, and Milan. As seen from Figure 6, an abundant increase in urban areas (in square metres) and the dramatic increase of FFCO$_2$ emissions have become concurrent.

Second, areas with a decrease in croplands (rainfed, irrigated, and post-flooding) inside five cities (Beijing, Shanghai, Tianjin, Shenyang, and Wuxi) showed a significant high value in FFCO$_2$ emissions. A slight similar co-response can be identified in the grasslands or mosaic natural vegetations (tree, shrub, herbaceous cover) (>50%) in Tianjin and Wuxi. This indicates that agriculture within cities is especially sensitive to the variation of FFCO$_2$ emissions than other land cover types. Only croplands, which have been rainfed, irrigated, or postflooded, with long-term planning, can be changed to compensate for FFCO$_2$ emissions.

Third, moisture also plays an important role in adjusting the variation of FFCO$_2$ emissions. Cropland moisture enhances the compensating effect of croplands on FFCO$_2$ emissions (Gervois et al 2008, Li et al 2018a, Tacconi and Mutaqin 2019).

The results in Dalian are completely inconsistent with other cities. In many areas (with cropland; mosaic natural vegetation (tree, shrub, and herbaceous cover) (>50%)/ cropland; tree cover, broad-leaved, deciduous, and closed to open (>15%); sparse vegetation (tree, shrub, and herbaceous cover) (<15%), regardless of whether the area is growing or declining, FFCO$_2$ emissions remain fairly static. In fact, although the cropland (rainfed) has been enlarged, FFCO$_2$ emissions in the district still are remarkably high.

Figure 6. FFCO$_2$ emission changes varying with the land cover changes in the six hotspot cities.
To further accurately estimate FFCO$_2$ emission sources and croplands altogether and protecting and dations would be better suited here: reducing moist acts as a sink, hinting that a different set of recommen-

approximate the FFCO$_2$ to range from 80% from 2000 age 60.78%, in Wuxi in Beijing coal in all six cities, among which the range was 38.64% in China cement production between 2010 and 2012 occurred bon emissions from the burning of fossil fuels and 17 different sources of CO$_2$ emissions from fossil emissions relies partially on city and regional actions et al 2016 this first study to investigate the effective-

ness of 22 kinds of land cover changes on FFCO$_2$ emis-

tions inside cities should play an essential role. Our results provide evidence for the importance of taking better care of moist croplands inside of large metropo-

tic areas. However, in Dalian, it appears moist croplands act as a net CO$_2$ source, and native vegetation acts as a sink, hinting that a different set of recommenda-

tions would be better suited here: reducing moist croplands altogether and protecting and/or reintrodu-

cing native vegetation.

4.2. FFCO$_2$ emissions from 17 sources

To further accurately estimate FFCO$_2$ emission sources from human activities, it is especially important to develop an understanding between the different specific sources of FFCO$_2$. Figure 7 presents the proportion of the 17 different sources of CO$_2$ emissions from fossil fuel combustion and industrial processes for the six cities in 2017. First, in terms of total consumption the top three cities is Shanghai (187.49 Mt), Tianjin (132.01 Mt), and Beijing (102.62 Mt). Second, the primary source strength of FFCO$_2$ emissions was the use of raw coal in all six cities, among which the range was 38.64% in Beijing (the city with the lowest percentage) to 60.78%, in Wuxi (the city having the largest percentage). These results are lower than previous work which approximate the FFCO$_2$ to range from 80% from 2000 to 2013 (Liu et al 2015b), 60.93% in 2014 (Xu et al 2018), and 70% from 2015 to 2018 (Geng et al 2011) in China. Third, we find that the second most significant source of FFCO$_2$ emissions varies from city to city: Wuxi (industrial processes, 12.99%), Beijing (natural gas, 14.85%), Shanghai (fuel oil, 12.57%), Tianjin (coke, 14.30%), Shenyang (diesel oil, 11.57%) and Dalian (diesel oil, 12.82%). These combined results demon-

strate on one hand, the reason for Wuxi being the fastest rising city in our modeled FFCO$_2$ emission rank list, and on the other hand, a significant move towards clean energy in Beijing. It is clear that the energy structures of the six cities are different and hence the policy solutions to reduce FFCO$_2$ should also be different.

4.3. Patterns of development and policy implication

Nationally, from 2000 to 2015, FFCO$_2$ emissions continued to rise over time, while the spatial distribu-

tion became noticeably uneven among cities. At the city scale, significant clusters centred over inner cities expanded outward over time, which became unstable with the development of economic and other special development zones. A local indicator of multivariate spatial association displayed more positive clusters. We find that inside most megacities, changes in urban and cropland (rainfed, irrigated, and post-flooding) types are the 2 main factors corresponding to changes in FFCO$_2$ emissions. Wettability in cropland areas inside of cities plays a positive role in compensating FFCO$_2$ emissions. Finally, inside of inner cities, the major source of FFCO$_2$ emissions was the use of raw coal, although considerably less so than in previous studies’ results. Additionally, differences in the industrial structure and energy efficiency are also responsible for bringing about different FFCO$_2$ emission structures in the six chosen cities.

