Evaluating a high-resolution urban fossil CO2 emissions inventory using eddy-covariance flux measurements and source partitioning

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Abstract

We present the first quantitative comparison of source-partitioned CO2 flux measurements with a high-resolution urban fossil CO2 emissions inventory. We use tower-based measurements of CO and 14C to partition net CO2 flux measurements into fossil and biogenic components in a suburban environment. A flux footprint model is used to quantify spatial patterns in fluxes. The partitioned fossil CO2 emissions are compared to a 200-m resolution emissions inventory (Hestia). The results indicate that Hestia and the partitioned flux data agree remarkably well on a seasonal average scale. The Hestia inventory is biased by 3.2% (cold season) and 9.1% (warm season). Their temporal-spatial patterns match closely. In addition, biogenic CO2 uptake is 25% of local fossil emissions during afternoon in the cold season. This work demonstrates the effectiveness of using eddy-covariance flux measurements both for evaluating urban emissions inventories and for quantifying urban ecosystem fluxes.

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Key Points:

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24	•	Urban CO ₂ flux measurements are partitioned into fossil and biogenic components
25		using CO and ¹⁴ C measurements and a flux-gradient method.
26	•	The partitioned fossil CO_2 emissions show remarkable consistency of the compar-
27		ison with an emissions inventory in time and space.
28	•	Biogenic CO_2 fluxes within the city are non-negligible in the cold season and need
29		to be considered in urban CO_2 monitoring.

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30 Abstract

We present the first quantitative comparison of source-partitioned CO_2 flux mea-31 surements with a high-resolution urban fossil CO_2 emissions inventory. We use tower-32 based measurements of CO and 14 C to partition net CO₂ flux measurements into fos-33 sil and biogenic components in a suburban environment. A flux footprint model is used 34 to quantify spatial patterns in fluxes. The partitioned fossil CO_2 emissions are compared 35 to a 200-m resolution emissions inventory (Hestia). The results indicate that Hestia and 36 the partitioned flux data agree remarkably well on a seasonal average scale. The Hes-37 38 tia inventory is biased by 3.2% (cold season) and 9.1% (warm season). Their temporalspatial patterns match closely. In addition, biogenic CO_2 uptake is 25% of local fossil 39 emissions during afternoon in the cold season. This work demonstrates the effectiveness 40 of using eddy-covariance flux measurements both for evaluating urban emissions inven-41 tories and for quantifying urban ecosystem fluxes. 42

⁴³ Plain Language Summary

This work presents the first comparison of two innovative approaches for quanti-44 fying urban CO_2 emissions from the combustion of fossil fuels. Both approaches can quan-45 tify emissions from neighborhoods with hourly time resolution. These methods show very 46 similar results concerning the seasonal-mean fossil CO_2 emissions, as well as the emis-47 sions variation in time and space. We also find relatively large biological CO_2 exchange, 48 even during winter when the biosphere is often assumed to be dormant. The results show 49 great promise for these new methods of quantifying source, space and time resolved CO_2 50 exchanges, and emphasize the need to take biological CO_2 fluxes into account when at-51 tempting to quantify fossil CO_2 emissions using atmospheric measurements. 52

53 1 Introduction

Cities are becoming the focus for formulating and implementing carbon dioxide (CO_2) 54 emissions mitigation efforts (Hutyra et al., 2014; Lee & Koski, 2014; Bulkeley, 2013). Eval-55 uating the effectiveness of emissions reduction efforts requires accurate and independent 56 CO_2 emissions estimates (Lauvaux et al., 2020; Turnbull et al., 2018). Although cities 57 cover only 3% of the global land area, urban areas are home to 55% of the world's pop-58 ulation, a proportion that is expected to increase to 68% by 2050 (Chaouad & Verze-59 roli, 2018). Overall, more than 70% of global fossil fuel CO₂ (CO₂ff) emissions are from 60 urban areas (Edenhofer et al., 2015). Efforts to assess and mitigate CO_2 emissions can 61 provide benefits for urban sustainability and balanced economic growth (Hsu et al., 2019). 62

Urban areas are consistently reported as a net source of CO_2 (Velasco & Roth, 2010). 63 The temporal variation of urban CO_2 is dependent on human activities and urban ecosys-64 tems (McKain et al., 2012; Pataki et al., 2006). The eddy-covariance technique has been 65 applied to measure urban CO_2 emissions for about two decades. This method has been 66 demonstrated in many cities (Björkegren & Grimmond, 2018; Ao et al., 2016; Lietzke 67 et al., 2015; Järvi et al., 2012; Christen et al., 2011; Vogt et al., 2006; Nemitz et al., 2002; 68 Grimmond et al., 2002). The attribution of urban CO₂ flux measurements is challeng-69 ing due to the spatial heterogeneity, mixed emission sources and sinks, and limited spa-70 tial coverage of flux measurements (Aubinet et al., 2012). Although most of urban flux 71 studies focus on the total observed CO_2 flux, a few studies attempt to partition net flux 72 measurements into fossil and biogenic components accounting for the temporal and spa-73 tial variability of the multiple sources and sinks. Menzer and McFadden (2017) modeled 74 fossil CO_2 emissions based on winter data and extrapolated them to the growing sea-75 son to estimate biogenic fluxes. Ishidoya et al. (2020) demonstrated partitioning of CO_2 76 fluxes into liquid and gaseous fossil fuel components using O_2 and CO_2 measurements. 77

