A Comparative Analysis of Anthropogenic CO₂ Emissions at City Level Using OCO-2 Observations: A Global Perspective

Peng Fu, Yanhua Xie, Caitlin E. Moore, Soe W. Myint, and Carl J. Bernacchi

1Carl R. Woese Institute for Genomic Biology, University of Illinois at Urbana-Champaign, Urbana, IL, USA; 2Department of Plant Biology, University of Illinois at Urbana-Champaign, Urbana, IL, USA; 3Nelson Institute Center for Sustainability and the Global Environment, University of Wisconsin-Madison, Madison, WI, USA; 4School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA; 5USDA ARS Global Change and Photosynthesis Research Unit, Urbana, IL, USA

Abstract
Satellite observations of anthropogenic carbon dioxide (CO₂) emissions within urban settings offer unique potential to understand carbon sources and sinks and evaluate carbon mitigation strategies. Despite availability of column-averaged dry air mole fraction of CO₂ (XCO₂) from Orbiting Carbon Observatory-2 (OCO-2), temporal variations of XCO₂ and their drivers in cities remain poorly understood due to inconsistent definitions of urban extent, diverse urban forms, and unresolved impacts of urban vegetation on carbon fluxes. To this end, this study revealed that OCO-2 XCO₂ measurements from 2014 to 2018 exhibited statistically significant seasonal and trend components for each city. A correlation analysis suggested a weak association between XCO₂ trends and fossil fuel CO₂ emissions (FFCO₂) trends but a close relationship between yearly average XCO₂ and FFCO₂ trends. Vegetation abundance exhibited a negative relationship with the XCO₂ seasonality, though it only explained 21% of the variance. No statistically significant relationship between urban morphological factors (areal extent, complexity, and compactness) and temporal XCO₂ components was observed. However, urban morphological factors had a close relationship with the total amount of FFCO₂ aggregated over the study period. Thus, it was speculated that urban morphological factors exerted their influence on XCO₂ through fossil fuel consumption. When only cities of high normalized difference vegetation index seasonality were used, statistically significant correlation coefficients between urban morphological factors and winter/summer averaged XCO₂ measurements were found. The variations of these correlation coefficients between leaf-on and leaf-off seasons stress the important role that urban trees play in mitigating carbon emissions in cities.

1. Introduction
Cities are a major source of greenhouse gas (GHG) emissions and account for ~70% of energy-related carbon dioxide (CO₂) emissions worldwide (Duren & Miller, 2012; International Energy Agency, 2008). Social and economic activities in urban areas, because of their large magnitude, lead to carbon flows roughly estimated to be responsible for up to 80% of the total anthropogenic flux of CO₂ in North America (Gurney et al., 2018; Jones & Kammen, 2014). As the urban population is expected to surpass 9 billion by 2050 (United Nations, 2014), many cities are implementing strategies for reducing carbon emissions due to increased pressure to abate climate change impacts and improve air quality for public health. Organizations such as the C40 Cities Climate Leadership Group, Cities Alliance, and the Global Covenant of Mayors for Climate and Energy are positioned to help cities implement policies and share practices for mitigating urban emissions. As a result, accurate quantification of anthropogenic CO₂ emissions is of importance to verify, monitor, and report the efficiency of emission reduction strategies. Recently, the Second State of the Carbon Cycle Report called for a better characterization of urban carbon emissions, which is critical to understanding global anthropogenic carbon flux, drivers of fossil fuel-based consumption, and available policy options to cities in emissions mitigation (Gurney et al., 2018).

Both bottom-up and top-down approaches have been used to estimate carbon emissions in urban areas (Gurney et al., 2009; Gurney et al., 2012; Newman et al., 2016; Sargent et al., 2018; Turnbull et al., 2015). Bottom-up approaches generally involve integration of reported inventories from various sources (e.g.,
transportation, building, and industrial activities), while top-down approaches are associated with atmospheric GHG concentrations measured from surface monitoring stations or dedicated satellite sensors. Since most cities lack independent and comprehensive carbon inventories (Hutyra et al., 2014), carbon emissions estimated using bottom-up approaches may not exhibit reliable trends comparable at both intracity and intercity levels. In contrast, atmospheric carbon concentrations measured from surface stations or satellite sensors, together with inverse modeling (e.g., Hybrid Single-Particle Lagrangian Integrated Trajectory model by Stein et al., 2015), offer an alternative approach to evaluate carbon inventories and detect trends attributable to policy, regulation, or economic changes (Sargent et al., 2018; Stein et al., 2015). For example, Mitchell et al. (2018) showed divergent trends in CO₂ emissions using a decadal record of atmospheric CO₂ from five monitoring stations with strikingly different urban characteristics (urban core, residential, and rural) within the Salt Lake Valley region. Their study highlighted the necessity to build multiple network stations in urban areas to monitor surface GHG concentrations in both spatial and temporal domains. As such, carbon monitoring projects to build observational networks were initiated in many large cities such as Los Angeles (Feng et al., 2016), Salt Lake City (McKain et al., 2012), Paris (Bréon et al., 2015), Portland, Oregon (Rice & Bostrom, 2011), Boston (McKain et al., 2015), Indianapolis (Lauvaux et al., 2016), and Washington, DC/Baltimore (Mueller et al., 2018).

