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A decade of CO₂ flux measured by the eddy covariance method including the COVID-19 pandemic period in an urban center in Sakai, Japan

Masahito Ueyama *, Tsugumi Takano

Graduate School of Life and Environmental Sciences, Osaka Prefecture University, 1-1 Gakuen-cho, Naka-ku, Sakai, Osaka, 599-8531, Japan

A R T I C L E   I N F O

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A B S T R A C T

Cities constitute an important source of greenhouse gases, but few results originating from long-term, direct CO₂ emission monitoring efforts have been reported. In this study, CO₂ emissions were quasi-continuously measured in an urban center in Sakai, Osaka, Japan by the eddy covariance method from 2010 to 2021. Long-term CO₂ emissions reached 22.2 ± 2.0 kg CO₂ m⁻² yr⁻¹ from 2010 to 2019 (± denotes the standard deviation) in the western sector from the tower representing the densely built-up area. Throughout the decade, the annual CO₂ emissions remained stable. According to an emission inventory, traffic emissions represented the major source of CO₂ emissions within the flux footprint. The interannual variations in the annual CO₂ flux were positively correlated with the mean annual traffic counts at two highway entrances and exits. The CO₂ emissions decreased suddenly, by 32% ± 3.1%, in April and May 2020 during the period in which the first state of emergency associated with COVID-19 was declared. The annual CO₂ emissions also decreased by 25% ± 3.1% in 2020.

Direct long-term observations of CO₂ emissions comprise a useful tool to monitor future emission reductions and sudden disruptions in emissions, such as those beginning in 2020 during the COVID-19 pandemic.

1. Introduction

Urban areas account for 30–50% of total anthropogenic carbon dioxide (CO₂) emissions (Mills, 2007; Satterthwaite, 2008). To minimize anthropogenic climate change, efforts reducing greenhouse gases (GHGs) emissions have been made under the United Nations Framework Convention on Climate Change. Under the Paris Agreement, countries are required to accurately and transparently assess necessary reductions. To evaluate emission reductions, the accurate measurements of CO₂ emissions are important, because emission inventories contain uncertainties and direct measurements provide an opportunity improving them (Janardanan et al., 2016).

Long-term CO₂ emissions in cities vary owing to changes in economic activities, technology, urban development and emission reduction policies. Although global GHGs emissions are continuously increasing, emissions in developed countries, such as the United States and European countries, are decreasing on a decadal scale (Friedlingstein et al., 2020). In Japan, national emissions increased from 2009, during the global financial crisis, to 2013 and decreased thereafter (National Institute for Environmental Studies, 2020). Point source emissions (e.g., power plants and incinerators) can be effectively considered in emission inventories because of the readily available statistics pertaining to these sources (Oda and Maksyutov, 2011). It is often difficult to detect temporal changes in emissions based on inventories of other sources, including those encompassing industrial, residential, commercial, and transportation sources, because a variety of sources exists within a given city (Oda et al., 2019).

Direct CO₂ emissions in urban areas have been continuously monitored by the eddy covariance method to evaluate important drivers of CO₂ emissions and quantify annual emissions. This method has been widely employed to continuously monitor terrestrial carbon fluxes at more than 900 locations (Pastorello et al., 2020), and is now applied in various urban areas (Oke et al., 2017; Nordbo et al., 2012; Velasco and Roth, 2010). Temporal variations in CO₂ emissions are mainly driven by space heating and automobile traffic (Liu et al., 2012; Pawlak et al., 2011; Ward et al., 2015) but are also influenced by human and soil respiration processes (Moriwaki and Kanda, 2004; Velasco and Roth, 2010). Inter- and intracity variations in emissions are associated with the greenspace fraction within a given area (Nordbo et al., 2012; Ueyama and Ando, 2016). Due to the heterogeneous nature of cities,

* This paper has been recommended for acceptance by Admir Crso Targino.
* Corresponding author. Graduate School of Life and Environmental Sciences, Osaka Prefecture University, Sakai, Japan.
E-mail address: ueyama@envi.osakafu-u.ac.jp (M. Ueyama).
measured CO₂ emissions also depend on wind conditions, which reflect different land uses (Bergeron and Strachan, 2011; Liu et al., 2012, 2020a; Ueyama and Ando, 2016). Liu et al. (2012) reported that higher CO₂ emissions were observed under winds stemming from heavy traffic areas than those under winds stemming from other directions. Measured fluxes have also been considered to validate emission inventories in European cities (Helfter et al., 2016). Since the locations of urban flux measurements are scarce and only short-term data (e.g., shorter than a few years) have been reported, long-term CO₂ emissions in cities have rarely been reported (Liu et al., 2020a).