Sugawara et al. (2021) used a nearby tower to estimate the biogenic component of a total CO₂ flux measurement.

Quantification of anthropogenic CO_2 emissions is challenging due to the difficulty 80 of separating CO_2 ff emissions from biogenic CO_2 (CO_2 bio) fluxes (Miller et al., 2020; 81 Basu et al., 2020; Menzer & McFadden, 2017; Pataki et al., 2007). Previous studies have 82 demonstrated the feasibility of using 14 C isotope measurements to separate CO₂ff from 83 CO_2 bio fluxes (Basu et al., 2016; Turnbull et al., 2015; Miller et al., 2012), but flask mea-84 surements of ${}^{14}C$ are expensive and discontinuous. Continuous measurements of carbon 85 monoxide (CO) provide another approach to track CO_2 ff emissions (Silva et al., 2013; Levin & Karstens, 2007; Turnbull et al., 2006). Uncertainties in the CO to CO₂ff ratio, 87 which vary as a function of emission sectors, complicate the attribution of urban CO_2 88 fluxes. These methods have not yet been applied to eddy-covariance flux measurements. 89

Emissions inventories use activity data to aggregate source-specific and total emis-90 sions (Boden et al., 2009; Gurney et al., 2009; Olivier & Janssens-Maenhout, 2012), but 91 the differences among inventories are sizeable (Gately & Hutyra, 2017; Oda et al., 2019). 92 Atmospheric inversions use inventories as prior estimates of emissions and optimize the 93 emissions using atmospheric mole fraction observations (Bréon et al., 2015; Turner et al., 94 2016; Staufer et al., 2016; Lauvaux et al., 2016; Kunik et al., 2019; Lauvaux et al., 2020). 95 Determination of the uncertainty in the inversion results hinges on estimates of errors 96 in atmospheric transport models (Deng et al., 2017; Sarmiento et al., 2017) and emis-97 sions inventories (Wu et al., 2018). The Hestia emissions inventory (Gurney et al., 2012) 98 was developed in part to support the Indianapolis Flux Experiment (INFLUX) and uses 99 energy consumption, population density, and traffic data to quantify CO_2 ff emissions for 100 an entire urban landscape at an approximately 200-m and hourly resolution. The high-101 resolution performance of the Hestia inventory has not yet been evaluated using atmo-102 spheric observations. 103

This study compares seven months of source-partitioned CO₂ eddy-covariance flux 104 measurements with a high-resolution emissions inventory (Hestia) in a suburban region 105 of Indianapolis, Indiana, USA. We partition the total CO₂ flux measurements into CO₂ff 106 and CO₂bio components using a flux-gradient relationship (Stull, 2012; Ishidoya et al., 107 2020) and atmospheric CO measurements. ¹⁴C isotope measurements are used to esti-108 mate the CO to CO₂ff ratio and reduce the uncertainty in the flux decomposition. Our 109 source decomposition methods are similar to those used by Ishidoya et al. (2020) and 110 Sugawara et al. (2021). In addition, we use a flux footprint model (Kljun et al., 2015, 111 2004) to match each flux measurement in space and time with the Hestia inventory to 112 provide a direct comparison of independent estimates of fossil CO_2 emissions at high spa-113 tial and temporal resolution. This is, to our knowledge, the first such comparison of these 114 innovative and independent assessments of high-resolution urban CO_2 emissions, and is 115 timely given the growing interest in studies of urban systems. 116

117 2 Data and Methods

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2.1 Site Descriptions and Atmospheric CO₂ Flux Measurements

The INFLUX observation network (Davis et al., 2017) measures atmospheric CO₂ 119 and CO mole fractions, and net CO_2 fluxes in and around Indianapolis, IN (Figure 1). 120 The locations, sampling heights and measurements at these sites are described by Miles 121 et al. (2017) and instrument performance by Richardson et al. (2017). ¹⁴C isotope mea-122 surements, which are related to CO₂ff emissions, are collected weekly using a flask sam-123 pling system (Turnbull et al., 2015). We focus on seven months (January to July, 2013) 124 of eddy-covariance flux measurements at Tower 2 located in a heterogeneous suburban 125 environment (Figures 1 and S1). There is a highway to the north, urban vegetation to 126 the south, and neighborhoods with detached houses. The heterogeneous surroundings 127