This spatial pattern of FFCO$_2$ emissions can be fragmented. First, new Chinese policies such as ‘the Silk Road Economic Belt’, the ‘21st-Century Maritime Silk Road’, the ‘Yangtze River Economic Belt’ and ‘New Urbanization’ are expected to lead to enhanced development in some sub-regions of Western China.
However, new movement into ‘Internet +’ may help to break this spatial pattern. Take Wuxi as an example. During the study period, FFCO$_2$ emission in Wuxi increased the fastest compared with the other cities. Wuxi’s GDP in EUR increased by a factor of 5.64 times from 2000 to 89.05 billion in 2011 (Rank 7). However, the city also has transformed its industrial base into one related to high-tech, and hopes to become a leader in the shift from fossil fuel to clean energy.

The spatiotemporal variability of the terrestrial biosphere has also been shown to play a significant role in terms of the spatial pattern of observed FFCO$_2$ emissions. This role inside of cities is a critical and non-negligible aspect to determine the balance between direct anthropogenic emissions and indirect ones via land-use changes can significantly change the balance in China’s present spatial pattern of FFCO$_2$ emissions, and offset goals for a low carbon and more sustainable future.

5. Conclusions

We have delineated the overall spatiotemporal pattern of FFCO$_2$ emissions in China from 2000 to 2015. High FFCO$_2$ emissions were mainly concentrated in Eastern China. The emission from the 28 highest emitting cities and the intensity of high vegetation covers kept increasing upwards (value) and diffusing outwards (spatially). The top three cities (Beijing, Shanghai, and Tianjin) and three most changed cities (Wuxi, Dalian, and Shenyang) in terms of FFCO$_2$ were chosen for exploring the local spatiotemporal patterns.

First, city inner districts (except Dalian) have always had high FFCO$_2$ emissions. The outward expansion degree and speed were positive in all cases, but different from city to city. Shanghai underwent the most distinct change, nearly returning to its original spatial pattern after undergoing extensive expansion. The other 5 city-clusters kept expanding throughout the 15 years, with lesser expansion found in Dalian and Shenyang, and dramatic expansion happening in Beijing, Tianjin and Wuxi.

Second, areas with high vegetation and water also reveal positive clusters. Using a multivariate local analysis in combination with 22 LC factors revealed that croplands (other than Dalian), native vegetation (in Dalian), and humidity cover play an important role in the variation in the FFCO$_2$ emissions.

The impact of the 22 LC classes reveals both anthropogenic and natural influences impact the FFCO$_2$ emissions at the same time. Increase in urban areas accelerate FFCO$_2$ emissions, while cropland vegetation covers in some cases mitigate these increases. Other vegetation/moisture covers reveal positive clusters, but only have a minimal to no effect. This indicates that combining vegetation and moisture, is a practical way to regulate and reduce FFCO$_2$ emissions everywhere except Dalian, where protection and/or restoration or native vegetation is a more practical way.

The primary source of FFCO$_2$ emissions is still found to be coal in all six cities, although the fraction of coal has been decreasing. Natural gas in Beijing, and industrial processes in Wuxi and Dalian have played increasingly significant roles. The overall FFCO$_2$ emissions structures in the six cities are quite different, with changes in Wuxi’s industrial policy demonstrating clearly these divergent impacts on FFCO$_2$ emissions.

Our current findings expand on prior work relating to the spatiotemporal patterns, factors and underlying sources of China’s FFCO$_2$ emissions at a high resolution, by combining satellite observations and bottom-up inventory data. These findings provide support for future studies into the role of global vegetation changes in mitigating anthropogenic CO$_2$ emissions. Considering China’s gradual approach to economic transition away from being a resource-dependent economy, a deeper understanding of the changes in the spatial patterns of FFCO$_2$ emissions may upset this planned goal.

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Data availability

The FFCO$_2$ emissions dataset (1 km) from the ODIAC is openly available through the Centre of Global Environment Research at http://db.cger.nies.go.jp/dataset/ODIAC/ with a DOI (10.17595/20170411.001); the 1st CCI LC maps (300 m) can be downloaded from http://maps.elie.ucl.ac.be/CCI/viewer; and the 17 different city-level fossil fuel CO$_2$ emissions can be obtained freely through the CEADs at www.ceads.net.
Competing interests

The authors declare that they have no conflicts of interest.

Appendix

Legend of figure 1(a).

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