Since early 2020, economic activity has been restricted due to the COVID-19 pandemic, and CO₂ emissions in cities have been estimated to decrease during this period. Le Queré et al. (2020) estimated an 11%–25% reduction in the global CO₂ emissions based on 69 countries, which represented 97% of global CO₂ emissions, in early April below pandemic conditions depending on the policies of these countries. Based on an emission inventory in the first half of 2020, Liu et al. (2020b) estimated an 8.8% reduction in global CO₂ emissions based on emission reductions attributed to power plants, ground transportation, and industry in the United States, European countries, India and China. A few reports based on measurements indicated that COVID-19 lockdown measures reduced CO₂ emissions originating from nonpoint sources in European cities (Papale et al., 2020; Lamprecht et al., 2021; Matthews and Schume, 2022).

In this study, we report a decade of CO₂ flux data measured by the eddy covariance method in an urban center, Sakai, Osaka, Japan, from 2010 to 2021. We hypothesize that CO₂ emissions in the city center decreased during the last decade, possibly due to technological advances and long-term economic reduction in Japan. Long-term measurements allowed hypothesis testing and evaluation of the decadal variation in CO₂ emissions in the urban area. To evaluate how accurately the local government estimated CO₂ emissions, measured fluxes were compared to an emission inventory of the local government. Finally, we report the emission reduction attributed to the states of emergency declared in 2020 and 2021 due to the COVID-19 pandemic.

2. Materials and methods

2.1. Observations and data preparation

Measurements were conducted in a densely built-up urban center, Sakai, Osaka, Japan. Sakai is the second largest city in the Osaka Prefecture. The population density in the city center (i.e., Sakai ward) slightly increased from 6213 km⁻² in 2009–6280 km⁻² in 2020. The land cover contributing 80% to the flux footprint during the daytime (Fig. 1, S1, and S2; Table S1) consists of 61% buildings, 26% roads, and 9% vegetation across all wind sectors (Takano and Ueyama, 2021). The climate of the city is temperate. Further details are available in the Supporting Material (SM1).

We measured the CO₂ flux at a 17-m ladder tower atop a 96-m city office building starting in November 2009. The eddy covariance method was applied 111.7 m above the ground involving a sonic anemometer (SAT550, Sonic, Japan) and an open-path gas analyzer (LI-7500, Li-Cor, USA) until October 2018 and a sonic anemometer (CSAT3, Campbell Scientific Inc., USA) and open-path gas analyzer (EC150, Campbell Scientific Inc., USA) after October 2018. The air temperature, relative humidity, and solar radiation were also simultaneously measured at 111 m above the ground. Hourly traffic counts at two nearby highway entrances and exits were provided by the Hanshin Expressway Company.

Relevant corrections and quality control were applied to the
measured fluxes. Details on the observations, data processing, and flux footprint are provided in the Supporting Material (SM2; Fig. S3) and our previous studies (Ando and Ueyama, 2017; Takano and Ueyama, 2021; Ueyama and Ando, 2016, 2020; Ueyama et al., 2021). The potential magnitude of the storage term is also explained in the Supporting Material (SM3; Figs. S4 and S5).

We considered the CO$_2$ fluxes measured in the western sector from the tower (wind direction: 155°–335°; Figs. 1 and S1), which represents the densely built-up urban center. A previous study (Ueyama and Ando, 2016) reported that the eastern sector only produced CO$_2$ emissions accounting for 60% of those produced in the western sector (Fig. S6) because the eastern sector consists of residential areas. Consequently, we could not treat the CO$_2$ fluxes of these two sectors as homogeneous fluxes.