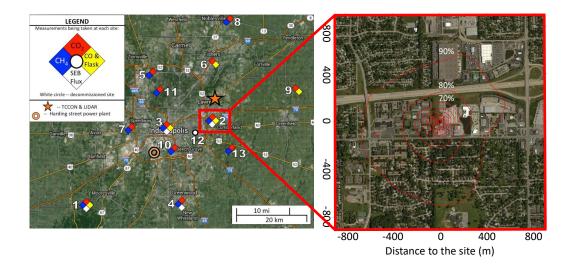


Figure 1. The Indianapolis Flux Experiment (INFLUX) measurement network in Indianapolis, IN (left) and cumulative flux footprints from January to July in 2013 at Tower 2 (right). The contours in the right panel represent the percentage of the time-integrated flux that comes from within that boundary. The color of the marker in the left panel represents the measurements at each site: red for CO_2 , yellow for CO and ¹⁴C, blue for CH_4 , and white for surface energy balance fluxes. The coordinates in the right panel are the distance (m) to the measurement site.

present a good test of our ability to partition net CO_2 flux measurements into biogenic and fossil fuel components.

The flux instrumentation, which includes a sonic anemometer (Campbell Scientific, 130 CSAT-3) and a high-frequency open-path infrared CO_2 sensor (LI-COR Environmen-131 tal, LI-7500), is mounted at 30 m above ground level (AGL) on Tower 2. The eddy-covariance 132 technique measures the covariance between fluctuations in vertical wind velocity and CO_2 133 density to detect the integrated exchange of CO_2 between land and atmosphere (Lee et 134 al., 2004; Foken & Napo, 2008; Aubinet et al., 2012). We use flux calculation and filter-135 ing methods recommended by Vickers and Mahrt (1997). We filter out extreme values 136 outside 3.5 σ range of the data (0.2% of data are filtered out) and nighttime fluxes dur-137 ing weak turbulence conditions when the friction velocity is less than 0.2 m/s (3.6% of 138 data are filtered out) (Gu et al., 2005). Negative fluxes confirm the predominant role of 139 photosynthesis from the urban vegetation around this site (Figure S2). We define the 140 cold season as January to March (JFM) and the warm season as April to July (AMJJ) 141 based on the presence of negative total CO_2 fluxes during the daytime in the warm sea-142 son (Figure S3). 143

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2.2 Partitioning Fossil Fuel and Biogenic CO₂ Fluxes

To partition fossil fuel and biogenic components from the net CO_2 flux measure-145 ments, we apply a flux-gradient method and atmospheric CO measurements. We mea-146 sure CO_2 and CO mole fractions at 10 m and 40 m heights AGL at Tower 2 (Miles et 147 al., 2017). We use the eddy-covariance flux measurement and measured vertical gradi-148 ent in CO_2 to solve for the eddy diffusivity, and use that eddy diffusivity and the CO 149 vertical gradient to solve for the CO flux, as shown in the supporting information. There 150 are three assumptions in this method: (1) Turbulent eddies are small enough that lo-151 cal scalar gradients are proportional to turbulent fluxes; (2) CO and CO₂ are subject 152 to the same vertical mixing processes; (3) Within the turbulent flux footprint, CO is mainly 153

produced by fossil fuel combustion. We filter out counter-gradient fluxes, and limit the eddy diffusivity and CO flux within 3.5 σ range of their estimates to screen out extreme values caused by tiny denominators.

The emission ratio of CO to CO_2 ff is estimated from flask measurements of ^{14}C 157 and CO measurements (Turnbull et al., 2015). The urban CO enhancements are esti-158 mated by the differences between Tower 2 and upwind background sites (Tower 1 or 9 159 depending on the wind direction). The median and mean values of CO to CO₂ff ratios 160 are 9.52 and 8.98 ppb ppm^{-1} (cold season) and 9.13 and 9.02 ppb ppm^{-1} (warm sea-161 son) (Figure S4). We use 9 ppb ppm^{-1} as an approximate value to infer CO₂ff emissions. 162 To test the uncertainty of using different ratios on the flux decomposition, we vary the 163 emission ratio to 11 and 7 ppb ppm^{-1} based on the range of values estimated by Turnbull 164 et al. (2015). Since traffic emissions are likely to have a higher ratio and residential emis-165 sions have a smaller ratio. We add another scenario with a CO to CO_2 ff ratio of 15 ppb 166 ppm^{-1} for northerly winds from the highway, and 7 ppb ppm^{-1} for the other wind di-167 rections. 168

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2.3 Flux Footprint and Emissions Inventory