In addition to measurements from surface monitoring networks, spaceborne carbon observations have also been widely used to quantify carbon sources and sinks (Detmers et al., 2015; Lindqvist et al., 2015; Parazoo et al., 2013; Reuter et al., 2013; Schneising et al., 2014). Remote sensing-based atmospheric carbon concentrations may be better than those from surface monitoring stations in detecting emission trends due to its synoptic coverage and insensitivity to atmospheric motions (McKain et al., 2012). The dedicated satellites such as the Greenhouse Gases Observing Satellite (GOSAT; Kuze et al., 2009) and the Orbiting Carbon Observatory-2 (OCO-2; Crisp et al., 2004; Zhang et al., 2016) can provide accurate column-averaged retrievals of the dry air mole fraction of CO₂ (referred to as XCO₂; Buchwitz et al., 2017). Although these satellites were initially designed for understanding carbon fluxes at regional and continental scales, recent efforts have demonstrated their feasibility and effectiveness to examine anthropogenic carbon emissions in cities (Bovensmann et al., 2010; Hakkarainen et al., 2016; Janardanan et al. 2016; Kort et al., 2012). For example, using XCO₂ collected by the GOSAT, Kort et al. (2012) revealed an elevated carbon concentration of 3.2 ± 1.5 ppm in the city of Los Angeles relative to its rural part, which was consistent with the column enhancements (2–8 ppm) calculated using ground-based XCO₂ observations (Wunch et al., 2009). Hakkarainen et al. (2016) showed small isolated emission areas from cities were detectable from detrended and deseasonalized OCO-2 observations and a positive correlation between XCO₂ anomalies and emission inventories. Despite successful analysis of spaceborne carbon data in cities, only a few studies focus on intercity and intracity comparisons of emission trend that can be expected to shed light on the impacts of urbanization processes and patterns (e.g., urbanization intensity and urban form) in different environmental settings on the carbon cycle (Mitchell et al., 2018). As cities release the majority of energy-related carbon dioxide (~70% worldwide), quantification of XCO₂ trend among cities may also help understand the emission trend, facilitating evaluation of the effectiveness of carbon mitigation strategies.

The availability of XCO₂ retrievals from satellite sounders enables large-scale analysis of seasonal variations of carbon dioxide (Kulawik et al., 2016; Lindqvist et al., 2015; Reuter et al., 2013) that are mainly dominated by terrestrial biogenic carbon fluxes (Keppel-Aleks et al., 2012; Palmer et al., 2008). These seasonal variations, however, were not well understood in and among cities due to inconsistent definitions of urban extent, diverse urban forms, and presence of patchy vegetation in cities that induce uncertainty into the understanding of timing, magnitude, and direction of carbon fluxes (Hardiman et al., 2017; Hutyra et al., 2014; Raciti et al., 2012). In fact, most studies associated with urban carbon fluxes have been focused on a single city, making them spatially limited (e.g., eddy covariance flux towers; Bergeron & Strachan, 2011; Coutts et al., 2007; Järvi et al., 2012). This lack of intercomparisons among cities hinders understanding variations in vegetation abundance and urban morphological factors such as urban size and compactness and their impacts on carbon emissions. Therefore, based upon the XCO₂ retrievals from the OCO-2 satellite, this study attempted to provide a better understanding of temporal variations of XCO₂ among selected cities (48 cities in total based on data availability, further details in section 2.2) by addressing the following research questions (with hypothesis listed for each question):
1. How do interannual trends of $X_{CO_2}$ measurements correlate with those estimated from inventory of fossil fuel carbon dioxide emissions (FF$CO_2$)? (A high trend in fossil fuel consumption and its CO$_2$ emissions will lead to a high trend in satellite detected $X_{CO_2}$ measurements.)

2. How does urban vegetation abundance affect the intraannual variations of $X_{CO_2}$ measurements? (More vegetation abundance in a city will lead to higher seasonality of $X_{CO_2}$ measurements.)

3. What are the impacts of urban morphology (i.e., urban size, compactness, and complexity) on $X_{CO_2}$? (A compact city of small size and simplified shape will release fewer CO$_2$ emissions, as measured by $X_{CO_2}$, compared to a disperse city of large size and complex shape.)