The data gaps associated with a low quality or east-wind conditions were filled using machine-learning (ML) and mean diurnal variation (MDV; Falge et al., 2001) methods. We applied the ensemble mean of three ML methods: random forest, extra tree, and gradient boosting regression methods. These ML methods were applied with a three-year moving window. The determination coefficient ($R^2$) was 0.19 for each regression model. The MDV method was applied with a one-month moving window. MDV-based gap-filling was conducted 100 times based on the bootstrapping technique. Unless otherwise stated, the CO$_2$ fluxes in this study are based on gap-filled data obtained with the ML method, because $R^2$ for the MDV method (0.08) was lower than that for the ML method. Owing to a severe malfunction in 2018, the data in 2018 contained long gaps. Thus, we did not calculate the annual flux in 2018. Further details are available in the Supporting Material (SM4; Fig. S7).

2.2. Human activities during the pandemic period

Since a full description is provided in the Supporting Material (SM5), we briefly explain the conditions during the COVID-19 pandemic period in Japan. In Japan, human activities were gradually influenced starting in February 2020. The first state of emergency was declared from April 7 to May 25, 2020. There were three waves of COVID-19-related effects in Japan before the end of the study period (March 31, 2021). The second state of emergency was declared from January 14 to February 28, 2021. During these two states of emergency, the Japanese government requested that citizens remained at home, that businesses limited their activities, and that business enterprises implemented remote work. These measures were voluntary, in contrast to the strict lockdown measures enforced in other countries. In this study, we defined the pandemic period as starting in March 2020 based on the above-mentioned conditions in Japan. To better understand the human activities associated with the pandemic, we obtained mobility trends for the Osaka Prefecture from Apple, which represent relative trends compared to the activity on January 13, 2020 (Apple Inc., 2021).

2.3. Emission inventory

We downscaled the CO$_2$ emission inventory developed by Sakai city from the entire city scale to the flux source area in regard to the western sector. The purpose of employing the inventory was 1) to compare the measurements and inventory currently developed by the local government and 2) to perform source partitioning based on various CO$_2$ sources rather than developing a comprehensive site-specific inventory. In the inventory, CO$_2$ emissions across the entire city were estimated at the annual time scale in terms of industry, residence, consumers, waste disposal, and transportation. The emission inventory is currently available until 2017. Full descriptions of the inventory and downscaling method are available in the Supporting Material (SM6).

The city-scale CO$_2$ emissions reported in the inventory were downscaled into those at the scale of the daytime source area based on back-calculation with the bottom-up method considering local government data. For comparison, we chose the daytime source area of the western sector (Figs. 1 and S2) rather than the nighttime source area (Fig. S1) because the nighttime fluxes were lower and less varied by the wind sector than were the daytime fluxes (Fig. S6). We eliminated CO$_2$ emissions originating from sources not located within the source area.

CO$_2$ emissions originating from human respiration were estimated based on the population density (Moriwaki and Kanda, 2004), although this term was not included in the inventory developed by the local government.

3. Results

3.1. CO$_2$ emission trend

The measured annual CO$_2$ emissions remained stable throughout the decade from 2010 to 2019, although statistically insignificant decreasing trends were detected (Fig. 2; Table 1). By decomposing the annual fluxes into seasonal mean fluxes, a significant decreasing trend of the measured CO$_2$ fluxes was estimated in only the spring season, while an increasing trend was estimated in the winter season (Fig. S8a). Based on the measurements, the long-term CO$_2$ emissions reached 22.2 ± 2.0 kg CO$_2$ m$^{-2}$ yr$^{-1}$ from 2010 to 2019 (± denotes the standard deviation) according to the gap-filled data obtained with the ML method and 18.5 kg CO$_2$ m$^{-2}$ yr$^{-1}$ according to the gap-filled data obtained with the MDV method (Table 1).