A flux footprint, which is defined as the contributing area upwind from the mea-170 surement site (Leclerc & Foken, 2014), is essential to account for the spatial heterogene-171 ity of emission sources. We use a two-dimensional flux footprint model (Kljun et al., 2015, 172 2004) to match with the Hestia inventory. Tower-based measurements of wind field and 173 boundary layer characteristics are used to estimate the input parameters of the footprint 174 model (*i.e.* roughness length, Obukhov length, friction velocity, standard deviation of 175 lateral velocity fluctuations, etc.). The size of footprint depends on measurement height, 176 surface roughness, and atmospheric thermal stability. The footprint will increase with 177 an increase in measurement height, with a decrease in surface roughness, and with an 178 increase in atmospheric thermal stability (Burba & Anderson, 2010). The spatial res-179 olution of the footprint model is approximately two meters. We match every flux foot-180 print with Hestia via a convolution of the influence function with the Hestia emissions. 181

182 **3 Results**

Net CO_2 flux measurements, decomposed as a function of time and space, behave 183 as expected given the environment surrounding the tower. Observed CO_2 emissions are 184 larger in the cold season than the warm season (Figure 2a), perhaps due to increased emis-185 sions from building heating around the tower (Figures 1 and S1). In the cold season, there 186 are two prominent peaks in emissions likely corresponding to peaks in traffic volume dur-187 ing rush hours. In the warm season, fossil fuel CO_2 emissions are mixed with photosyn-188 thesis and respiration from urban vegetation within the flux footprints. The daytime pho-189 to synthetic uptake of CO_2 indicates the role of urban vegetation. The spatial patterns 190 of flux data show high emissions from the north, and lower emissions or net uptake from 191 the south (Figures 2b and 2c), consistent with the highway to the north and urban veg-192 etation to the south of the tower (Figures 1 and S1). 193

Partitioning of the net observed CO_2 fluxes into fossil and biogenic components yields 194 broadly plausible temporal behavior of these flux components (Figure 3). While substan-195 tially smaller than the estimated CO_2 ff emissions, the cold season CO_2 bio uptake is 25% 196 of urban CO₂ff emissions during the afternoon (Figure 3a), which is non-negligible and 197 need to be considered to obtain accurate CO_2 ff emissions. A typical pattern of ecosys-198 tem fluxes emerges in the warm season (Figure 3b). The warm season CO_2 bio fluxes are 199 equal in amplitude to the CO_2 ff emissions, emphasizing the importance of accounting 200 for CO₂bio fluxes in attempts to quantify urban CO₂ff emissions. 201

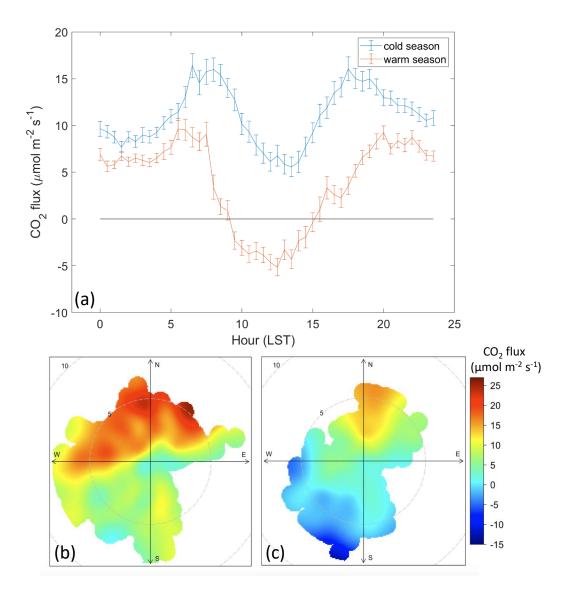


Figure 2. Diurnal variation of seasonally-averaged CO_2 flux measurements during the cold (JFM) and warm (AMJJ) seasons in 2013 (a). Error bars indicate the standard errors of the seasonal means. Spatial variation of time-averaged CO_2 fluxes in the cold (b) and warm (c) seasons. Color indicates flux magnitude. The radial coordinate corresponds to wind speed (m s⁻¹) and the polar coordinate defines wind direction.

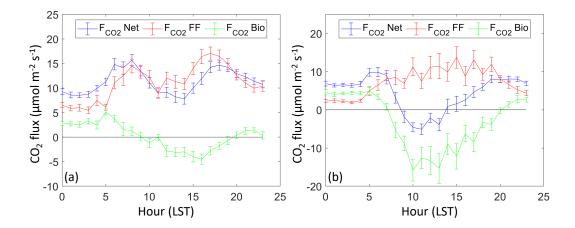


Figure 3. Diurnal variation of seasonally-averaged net CO_2 flux measurements ($F_{CO2}Net$) and the partitioned fossil fuel ($F_{CO2}FF$) and biogenic ($F_{CO2}Bio$) fluxes in the cold (JFM) (a) and warm (AMJJ) (b) seasons in 2013. Error bars are the standard errors of the seasonal means.