By addressing these scientific questions, the objectives of this study are threefold: (1) to explore if and how satellite-based CO$_2$ retrievals can help track fossil fuel consumptions in urban areas over time and thus can help evaluate mitigation strategies deployed in cities; (2) to reveal the impacts of urban vegetation abundance on seasonal variations of $X_{CO_2}$, so that human-induced carbon emissions can be isolated and identified; and (3) to examine whether urban form (compact or dispersed urban form) based mitigation strategies would be helpful to reduce carbon emissions in cities.

2. Data and Methods

2.1. Data

In this study, version 9 OCO-2 $X_{CO_2}$ measurements from September 2014 to September 2018 were downloaded (available at https://disc.gsfc.nasa.gov/datasets?project=OCO) and used (Eldering et al., 2017). The satellite was launched in July 2014 and joined the “afternoon constellation” of satellites (also referred to as A-train, L’Ecuyer & Jiang, 2010) in sun-synchronous orbit with a nominal crossing time of 1:30 PM LT (local time). On board the satellite, three grating spectrometers are available to record 24 high-resolution spectra per second at wavelengths of approximately 0.76, 1.61, and 2.06 μm, respectively (Crisp et al., 2017). Each spectrometer can continuously provide across-track measurements in eight independent footprints (each footprint is less than 3 km$^2$), which have a spatial resolution of 1.3 × 2.25 km$^2$ at nadir view. The OCO-2 satellite is configured to alternate between nadir and glint modes and is occasionally switched to the target mode to collect measurements for ground validation sites (Schwandner et al., 2017). With the collected high-resolution spectra, $X_{CO_2}$ is estimated using the Atmospheric CO$_2$ Observations from Space algorithm with a retrieval accuracy of better than approximately 1 ppm (Crisp et al., 2017; O’Dell et al., 2012). Since these $X_{CO_2}$ measurements have large gaps in spatial coverage at the original configured temporal interval (16 day), monthly mean composites of $X_{CO_2}$ retrievals within each city boundary (delineated using the algorithm outlined in section 2.2) were used for revealing both seasonal and interannual variations (section 2.3).

Vegetation abundance in each city was estimated using version 6 Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua monthly NDVI (normalized difference vegetation index) data (MYD13A3; Didan, 2015). Compared to EVI (enhanced vegetation index), NDVI is better suited for representing vegetation abundance in urban environments (e.g., Weng et al., 2004). The NDVI data were provided in the sinusoidal projection with a spatial resolution of ~1 km. The MYD13A3 product rather than the MOD13A3 (MODIS Terra) product was used since the former has a similar overpassing time as the OCO-2 satellite. Within each city boundary, pixels with a NDVI value larger than 0.05 were used and their values were summed up to form an integrated NDVI variable ($NDVI_{integ}$) to represent the total amount of vegetation in each city. The monthly $NDVI_{integ}$ variations were also subjected to the modeling of the seasonal component as outlined in section 2.3.

The FF$CO_2$ emission data were obtained from the 2018 version ODIAC (Open-source Data Inventory for Anthropogenic CO$_2$) emission estimates and projections (Oda et al., 2018; Oda & Maksyutov, 2011). The ODIAC emission data were initially developed for operational carbon flux inversions. It is a global carbon emission product for fossil fuel combustion and was estimated using point source carbon emissions and satellite images of nighttime light. The data product has a spatial resolution of 1 km and is distributed on a monthly basis. For each city, the total value of FF$_{CO_2}$ aggregated over the study period and the monthly total value of FF$_{CO_2}$ were quantified. Trends in the monthly total FF$_{CO_2}$ for the 48 cities were estimated using the modeling procedures in section 2.3.
2.2. Urban Extent and Morphological Factors

Urban extents for the selected 48 cities (Figure 1a, a list of cities were provided in supporting information Table S1) were delineated from the Global Human Settlement (GHS) BUILT-UP Grid product (Pesaresi et al., 2016). These 48 cities were selected since they have enough time series monthly $X_{CO_2}$ measurements (at least 16 monthly observations over the study period and at least 10 $X_{CO_2}$ measurements in a month for a city) for seasonal and interannual modeling. Additionally, these 48 cities provided a diverse set of city size and urban form that could be expected to provide insights into the understanding of potential drivers and mitigation strategies for urban carbon emissions.

The GHS BUILT-UP Grid is one of the dedicated urban extent products describing temporal and spatial evolutions of urban areas at the global scale. The built-up grid was produced using machine learning algorithms that can automatically process multisource data sets such as Landsat images, census data, and crowdsourcing information (Pesaresi et al., 2016). The built-up data were made public by the European Commission science hub (https://ec.europa.eu/jrc/en) and were available for four epochs: 1975, 1990, 2000, and 2014. In this study, the built-up map in 2014 at 38-m spatial resolution was used as it is the closest to the study period and suitable for city-level analysis. At present, the GHS BUILT-UP Grid is the most accurate urban extent product as evaluated in Europe and the United States with the Kappa coefficient (a statistic to indicate the accuracy level of land cover maps) slightly larger than 0.3 (Pesaresi et al., 2016).