Based on the emission inventory downscaled to the flux source area, CO$_2$ emissions originating from traffic were estimated to account for
approximately 60% of the total CO₂ emissions (Fig. 2b and c; Table 1). The remaining CO₂ emissions were estimated to originate from the industrial sector (0–7%), commercial and waste sector (9–13%), residential sector (12–13%), and human respiration (7%), whose relative contributions slightly differed among the defined source areas (Fig. 2b and c). Since the emissions originating from electricity were excluded from the downscaled inventory, the CO₂ emissions stemming from the industrial, residential, commercial and waste sectors were attributed to gas/oil consumption. Regarding the areas contributing 80% and 50% to the flux footprint, the annual CO₂ emissions in the inventory were 40% higher than the CO₂ emissions in the study area (Fig. 2b and c).}

The interannual variations in the measured annual CO₂ flux were positively correlated with the mean annual traffic count at the nearby highway entrances and exits (Fig. 3; $R^2 = 0.89, p < 0.01$ for the ML method; $R^2 = 0.56, p = 0.01$ for the MDV method) during the study period including 2020. Although the correlation for the ML method might artificially increase owing to the gap-filling, a significant correlation was determined for the MDV method. The high correlation with the traffic count was consistent with the inventory-based estimates indicating that emissions originating from traffic strongly contributed to CO₂ emissions in the study area (Fig. 2b and c).

The inventory provided details on traffic emissions (Fig. 4). Among the various vehicle types, passenger cars and ordinary trucks accounted for more than 60% of the total emissions in the study region (Fig. 4a). Hence, we obtained detailed statistics regarding gasoline consumption (Fig. 4b, d, f, h, j) and diesel consumption (Fig. 4c, e, g, i, k). Despite a reduced emission factor due to a higher gasoline mileage (Fig. 4d and e),
the trip distance per vehicle increased from 2010 to 2018 (Fig. 4f and g), where a sudden jump in the trip distance was caused by the road traffic census conducted only every few years. Owing to an overwhelming increase in the trip distance (Fig. 4f, g) and a decreased emission factor (Fig. 4d and e), the inventory-based traffic CO$_2$ emissions were estimated to only slightly increase during the study period (Fig. 4h and i). The other statistics on oil sales indicated that gasoline consumption decreased (Fig. 4j) but that vehicle diesel consumption increased since 2013 (Fig. 4k). Since the decrease in CO$_2$ emissions attributed to the above reduction in gasoline consumption was greater than the increase in emissions attributed to an increase in diesel consumption, the total CO$_2$ emissions in the Osaka Prefecture decreased (Fig. 4j and k). This result is inconsistent with the results in shown in Fig. 4h and i. It should be noted that the traffic emissions depicted in Fig. 2 represent the sum of the other traffic emissions in addition to those of passenger cars and ordinary trucks, as shown in Fig. 4.

3.2. Seasonal variations in the CO$_2$ flux

The seasonal variations in the CO$_2$ flux exhibited peaks in both summer and winter (Fig. 5a). The monthly mean CO$_2$ emissions increased with increasing the air temperature from 20 to 30 °C and with decreasing air temperature from 20 to 0 °C (Fig. 6; Fig. S11). Since traffic conditions did not change substantially throughout the seasons (Fig. 5c), the measured seasonality was caused by emissions originating from space heating and cooling applications. The seasonality in the
consumption of city gas and coal oil for commercial uses indicated two similar peaks in the area, although LPG exhibited only a winter peak (Fig. S9). Consequently, the mean seasonality in the monthly CO\textsubscript{2} fluxes from 7 a.m. to 6 p.m. during the COVID-19 pandemic (b). Seasonal variations in the traffic counts at the nearby highway entrances/exits (c). Weekly moving mean of the mobility trend, as reported by Apple for the Osaka Prefecture in 2020 and 2021 (d). The pink vertical shadows indicate the states of emergency announced by the government. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