The seasonally-averaged eddy-covariance CO_2 ff emissions estimates show remarkable similarity to the Hestia inventory when matched in space and time using flux footprints. Seasonal-mean CO_2 ff emissions differ (Hestia minus OBS) by 0.36 μ mol m⁻² s⁻¹ (3.2% of the mean partitioned CO_2 ff emissions) in the cold season (Figure 4a) and 0.62 μ mol m⁻² s⁻¹ (9.1% of the mean partitioned CO_2 ff emissions) in the warm season (Figure 4b). The corresponding root mean square errors (RMSEs) are 8.91 μ mol m⁻² s⁻¹ and 7.54 μ mol m⁻² s⁻¹, which include random measurement errors in the flux data.

The temporal patterns of seasonally-averaged Hestia and eddy-covariance CO₂ff emissions also agree remarkably well (Figures 4c and 4d). The correlation coefficients of the seasonal-mean diurnal variations are 0.86 (cold season) and 0.93 (warm season). The Hestia emissions are smaller during the night and higher during the day compared to the partitioned observations in the cold season (Figures 4c and S5a), and consistently slightly higher than the partitioned observations in the warm season (Figures 4d and S5b).

We also find consistency in the comparison of eddy-covariance and Hestia CO₂ff emissions as a function of wind direction (Figure S6 and Table 1). In the cold season, the Hestia emissions are higher than the observed CO₂ff emissions for all wind directions except the north, west and northwest wind (Table 1). A similar pattern exists in the warm season. Since residential buildings lie upwind in the west and northwest wind directions (Figures 1 and S1), we infer that residential emissions may be the source of this discrepancy.

These results are somewhat sensitive to the choice of CO to CO₂ff emission ratio 222 in the flux decomposition. Seasonal-mean flux bias and bias percentage change signif-223 icantly when the emission ratio varies from 9 ppb ppm^{-1} to 11 or 7 ppb ppm^{-1} (Table 224 S1 and Figure S7a). The temporal variations are not highly sensitive to this choice (Fig-225 ure S7b). The scenario with the space-varying emission ratio (15 & 7 ppb ppm⁻¹), which 226 may be more realistic than a constant ratio, does not significantly change compared to 227 the default scenario (9 ppb ppm^{-1}) either the comparison of the diurnal variation (Fig-228 ure S7b) or the bias estimation (Table S1). 229

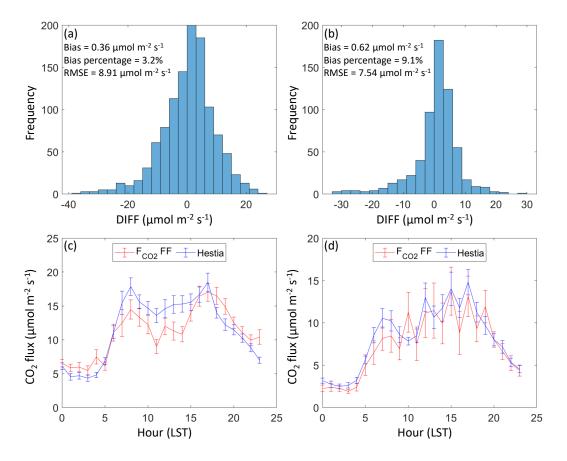


Figure 4. Histogram of flux differences between the Hestia inventory and the partitioned fossil fuel CO_2 emissions (Hestia minus OBS) in the cold (JFM) (a) and warm (AMJJ) (b) seasons in 2013. Bias, bias percentage compared to the mean partitioned CO_2 ff emissions, and root mean square error (RMSE) are listed. Diurnal variation of seasonally-averaged CO_2 ff emissions in the cold (c) and warm (d) seasons. Error bars are the standard errors of the seasonal means.

	DIFF	Ν	NE	Е	SE	S	SW	W	NW
Cold	Median	-2.00	3.32	2.88	3.45	4.14	3.15	-4.47	-2.14
Season	Mean	-1.93	5.88	4.88	3.58	3.84	1.89	-4.72	-1.87
(JFM)	\mathbf{RMSE}^{a}	10.98	9.27	8.22	5.63	7.45	8.00	10.40	9.06
Warm	Median	2.49	3.34	1.92	1.98	0.98	0.42	-2.71	-4.27
Season	Mean	5.31	3.61	0.92	1.37	0.52	-1.32	-4.17	-5.21
(AMJJ)	RMSE	8.24	9.32	5.19	5.54	5.97	8.62	8.47	13.66

Table 1. Statistics of flux differences (μ mol m⁻² s⁻¹) between the Hestia inventory and the partitioned fossil fuel CO₂ emissions (Hestia minus OBS) for different wind directions.