To derive urban extent from the GHS BUILT-UP Grid, the City Clustering Algorithm (CCA; Rozenfeld et al., 2008) was applied to the 48 cities. The CCA has been widely used for environmental applications in cities (e.g., Gudipudi et al., 2016; Peng et al., 2012; Zhou et al., 2013) due to its simplicity and automation nature. The algorithm has only one parameter (cell size) that allows for aggregation of urban clusters consistently.

Figure 1. The geographic location of the selected 48 cities (a), and urban extents extracted from the Global Human Settlement BUILT-UP Grid product (0 for nonurban areas, and 1 for urban areas) using the City Clustering Algorithm (Rozenfeld et al., 2008) for New York City (b), London (c), and Guangzhou-Shenzhen-Dongguan (d).
among different cities. Figures 1c–1d show three examples of urban extent polygons extracted from the GHS BUILT-UP grid product using the CCA. Further technical details of the CCA can be found in Rozenfeld et al. (2008).

Based on urban extent polygons, urban morphological factors including urban size, compactness index (Li & Yeh, 2004), and area weighted mean shape index (McGarigal & Marks, 1995) were calculated for each city (Table 1). The selected indices can represent cities’ areal extent, compactness, and complexity and can be used to help differentiate cities between compact and dispersed forms (Huang et al., 2007). The correlation analysis was performed to observe the relationship between urban morphological variables and yearly averaged $X_{CO_2}$ measurements at city level.

### 2.3. Seasonal and Trend Modeling

The seasonal and trend modeling for monthly $X_{CO_2}$, $FF_{CO_2}$, and NDVI$_{integ}$ observations was achieved using equation (1).

$$y = a + b \cos \left( \frac{2\pi t}{f} \right) + c \sin \left( \frac{2\pi t}{f} \right) + d^* t$$

(1)

In equation (1), $a$ refers to the yearly averaged $X_{CO_2}$, $FF_{CO_2}$, or NDVI$_{integ}$ from 2014 to 2018 (i.e., the annual mean value of $X_{CO_2}$, $FF_{CO_2}$, or NDVI$_{integ}$ over a 4-year period), $b$ and $c$ are the coefficients of the seasonal component, $d$ is the coefficient for the interannual component, $f$ is sampling frequency ($f = 12$ for a year), and $t$ is the sampling interval. The purpose of equation (1) is to decompose time series satellite measurements including $X_{CO_2}$, $FF_{CO_2}$, or NDVI$_{integ}$ into three components: annual mean (coefficient $a$), seasonality (coefficients $b$ and $c$), and trend (coefficient $d$). The decomposition allows for the reduction of discrete, large amounts of satellite measurements to several meaningful parameters that can help examine temporal patterns of $X_{CO_2}$, $FF_{CO_2}$, or NDVI$_{integ}$ and their possible relationships. Statistical indicators including coefficient of determination ($R^2$) and root mean square error (RMSE) were used to evaluate the fitting performance. The amplitude of the seasonal component ($S_{amp}$) was thus computed as $\sqrt{b^2 + c^2}$. For the optimization of equation (1), the robust linear regression using iteratively reweighted least squares was utilized (Welsch, 1977). To ensure that interannual trends in $X_{CO_2}$, $FF_{CO_2}$, and NDVI$_{integ}$ were estimated with statistical significance, the Mann Kendall Trend Test (Gibbons & Chakraborti, 2011) was applied to the original satellite observations. As NDVI did not show an interannual trend component with statistical significance, only its seasonal component over the study period was computed in this study. The Pearson’s correlation coefficient and linear regression were used to understand the temporal variations of $X_{CO_2}$ and other variables (NDVI seasonality and $FF_{CO_2}$ trend).

| Table 1 | Urban Morphological Variables Used in This Study |
|---------|-----------------------------------------------|
| Indicators | Abbreviation | Equation |
| Urban size | US | $\left(\frac{\sum P_i}{P_i}\right)/n^2$ |
| Compactness index | CI | $\left(\frac{0.25p_j}{\sqrt{a_j}}\right)\left(\frac{a_j}{n\sum a_j}\right)$ |
| Area weighted mean shape index | AWMSI | $\left(\frac{n}{\sum a_j}B_{\frac{j}{C_4}}\right)$ |

Note. In the two equations, $i$ is the number of patches within the city boundary ($n = 1$ for this study), $j$ is the number of patch type ($j = 1$ for this study), $Pi$ is the perimeter of patch $i$, $Pi$ is the perimeter of a circle with the same areal extent as patch $i$, and $a_i$ is the areal extent of patch $i$. The seasonal and trend modeling for monthly $X_{CO_2}$, $FF_{CO_2}$, and NDVI$_{integ}$ observations was achieved using equation (1).
3. Results