### 3.3. COVID-19 impact on the CO\textsubscript{2} flux

During the COVID-19 pandemic in 2020, the annual CO\textsubscript{2} emissions decreased by 5.5 ± 0.8 kg CO\textsubscript{2} m\textsuperscript{-2} yr\textsuperscript{-1} or 25% ± 3.1% below the mean level between 2014 and 2019 (Fig. 3). The plus/minus symbol denotes the standard deviation associated with data gap-filled with the different ML methods. CO\textsubscript{2} emissions started to decrease in March 2020 owing to the decreased human activity associated with the pandemic (Fig. 5c and d). The measured CO\textsubscript{2} emissions suddenly decreased by 32% ± 3.1% in April and May 2020 below those in normal years (2014–2019, except 2018). During this period, the first state of emergency was declared. Since the number of newly confirmed cases increased starting in March, human activities decreased before the state of emergency owing to an increase in the number of newly confirmed cases. Traffic counts also decreased starting in March, by 29% from April to May 2020 and by 13% from June to September 2020. The reduction in CO\textsubscript{2} fluxes subsequently diminished after that, but emissions remained 16% lower than those in normal years until the second state of emergency. Since the number of newly confirmed cases increased starting in late December, human activities decreased. Then, the second state of emergency was declared (Fig. 5d). However, the second state of emergency did not further decrease CO\textsubscript{2} emissions (Fig. 5a). The CO\textsubscript{2} emissions measured during the pandemic period were lower than those expected based on the mean air temperature (Figs. 6 and S11). The slope between the CO\textsubscript{2} flux and air temperature did not differ between the pandemic period and normal years during the winter season, although the correlation was higher than that during the pre-pandemic period. This result suggests that temperature-driven CO\textsubscript{2} emissions did not change during the pandemic period.

The diurnal patterns of the measured CO\textsubscript{2} emissions demonstrated decreased daytime CO\textsubscript{2} emissions during the pandemic period (Fig. 7). The daytime reduction was greater from March to May 2020 (30%) than that from June to August 2020 (21%), from September to November 2020 (12%) or from December 2020 to February 2022 (18%) (Fig. 7). The emission reduction at night was not obvious during the pandemic period. The daytime reduction was greater from March to May 2020 (30%) than that from June to August 2020 (21%), from September to November 2020 (12%) or from December 2020 to February 2022 (18%) (Fig. 7). The emission reduction at night was not obvious during the pandemic period. The daytime traffic counts at the highway entrances and exits also decreased by 17% from March to May, by 12% from June to August, by 13% from September to November, and 11% from December to February during the pandemic period (Fig. 7e–h).

### 4. Discussion

#### 4.1. Variations in the measured CO\textsubscript{2} emissions

Throughout the decade from 2010 to 2019, the annual CO\textsubscript{2} emissions remained stable (Fig. 2). The absence of a significant long-term trend could be explained by the different trends in different seasons (Fig. S8).
The CO₂ emissions in summer and winter were mostly associated with the air temperature (Fig. 6). The interannual variations in the air temperature could influence the need for air conditioning, which could mask long-term trends and hamper statistical testing. The air temperature could influence the need for air conditioning, which could decrease in CO₂ (National Institute for Environmental Studies, 2020), and those in the air temperature (Fig. 2). The increased trip distance indicated that the people in the Osaka Prefecture began to use their cars for longer distances. The traffic counts considered were determined at only two entrances/exits of the nearby highway and thus likely underrepresented the traffic dynamics within the source area. This could in part explain the different diurnal patterns between the CO₂ flux and traffic counts (Fig. 7), although other factors, such as the storage term (Figs. S4 and 5), could also explain the observed discrepancy. The recently available big data based on mobile GPS data could be useful to estimate traffic dynamics at large spatio-temporal scales (Yamagata et al., 2018, 2019). These data could help interpret the measured CO₂ fluxes and reduce uncertainties associated with the gap-filling.

The estimated contributions (60%; Table 1) of traffic emissions were similar to those reported in other urban flux studies. Stagakis et al. (2019) summarized the contributions of CO₂ sources to measured fluxes in nine different urban areas, and found that the traffic contribution to CO₂ fluxes ranged from 31% in Florence to 80% in Mexico City. The magnitudes of the traffic emissions (16–17 kg CO₂ m⁻² yr⁻¹; Table 1) were similar to those estimated in urban areas in Edinburgh, Beijing, and Basel where heavy-traffic roads were located within the flux source area (Stagakis et al., 2019). The contributions of building emissions (i.e., sum of residential and commercial sectors emissions in this study; 8 kg CO₂ m⁻² yr⁻¹; Table 1) were similar to those estimated in cities in temperate climates (Vancouver, Basel, and Tokyo).