^{*a*}root mean square error

230 4 Conclusions and Discussion

The remarkably close agreement between the Hestia inventory and the partitioned 231 eddy-covariance flux measurements suggests that both methods have the ability to quan-232 tify urban fossil CO_2 emissions. Neither approach has yet been cross-validated at such 233 a high spatial and temporal resolution. The flux measurement partitioning is sensitive 234 to the CO to CO₂ff emission ratio, but the consistency of Hestia and flux data suggests 235 that flask measurements have accurately quantified that ratio. These results need to be 236 tested at other locations and over different periods of time. The success of this test sug-237 gests that these eddy-covariance flux decomposition methods can be used to quantify source-238 specific CO₂ emissions of neighborhood-scale urban metabolic processes. Further the suc-239 cessful comparison to Hestia suggests that the algorithms and input data used in the in-240 ventory system are accurate and precise even down to the fine resolution of the eddy-241 covariance flux measurements. 242

This study also shows the promise of using this approach for studying urban ecosys-243 tem CO_2 fluxes. Previous work has suggested that the edges found in urban ecosystems 244 lead to fundamentally different behavior of these ecosystems (Reinmann et al., 2020), 245 but these findings are largely based on chamber-scale flux measurements. It is not clear 246 whether or not, when upscaled to spatial domains that integrate across many edges such 247 as a suburban forest, existing ecosystem models and model parameters will suffice in de-248 scribing urban CO_2 bio fluxes. Current ecosystem models used in urban studies are largely 249 devoid of urban ecosystem flux measurements in either calibration or evaluation due to 250 lack of data (Wu et al., 2021; Hardiman et al., 2017). We suggest that the decomposi-251 tion methods can serve as a new approach for obtaining ecosystem flux data necessary 252 to develop the next generation of urban ecosystem models. 253

Finally, this study emphasizes the importance of urban ecosystem fluxes, both in 254 the growing/warm season and the dormant/cold season. The importance of these fluxes 255 has been shown in multiple observational (Miller et al., 2020; Turnbull et al., 2015) and 256 inversion (Lauvaux et al., 2020; Sargent et al., 2018; Wu et al., 2018) studies, but the 257 impact of uncertain biological fluxes has been shown to be large (Lauvaux et al., 2020; 258 Wu et al., 2018), and we have not had direct flux measurements available for evaluat-259 ing the modeled ecosystem flux priors. Further, a number of studies (Lauvaux et al., 2016; 260 Heimburger et al., 2017) have made the reasonable assumption of neglecting CO_2 bio fluxes 261 in the dormant season. This work shows that urban ecosystems in Indianapolis are mod-262 erately active even in the cold season. More urban flux measurements are needed to study 263 the range of urban ecosystem CO_2 fluxes. 264

265 Conflict of Interest

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The authors declare no competing interests.

²⁶⁷ Data Availability Statement

The Hestia inventory is available online (https://hestia.rc.nau.edu/), and other data used in this analysis are available on the INFLUX website (http://sites.psu.edu/influx/).

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Supporting Information for "Evaluating an emissions inventory using atmospheric CO_2 flux measurements and source partitioning in a suburban environment"

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Specific steps to partition anthropogenic and biogenic CO_2 flux components:

Step 1: Estimate the eddy diffusivity (K) by calculating the ratio of CO_2 flux measurements (F_{CO_2}) to the vertical gradients of CO_2 mole fractions (∇C_{CO_2}):

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$$K = -\frac{F_{CO_2}}{\nabla C_{CO_2}} \tag{1}$$

Step 2: Use the vertical gradients of CO mole fractions (∇C_{CO}) and the estimated eddy diffusivity (K) to calculate the CO fluxes (F_{CO}):

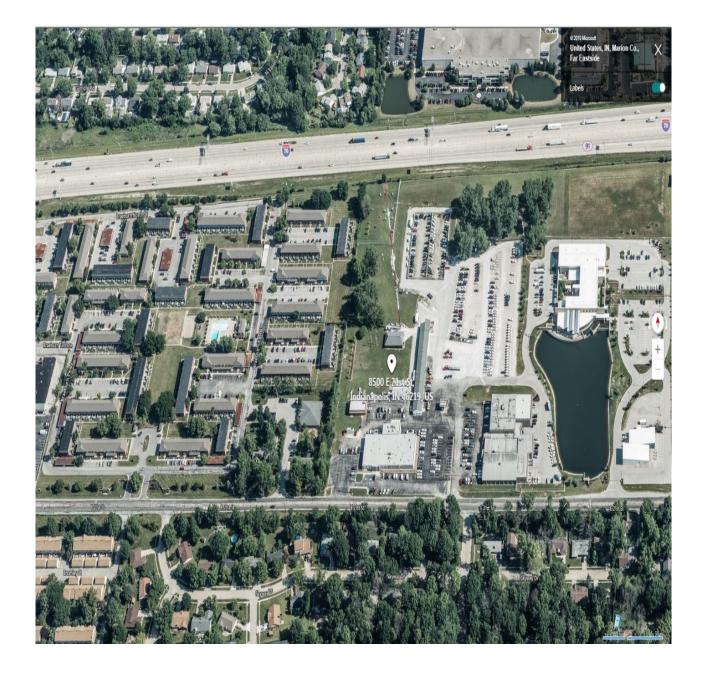
$$F_{CO} = -K\nabla C_{CO} \tag{2}$$

Step 3: Estimate the fossil fuel CO_2 emissions (F_{CO_2ff}) by combining the CO fluxes with the emissions ratio (R) of CO to CO_2ff :