3.1. Temporal Variations of $X_{CO_2}$, NDVI, and FF$_{CO_2}$ at City Level

Figure 2a shows an example of the modeling of $X_{CO_2}$ with both intraannual and interannual components (i.e., seasonality and trend components) for the city of Guangzhou-Shenzhen-Dongguan. The fitting procedure yielded an $R^2$ of 0.91, an RMSE of 1.3 ppm, an amplitude of seasonality of 2.50 ppm, and a slope value of 0.0083 ppm/day (i.e., ~3.03 ppm/year) from the satellite-based CO$_2$ measurements. The good performance of this fitting procedure was also evidenced by the statistical distribution of $R^2$ and RMSE values (Figure 2b) among the 48 cities selected in this study. It was observed that the $R^2$ value ranged from 0.74 to 0.96 with a mean value of 0.89 and the RMSE value ranged from 0.66 to 1.93 ppm with a mean value of 1.25 ppm.

Figures 2c and 2d present the seasonality amplitude and the trend (c) components estimated for the 48 cities. For example, in the city of Los Angeles, the seasonality and trend values were 2.41 ppm and 6.75 × 10$^{-3}$ ppm/day (i.e., 2.46 ppm/year), which were very similar to the observations as shown in Figure 1 of Kort et al. (2012). In addition, spatial patterns of CO$_2$ seasonality were not correlated well with those of CO$_2$ trend from 2014 to 2018 as indicated by a weak correlation coefficient of 0.22 between them. Large seasonality and
Trend values were mainly found in cities in China, Japan, India, and some European countries such as England. Only the seasonality component was used for modeling of NDVI \textsubscript{integ} since the interannual component was not detected with statistical significance (p value > 0.05 provided by the Mann Kendall Trend Test). This lack of statistical significance can be attributed to the relatively short-term NDVI observations used in this study as suggested by Fu (2019). Figure 3a shows an example of the seasonal modeling for New York City with an $R^2$ of 0.88, an RMSE of 428.09, and a seasonality amplitude of 1672.06. For the selected 48 cities, the seasonality modeling exhibited a relatively wider range of $R^2$ (0.48–0.98 with a mean value of 0.76) compared to that in Figure 2B. The RMSE values, as shown in Figure 3b, ranged from 3.60 to 428.09 with a mean value of 79.63. Overall, the $R^2$ and RMSE values suggested a good performance of seasonal modeling in NDVI \textsubscript{integ}. Figure 3c presents the spatial patterns of NDVI seasonality amplitude for the 48 cities with the value ranging from 3.77 to 1672.06.
For the modeling of FF$\text{CO}_2$, the seasonal component was not observed consistently among the selected 48 cities (only 14 of them exhibited a statistically significant seasonality component). Thus, only the trend component was computed for each city. Figure 4a shows an example of the trend modeling for Mumbai, India using the ODIAC FF$\text{CO}_2$ data (the seasonal cycle of FF$\text{CO}_2$ can also be observed). The modeling procedure exhibited a slope of 0.053 Mg/day with statistical significance ($p$ value < 0.01). Figures 4b and 4c show the statistical distributions and spatial patterns of FF$\text{CO}_2$ trend values for the selected 48 cities, respectively.

Although most (30) of the selected cities exhibited a trend value larger than 0 in FF$\text{CO}_2$, some cities (18) had a negative trend value, particularly in cities of developed countries such as the United States and Japan. This finding may signal the declined fossil CO$_2$ emissions in cities that supported implementation of renewable energy or had a low growth in gross domestic product (Le Quéré et al., 2019). In addition, it was observed that relatively larger trend values were found in areas between 25° and 130° longitude. This region consisted of cities with large population and/or high economic growth such as Beijing (China), Mumbai (India), and Bangkok (Thailand), and of cities with economic growth largely

![Figure 4.](image)

The modeling of the seasonal variations of FF$\text{CO}_2$ was not performed as not all cities exhibited a consistent seasonality component.

| Table 2 | The Pearson’s Correlation Coefficient Between FF$\text{CO}_2$ Trend and X$\text{CO}_2$, Trend and Yearly Average X$\text{CO}_2$ |
|---------|---------------------------------------------------------------|
| Correlation coefficient | FF$\text{CO}_2$ trend | FF$\text{CO}_2$, trend (only positive) |
| $X\text{CO}_2$ trend | 0.22 | 0.38 |
| Yearly averaged $X\text{CO}_2$ | 0.35 | 0.74 |

Note. Correlation coefficient values are statistically significant with p value <0.01.