The seasonal variation in CO₂ emissions was mostly explained by gas/oil consumption associated with changes in air temperature because the obtained traffic counts did not exhibit seasonal variations (Figs. 5 and 6). Heating in the nonresidential sector was achieved with petroleum (58%) and natural gas (28%) in Japan, whereas cooling was covered 4% by petroleum and 51% by natural gas (Institute of Energy Economics, Japan, 2017). The temperature influenced gas/oil consumption for heating and cooling purposes, which was estimated to contribute up to 30% to the total emissions (Fig. 2b and c). Gas/oil consumption occupied a smaller proportion of the total emissions than that of traffic. As a result, a low seasonality in the CO₂ flux was observed (Fig. 5a), and the coefficient of variance of the total CO₂ emissions was minimal (Fig. S8a). The obtained insignificant trend was also caused by the fact that the slight trend could not be suitably captured owing to uncertainties in the measurements. The determined insignificant decadal trend (~0.08 kg CO₂ m⁻² yr⁻²; p = 0.76 for the ML method; ~0.21 kg CO₂ m⁻² yr⁻²; p = 0.22 for the MDV method) was consistent with the trend estimated for the inventory (~0.29 kg CO₂ m⁻² yr⁻²; p = 0.15; Table 1). The trends were less notable than the results for Beijing, China (Liu et al., 2020a), which indicated that the annual CO₂ emissions decreased from 38 kg CO₂ m⁻² yr⁻¹ to 34 kg CO₂ m⁻² yr⁻¹, over nine years (~0.44 kg CO₂ m⁻² yr⁻²).

The insignificant trend of CO₂ emissions contradicted the trend of national CO₂ emissions in Japan, which decreased after a peak in 2013 (National Institute for Environmental Studies, 2020), and those in the entire city of Sakai, which also decreased after a peak in 2014. The decreases in CO₂ emissions reported in inventories were mostly attributed to decreased CO₂ emissions at point sources, such as power plants, not occurring in the flux source area. Since nonpoint sources, such as traffic, were estimated as the dominant emission sources within the source area (Fig. 2), the decadal change in nonpoint sources could be limited considering the lifespan of cars, and gradual change in human lifestyles.

Considering the relationship between traffic conditions and annual CO₂ emissions (Fig. 3) and the inventory indicating high contributions of traffic (Fig. 2b and c), the measured variations in the CO₂ flux could be associated with changes in traffic emissions. The high contribution of traffic was consistent with automobile measurements within the source area (Takano and Ueyama, 2021), showing that higher CO₂ concentrations were observed along heavy-traffic roads than those observed along low-traffic roads or commercial districts at the city center. Statistics suggested that the improved fuel efficiency of cars (Fig. 4d and e) and increased trip distance (Fig. 4h and i) nearly canceled each other during the study period, resulting in an insignificant trend of the CO₂ flux (Fig. 2). The increased trip distance indicated that the people in the Osaka Prefecture began to use their cars for longer distances. The traffic counts considered were determined at only two entrances/exits of the nearby highway and thus likely underrepresented the traffic dynamics within the source area. This could in part explain the different diurnal patterns between the CO₂ flux and traffic counts (Fig. 7), although other factors, such as the storage term (Figs. S4 and 5), could also explain the observed discrepancy. The recently available big data based on mobile GPS data could be useful to estimate traffic dynamics at large spatio-temporal scales (Yamagata et al., 2018, 2019). These data could help interpret the measured CO₂ fluxes and reduce uncertainties associated with the gap-filling.

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throughout the seasonal cycle was low (7.8%). The sensitivity of the CO$_2$ flux to low temperatures (0.67 g CO$_2$ m$^{-2}$ d$^{-1}$ °C$^{-1}$ with the ML method and 0.83 g CO$_2$ m$^{-2}$ d$^{-1}$ °C$^{-1}$ with the MDV method) was comparable to that reported in other cities: Łódź (0.77 g CO$_2$ m$^{-2}$ d$^{-1}$ °C$^{-1}$; Pavlak et al., 2011), Beijing (1.28 g CO$_2$ m$^{-2}$ d$^{-1}$ °C$^{-1}$; Liu et al., 2012), and London (7.41 g CO$_2$ m$^{-2}$ d$^{-1}$ °C$^{-1}$; Ward et al., 2015). The increased emissions in summer could be explained by the gas/oil consumption statistics for nonresidential sectors (Figs. S9 and S10) due to the severe summer temperatures in Japan (Kanda et al., 1997; Ueyama and Ando, 2016).