$$F_{CO_2ff} = \frac{F_{CO}}{R} \tag{3}$$

Step 4: Attribute the differences between the net flux measurements and the partitioned fossil fuel CO_2 emissions to estimate the biogenic CO_2 fluxes (F_{CO_2bio}):

$$F_{CO_2bio} = F_{CO_2} - F_{CO_2ff} \tag{4}$$



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Figure S1. Surface environment around Tower 2 (39.7978°N, 86.0183°W) in Indianapolis, IN.

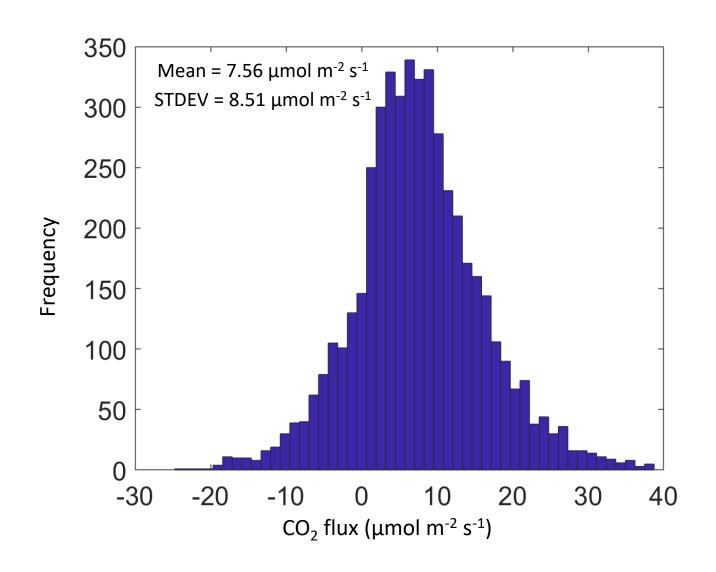


Figure S2. Histogram of eddy-covariance CO_2 flux measurements at Tower 2 from January to July in 2013.

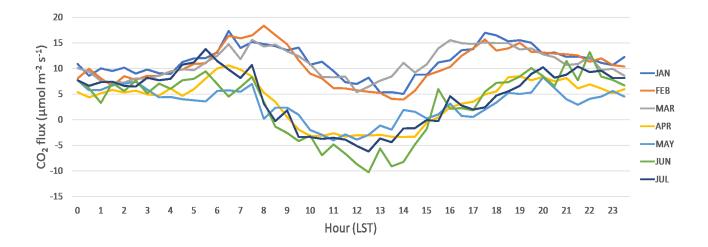


Figure S3. Diurnal variation of monthly-averaged eddy-covariance CO_2 flux measurements from January to July in 2013.

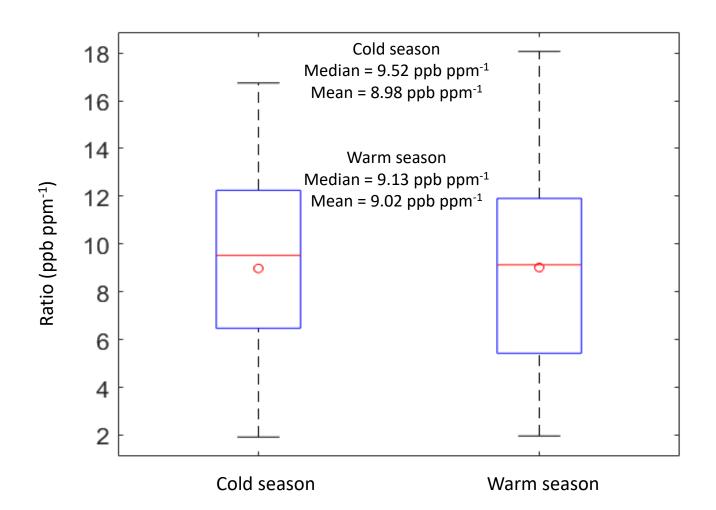
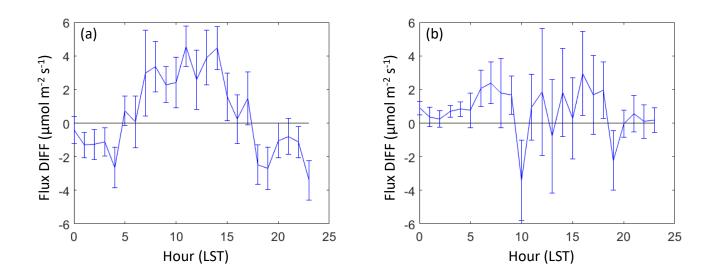