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varied from measurements used in this study were estimated based on satellite images with a correlation coefficient of 0.21. The correlation coefficient between \( X_{\text{CO}_2} \) trends and the NDVI seasonality was greater than 0.74 between \( X_{\text{CO}_2} \) trends and \( X_{\text{CO}_2} \) trends. In addition, a higher correlation coefficient (0.74) between \( X_{\text{CO}_2} \) trends (only positive values) and yearly averaged \( X_{\text{CO}_2} \) was observed relative to that between \( X_{\text{CO}_2} \) trends (both positive and negative values) and yearly averaged \( X_{\text{CO}_2} \). This suggested that the high dependence on and increasing use of fossil fuel led to the rising of the mean annual \( X_{\text{CO}_2} \). Further regression analysis as shown in Figure 5 suggested that \( X_{\text{CO}_2} \) trends could explain 55% of variance in the modeled yearly averaged \( X_{\text{CO}_2} \) among the 48 cities. Figure 6 shows that the yearly NDVI (log value) has a negative relationship with \( X_{\text{CO}_2} \) seasonality amplitude. Specifically, the regression analysis yielded a \( R^2 \) of 0.21. The correlation coefficient between the \( X_{\text{CO}_2} \) seasonality and the NDVI seasonality was −0.15. These findings revealed that \( X_{\text{CO}_2} \) seasonality was related to vegetation abundance (yearly NDVI can indicate the average vegetation abundance over the study period) in cities.

Although no significant correlation coefficients were found between urban morphological factors and \( X_{\text{CO}_2} \) (both seasonality and trend components), statistically significant correlation coefficient values between urban morphological factors and the total \( X_{\text{CO}_2} \) (Table 3) were identified. Specifically, urban size and area weighted mean shape index (AWMSI) had a positive relationship with \( X_{\text{CO}_2} \) with a correlation coefficient of 0.67 and 0.57, respectively, and compactness index (CI) exhibited a negative relationship with \( X_{\text{CO}_2} \) with a correlation coefficient of −0.52. This finding suggested that urban morphological factors including urban size, compactness, and complexity, potentially exerted influences on \( X_{\text{CO}_2} \) variations through the total \( X_{\text{CO}_2} \). Note that \( X_{\text{CO}_2} \) measurements used in this study were estimated based on satellite images of nighttime light, a good indicator for urban extent (e.g., Xie & Weng, 2016), which may reinforce the positive relationship between urban size and the total \( X_{\text{CO}_2} \) observed here. For cities with the NDVI\text{Integ} seasonality magnitude larger than 477.19 (as shown in Figure 3c, corresponding to a mean NDVI greenness value of 0.45), that is, Tokyo, Shanghai, Beijing, New York, Chicago, Johannesburg, Philadelphia, Atlanta, and Washington, DC (these cities have deciduous trees or vegetation showing strong seasonality), statistically significant correlation coefficients between urban morphological factors and summer/winter averaged \( X_{\text{CO}_2} \) measurements (calculated based on modeled monthly time series \( X_{\text{CO}_2} \) measurements) were observed. This statistical relationship was not statistically significant for cities with the NDVI\text{Integ} seasonality magnitude less than 477.19 (corresponding to a mean NDVI greenness value of 0.45). More specifically, for the selected cities with NDVI\text{Integ} seasonality magnitude larger than 477.19, averaged \( X_{\text{CO}_2} \) measurements showed a positive correlation coefficient of 0.26 with urban size, of 0.41 with AWMSI, and a negative correlation coefficient of −0.45 with CI in the leaf-off season (winter). In the leaf-on season (summer), averaged \( X_{\text{CO}_2} \) measurements exhibited a decreased positive coefficient of 0.11 with urban size, of 0.22 with AWMSI, and a negative correlation coefficient of −0.40 with

### 3.2. Impact Analysis on \( X_{\text{CO}_2} \) Variations

Table 2 shows the Pearson correlation coefficients between trends estimated from \( X_{\text{CO}_2} \) and those estimated from \( X_{\text{CO}_2} \). When both positive and negative \( X_{\text{CO}_2} \) values were considered, the correlation coefficient between \( X_{\text{CO}_2} \) trends and \( X_{\text{CO}_2} \) trends was 0.22, less than the correlation coefficient of 0.38 between positive \( X_{\text{CO}_2} \) trends and the corresponding \( X_{\text{CO}_2} \) trends. In addition, a higher correlation coefficient (0.74) between \( X_{\text{CO}_2} \) trends (only positive values) and yearly averaged \( X_{\text{CO}_2} \) was observed relative to that between \( X_{\text{CO}_2} \) trends (both positive and negative values) and yearly averaged \( X_{\text{CO}_2} \). This suggested that the high dependence on and increasing use of fossil fuel led to the rising of the mean annual \( X_{\text{CO}_2} \). Further regression analysis as shown in Figure 5 suggested that \( X_{\text{CO}_2} \) trends could explain 55% of variance in the modeled yearly averaged \( X_{\text{CO}_2} \) among the 48 cities. Figure 6 shows that the yearly NDVI (log value) has a negative relationship with \( X_{\text{CO}_2} \) seasonality amplitude. Specifically, the regression analysis yielded a \( R^2 \) of 0.21. The correlation coefficient between the \( X_{\text{CO}_2} \) seasonality and the NDVI seasonality was −0.15. These findings revealed that \( X_{\text{CO}_2} \) seasonality was related to vegetation abundance (yearly NDVI can indicate the average vegetation abundance over the study period) in cities.