4.2. Emission reduction during the pandemic

CO$_2$ emissions decreased due to the decrease in human activities during the COVID-19 pandemic period (Figs. 2 and 5–7). Despite the voluntary restrictions imposed in Japan, as opposed to the strict lockdown measures enforced in other countries, the measured emission reduction (32% during the first state of the emergency, and 25% in 2020) was comparable to that reported in other cities. Velasco (2021) estimated a 24% reduction in the CO$_2$ flux during the lockdown period and a 3.5% reduction in 2020 in a residential area in Singapore based on a certain inventory. Lamprecht et al. (2021) detected a 38% reduction in the measured CO$_2$ flux during the lockdown period in Innsbruck, Austria, associated with a reduction of up to 64% in traffic loads. Papale et al. (2020) reported that the reduction in the CO$_2$ flux measured with the eddy covariance method ranged from 8% to 75% during the lockdown period in eight European cities and depended on the intensity of the implemented lockdown measures. Only a weak rebound in the CO$_2$ flux was detected after the first state of emergency in this study because both the self-restraint and remote working conditions continued in Japan. Continued emission reduction contributed 25% to the reduction in the annual CO$_2$ emissions in 2020. The reduction measured in this study reflected a reduction in nonpoint source emissions but did not include point sources, such as power plants. Since the reduction in power plant emissions was reported to be smaller than that in nonpoint source emissions during the lockdown period (Le Quéré et al., 2020; Liu et al., 2020b), the emission reduction across the entire city or country could be smaller than that reported in this study.

4.3. Uncertainties in the measurements

Data selection in regard to the western sector led to uncertainties in the evaluation of the annual CO$_2$ emissions. Data selection was required to avoid uncertainties associated with spatial heterogeneity. After data selection, the dependency of the CO$_2$ flux on the wind sector was alleviated (Fig. S6) and low standard errors in the diurnal patterns were estimated (Fig. 7). Since the measurements were conducted well above the blending height, the impacts on the different flux footprints during each half-hour period could be smaller than those on measurements near the roughness sublayer. This was the advantage of the tall tower eddy covariance measurements, which represented large source areas (Matthews and Schume, 2022). For example, irrespective of the source area, the areal contributions of roads were not notably different (Table S1), because heavy-traffic roads were located within a grid in the western sector. The fraction of the downscaled CO$_2$ sources also did not differ among the various source areas for the western sector (Fig. 2b and c). At the same time, the ML regression results suggested the importance of the heterogeneity where footprint information was important for CO$_2$ flux prediction (Fig. S7), although there existed no clear direct relationship between footprint information and the CO$_2$ flux (data not shown).

Simple directional filtering could not completely alleviate the spatial heterogeneity because the flux footprint differed in each half-hour interval based on meteorological conditions. Uncertainties also hampered accurate comparison to the inventory (Fig. 2). Crawford and Christen (2015) developed a method to correct measured CO$_2$ fluxes with the spatial mean for Vancouver, Canada, based on detailed footprint analysis. Stagakis et al. (2019) also applied a similar method in a heterogeneous urban center in Heraklion, Greece. These methods did not require directional filtering, which could allow us to consider unfiltered data, including the eastern sector data, and could reduce the uncertainties associated with heterogeneity and gap filling. These methods could also enable detailed source attribution of the measured CO$_2$ fluxes at half-hourly intervals, facilitating an improved comparison to the inventory.

The different gap-filling methods produced a difference in the long-term CO$_2$ budgets of 3.5 kg m$^{-2}$ yr$^{-1}$ or 16% of the annual budget (Fig. 2; Table 1). Based on the estimated scores ($R^2 = 0.19$ for the ML method; $R^2 = 0.08$ for the MDV method), the above two gap-filling methods yielded a low variance. Model scores for the variance and bias often involve trade-off relationships, and thus a low-variance model does not necessarily suggest a low accuracy by definition (Raschka, 2015). This suggests that the models could predict the mean of each moving window (i.e., 3-years for the ML method and one month for the MDV method), although the variability was not predicted well. Thus, the gap-filled dataset could capture the interannual variation if the data gaps were random enough to not deteriorate the annual mean. The difference between the two gap-filled CO$_2$ emissions could be caused by differing window sizes and different definitions of the mean in feature space.