Figure S4. Ratios between the CO enhancements and the ¹⁴C-based CO₂ff during the cold (JFM) and warm (AMJJ) seasons in 2013. The red circle and line mark the mean and median, respectively. The bottom and top edges of the box indicate the 25th and 75th percentiles. The whiskers extend to the most extreme data points not considered outliers that are defined as more than 1.5 times the interquartile range away from the top or bottom of the box.



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Figure S5. Diurnal variation of seasonally-averaged flux differences between the Hestia inventory and the partitioned fossil fuel CO_2 emissions (Hestia minus OBS) in the cold (JFM) (a) and warm (AMJJ) (b) seasons in 2013. Error bars are the standard errors of the seasonal means.

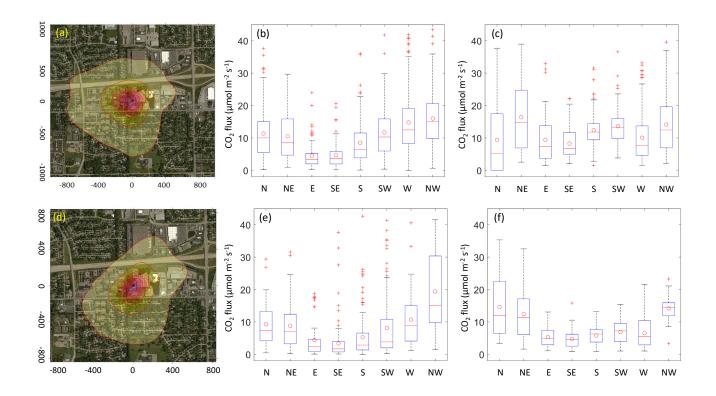
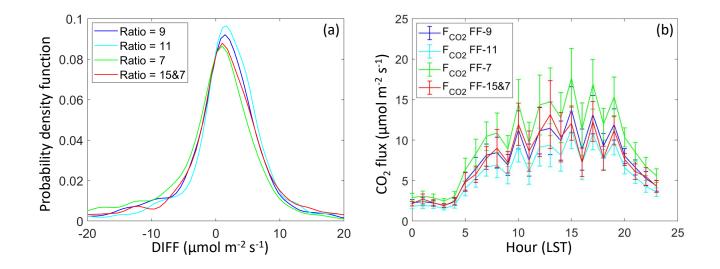


Figure S6. Cumulative flux footprints (a and d), the partitioned fossil fuel CO_2 emissions (b and e) and the Hestia inventory (c and f) for different wind directions. Panels a to c are in the cold season (JFM) and panels d to f are in the warm season (AMJJ) in 2013. The coordinates in the left panel indicate the distance (m) to the measurement site. In the middle and right panels, the red circles, the lines and the plus marks represent the mean, the median and the outliers, respectively. The bottom and top edges of the box indicate the 25th and 75th percentiles. The whiskers extend to the most extreme data points not considered outliers that are defined as more than 1.5 times the interquartile range away from the top or bottom of the box.





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Figure S7. Probability density function of flux differences between the Hestia inventory and the partitioned fossil fuel CO₂ emissions (Hestia minus OBS) for different CO to CO₂ff emission ratios (ppb ppm⁻¹) in the warm (AMJJ) season in 2013 (a). Ratio = 15&7 represents the ratio is 15 ppb ppm⁻¹ (traffic emissions) for the north wind and 7 ppb ppm⁻¹ (building emissions) for other wind directions. Diurnal variation of seasonally-averaged CO₂ff fluxes for different emission ratios in the warm season (b). Error bars indicate the standard errors of the seasonal means.

Table S1. Bias (μ mol m⁻² s⁻¹), bias percentage compared to the mean partitioned CO₂ff emissions (%), and root mean square error (μ mol m⁻² s⁻¹) of the Hestia inventory for different CO to CO₂ff emissions ratios (ppb ppm⁻¹) in the warm (AMJJ) season. Ratio = 15&7 represents the ratio is 15 ppb ppm⁻¹ (traffic emissions) for the north wind and 7 ppb ppm⁻¹ (building emissions) for other wind directions.

Ratio	9	11	7	15 & 7
Bias	0.62	1.86	-1.34	0.77
Bias PCT^a	9.1	33.3	-15.2	11.5
RMSE^{b}	7.54	6.76	9.44	8.86

^{*a*}percentage

^broot mean square error