Although no significant correlation coefficients were found between urban morphological factors and \( X_{\text{CO}_2} \) (both seasonality and trend components), statistically significant correlation coefficient values between urban morphological factors and the total \( X_{\text{CO}_2} \) (Table 3) were identified. Specifically, urban size and area weighted mean shape index (AWMSI) had a positive relationship with \( X_{\text{CO}_2} \) with a correlation coefficient of 0.67 and 0.57, respectively, and compactness index (CI) exhibited a negative relationship with \( X_{\text{CO}_2} \) with a correlation coefficient of −0.52. This finding suggested that urban morphological factors including urban size, compactness, and complexity, potentially exerted influences on \( X_{\text{CO}_2} \) variations through the total \( X_{\text{CO}_2} \). Note that \( X_{\text{CO}_2} \) measurements used in this study were estimated based on satellite images of nighttime light, a good indicator for urban extent (e.g., Xie & Weng, 2016), which may reinforce the positive relationship between urban size and the total \( X_{\text{CO}_2} \) observed here. For cities with the NDVI\text{Integ} seasonality magnitude larger than 477.19 (as shown in Figure 3c, corresponding to a mean NDVI greenness value of 0.45), that is, Tokyo, Shanghai, Beijing, New York, Chicago, Johannesburg, Philadelphia, Atlanta, and Washington, DC (these cities have deciduous trees or vegetation showing strong seasonality), statistically significant correlation coefficients between urban morphological factors and summer/winter averaged \( X_{\text{CO}_2} \) measurements (calculated based on modeled monthly time series \( X_{\text{CO}_2} \) measurements) were observed. This statistical relationship was not statistically significant for cities with the NDVI\text{Integ} seasonality magnitude less than 477.19 (corresponding to a mean NDVI greenness value of 0.45). More specifically, for the selected cities with NDVI\text{Integ} seasonality magnitude larger than 477.19, averaged \( X_{\text{CO}_2} \) measurements showed a positive correlation coefficient of 0.26 with urban size, of 0.41 with AWMSI, and a negative correlation coefficient of −0.45 with CI in the leaf-off season (winter). In the leaf-on season (summer), averaged \( X_{\text{CO}_2} \) measurements exhibited a decreased positive coefficient of 0.11 with urban size, of 0.22 with AWMSI, and a negative correlation coefficient of −0.40 with
CI. The differences in correlation coefficients for cities of high-NDVI seasonality between leaf-on and leaf-off seasons suggested that urban vegetation in these cities played an important role in regulating carbon emissions.

4. Discussion and Conclusions

This study focused on analysis of temporal CO₂ variations and their associations with vegetation abundance, fossil fuel consumption, and urban morphological factors at city level based on OCO-2 derived \( X_{\text{CO}_2} \) measurements. The CCA algorithm, due to its automated nature, enabled consistent delineation of urban extent from the existing land cover map product (i.e., the GHS BUILT-UP Grid) that provided a solid basis for the interannual and intraannual modeling of NDVI, \( X_{\text{CO}_2} \), and FF\(_{\text{CO}_2}\).

The results suggested that significant seasonality and trend variations could be detected from OCO-2 \( X_{\text{CO}_2} \) observations with an \( R^2 \) varying from 0.74 to 0.96 for the selected 48 cities (supporting information Table S1). The seasonal and trend modeling of \( X_{\text{CO}_2} \) measurements for each city considered possible variability of seasonality and trend particularly with the latitude, which may lead to better calculation of the \( X_{\text{CO}_2} \) anomalies for estimating anthropogenic carbon emissions (Hakkarainen et al., 2016). Based on the emission inventories, the selected cities exhibited both positive and negative FF\(_{\text{CO}_2}\) trends that may signal the efforts and strategies of each individual city to replace traditional fossil fuel consumption with clean energy (Le Quéré et al., 2019). However, such an understanding requires further confirmation with local authorities of each city to verify what efforts have been implemented for reducing fossil fuel consumption. The decomposition of \( X_{\text{CO}_2} \) measurements into the trend component also enabled tracking of fossil fuel consumptions over time (\( R^2 = 0.55 \) in Figure 5). Since the combustion of fossil fuels generally accounts for a major source of carbon emissions in urban areas (Marcotullio et al., 2018), temporal modeling of \( X_{\text{CO}_2} \) and FF\(_{\text{CO}_2}\) measurements would provide a rough but quick verification of carbon mitigation strategies in cities.