The low variance in the gap-filling models was in part caused by the storage term, because the measurements were conducted at high altitudes, and thus the storage term was significant (Figs. S4 and S5). The magnitudes of the storage term could differ with the meteorological conditions, and the diurnal variations in the measured CO$_2$ fluxes could thus differ even under the same emission characteristics. This could reduce the precision of the gap-filling results. Influences of the storage term were also reflected by the inconsistent diurnal patterns between the CO$_2$ flux and traffic counts.

4.4. Comparison to the emission inventory

Combining direct measurements with inventory-based data is useful to interpret measured fluxes (Figs. 2, 4, S9, and S10). The emission inventory provided detailed partitioning results of the potential urban CO$_2$ emissions. The measurements provided a data three years before the inventory data were published (Fig. 2), which could promote earlier decision-making and facilitate an independent assessment of carbon emission policies. Direct measurements obtained with the eddy covariance method could improve measurement, reporting and verification (MRV) of CO$_2$ emissions in urban areas.

The annual CO$_2$ emissions remained inconsistent between the measurements and the downscaled inventory data developed by the local government (Fig. 2b and c). This inconsistency could be explained by several factors. First, the statistics employed in the inventory were of a low temporal resolution (e.g., Fig. 4f and g) and outdated (e.g., land cover map for 2008), resulting in biased estimates for each year. The inventory did not consider the road type, although previous studies reported that high CO$_2$ emissions were only observed along heavy traffic roads and at intersections (Crawford and Christen, 2015; Stagakis et al., 2019). Low-traffic roads within the source area could cause overestimation of traffic CO$_2$ emissions. Owing to the heterogeneity, the spatial mismatch between the measurement and inventory data also caused uncertainties. Finally, the inventory did not consider the human and soil respiration, although human respiration was determined as a minor component in the study area. Although the inventory did not consider plant photosynthesis or respiration, these contributions could be negligible in the study area owing to the limited number of green spaces.

Helfter et al. (2016) reported that CO$_2$ emissions measured with the eddy covariance method and inventory-based emission data were highly consistent, within a 1% uncertainty in London. A similar accurate comparison is difficult to achieve in Japan because the inventories
developed by local governments are provided at the city-wide scale and the annual time scale. Thus, an inventory with a high spatiotemporal scale is required to achieve a similar comparison in Japan. Furthermore, owing to the uncertainties in the eddy covariance measurements, combining various measurements, such as gas concentration measurements (Lin et al., 2018; Mitchell et al., 2018; Sargent et al., 2018), could be helpful to accurately evaluate urban CO₂ emissions.

5. Conclusions

Direct CO₂ emissions were measured in an urban center, Sakai, Osaka, Japan, for 11 years, including the COVID-19 pandemic period starting in 2020. Throughout the decade, the annual CO₂ emissions remained stable. This may be attributed to offsetting changes in socioeconomic dynamics, such as the fuel efficiency and consumption in the traffic sector. Based on an emission inventory and correlation analysis, traffic emissions were determined as the major source of emissions in the flux source area. The reduction in human activities during the COVID-19 period led to the reduction of CO₂ emissions by 32% ± 3.1% during the first state of emergency and by 25% ± 3.1% in 2020 on an annual basis. The emission reduction during the second state of emergency was less notable than that during the first state of emergency, possibly due to acceleration of pandemic-related lifestyle changes. Despite the widespread regulation of socioeconomic activities during the pandemic, the reduction in CO₂ emissions was limited. This indicates that substantial changes in society could be required to balance CO₂ emissions throughout Japan, in addition to improving the energy efficiency of current social practices. Direct long-term observations of CO₂ emissions are useful tools to monitor future emission reduction and sudden disruptions in emissions, as those observed during the pandemic in 2020.

Author statement

Masahito Ueyama: Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing – original draft, Supervision, Visualization, Project administration, Funding acquisition. Tsugumi Takano: Investigation, Methodology, Software, Validation, Formal analysis, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2022.119210.

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