Overall, this study addressed three scientific questions. First, do interannual trends of \( X_{\text{CO}_2} \) measurements correlate with FF\(_{\text{CO}_2}\)? A statistically significant positive relationship between interannual trends of \( X_{\text{CO}_2} \) measurements and those estimated from FF\(_{\text{CO}_2}\) was observed. The correlation coefficient of 0.38 (between positive FF\(_{\text{CO}_2}\) trends and the corresponding \( X_{\text{CO}_2} \) trends) did not suggest a major influence of FF\(_{\text{CO}_2}\) trends on \( X_{\text{CO}_2} \) trends, but the regression analysis further suggested a major influence of FF\(_{\text{CO}_2}\), trends on the yearly average \( X_{\text{CO}_2} \). More specifically, the increasing use of FF\(_{\text{CO}_2}\) was much more easily to be observed using the annual average rather than the trend of \( X_{\text{CO}_2} \). Factors such as gross domestic product and population growth may also affect CO₂ emissions and concentrations and should be included in future studies to refine the conclusions. Second, how does urban vegetation abundance affect the intraannual variations of \( X_{\text{CO}_2} \) measurements? The vegetation abundance analysis showed a negative relationship between the yearly average NDVI and \( X_{\text{CO}_2} \) seasonality, demonstrating the potential role of vegetation, even in an urban environment, on partially mitigating CO₂ emissions. And third, what are the impacts of urban morphology (i.e., urban size, compactness, and complexity) on \( X_{\text{CO}_2} \)? No statistical relationship was observed between \( X_{\text{CO}_2} \) variations and urban morphological factors including urban size, compactness, and complexity. However, results did show a strong association between urban morphological factors and the total amount of FF\(_{\text{CO}_2}\) variations integrated over the four years. In addition, for cities of high NDVI\(_{\text{integ}}\) seasonality (larger than 477.19), correlation coefficient values (positive values) between urban size and AWMSI and \( X_{\text{CO}_2} \).
measurements were higher in winter than those in summer; correlation coefficient values (negative values) between CI and \(X_{CO_2}\) measurements were higher in summer than in winter. The difference in correlation coefficients between urban morphological factors and \(X_{CO_2}\) measurements between leaf-on and leaf-off seasons may be partially explained by the urban trees that are fully photosynthetic in summer to assimilate CO\(_2\). In many high-latitude cities during winter (the leaf-off season), urban trees (or vegetation with strong seasonality) are dormant and do not take up atmospheric CO\(_2\) via photosynthesis. Our results showed that winter averaged \(X_{CO_2}\) measurements had a positive correlation coefficient of 0.26 with urban size, of 0.41 with AWMSI, and a negative correlation coefficient of 0.45 with CI winter. In summer (the leaf-on season), averaged \(X_{CO_2}\) measurements were significantly reduced, which can be attributed to photosynthetic uptake of CO\(_2\) by urban vegetation, weakening the correlation between urban morphological factors and \(X_{CO_2}\) measurements as observed in winter. These findings highlight the role of urban vegetation in regulating CO\(_2\), implying a necessity to account for vegetation impacts on carbon cycles in urban areas that have been neglected or treated as constant (Hardiman et al., 2017; Sargent et al., 2018).

The positive relationship between FF\(_{CO_2}\) and urban size and complexity as well as the negative relationship between FF\(_{CO_2}\) and urban compactness highlighted that a small, compact city form would help reduce fossil fuel consumption in urban areas. CO\(_2\) emission related to transportation and building cooling (or heating) can be significantly reduced in a compact city with a smaller population size than those in disperse cities with a larger population size. For example, Gudipudi et al. (2016) also found that a compact city form by doubling the population density would lead to at least 42% reduction in the total CO\(_2\) emissions in buildings and on-road sectors. Given the positive relationship between FF\(_{CO_2}\) trends and \(X_{CO_2}\) trends, it was believed in this study that urban morphological factors may exert influences on \(X_{CO_2}\) variations through affecting FF\(_{CO_2}\) consumed in urban areas. Thus, our study stressed the importance for developments of adequate local policy measures to limit urban sprawl while considering prosperity of economic growth within urban areas.

Finally, it would be beneficial to refine this study by taking meteorological information at city scale such as wind into consideration for modeling \(X_{CO_2}\) over time in isolated emission areas (such as large cities; Fioletov et al., 2015). In this study, as the OCO-2 satellite may not provide complete \(X_{CO_2}\) measurements over each city, uncertainty exists in using partly covered \(X_{CO_2}\) measurements to represent those for the whole city. This uncertainty may be addressed and quantified by acquiring \(X_{CO_2}\) measurements from the OCO-3 satellite mission (Eldering et al., 2019) with a much higher density of sampling footprints and by using its Snapshot Area Mapping mode, which will enable OCO-3 to focus on CO\(_2\) hot spots, such as emissions from cities and power plants.

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