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1 **Urban Eddy Covariance – The INFLUX Network**

2

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10

11 **Abstract.** The eddy covariance method is used by various disciplines to measure atmospheric fluxes of
12 both vector and scalar quantities. One long-term, multi-site urban flux network experiment was the
13 Indianapolis Flux Experiment (INFLUX), which successfully deployed and operated eddy covariance
14 towers at eleven locations measuring fluxes from land cover types both in and surrounding the urban
15 environment in Indianapolis, Indiana, USA. The data collected from this network of towers have been
16 used to quantify urban greenhouse gas, energy, and momentum fluxes, assess the performance of
17 numerical weather and carbon cycle models, and develop new analysis methods. This paper describes the
18 available data associated with the INFLUX eddy covariance network, provides details of data processing
19 and quality control, and outlines the site attributes to assist in data interpretation. For access to the various
20 data products from the INFLUX eddy covariance work, please see the data availability section below.

21

22 **Short summary.** We present data from a network of instrumented towers in Indianapolis, used to study
23 the exchange of heat, water vapor, and carbon dioxide between the surface and atmosphere in the city of
24 Indianapolis, IN, USA. We explain what was measured, how we checked data quality, and why these
25 observations improve our overall understanding of the urban environment.

26 1 Introduction

27

28 Eddy covariance (EC) is a method for quantifying atmospheric fluxes of mass, energy, and momentum.
29 Near-surface EC measurements are commonly used to infer the exchange of these quantities between the
30 Earth's surface and the atmosphere. Using EC, investigators can monitor a system with minimal
31 disturbance over long periods, making it an attractive method for various disciplines (e.g., ecologists,
32 meteorologists, hydrologists) (Baldocchi et al., 2001). The foundation of the technique is to sample the
33 spectrum of turbulent eddies and the associated scalar constituents to calculate the covariance of the
34 vertical wind component and the variable of interest. This covariance can be used to quantify the
35 turbulent surface flux of a variable (vector or scalar) in many conditions (e.g. Yi et al. 2000). This method
36 typically uses fast response ($\geq 10\text{Hz}$) instruments to measure the three-dimensional wind and various
37 atmospheric scalars (e.g., CO_2 , H_2O , temperature). A comprehensive description of the EC method can be
38 found in Aubinet et al. (2012) and Burba (2013) or many micrometeorological-focused texts (Foken,
39 2008; Lee et al., 2004).

40

41 Urban environments are complex, challenging micrometeorological methods and theory that have been
42 developed largely for horizontally homogeneous systems. In urban environments, heterogeneity (e.g.,
43 thermal, aerodynamic) is the norm rather than the exception. One approach to urban EC, however, is to
44 require deployments in urban areas that are homogeneous for areas encompassing most of the EC flux
45 footprint (i.e., upwind area measured by the EC system) (Turnbull et al., 2025). When possible, this
46 greatly simplifies data interpretation.

47

48 A contrasting approach deploys EC flux measurements in heterogeneous settings and seeks to adapt our
49 analysis methods and theories to the inherently heterogeneous nature of the urban environment. At least
50 two issues emerge in this scenario. First, the EC flux measurements cannot be interpreted with respect to
51 a single set of land surface characteristics. EC measurements collected in heterogeneous environments
52 should be interpreted as a function of wind direction and atmospheric stability conditions, ideally with a
53 flux footprint model (e.g., Horst and Weil, 1992; Kljun et al., 2015), and combined with data sets that can
54 describe the urban landscape at a resolution that is finer than the flux footprint. Such data analysis is
55 complicated by the fact that typical flux footprint models (e.g., Horst and Weil, 1992; Kljun et al., 2015)
56 were developed for horizontally homogeneous environments and should therefore be used with caution in
57 highly heterogeneous systems.

58

59 A second complication that must be considered is the formation of internal boundary layers and secondary
60 circulations that can be created in heterogeneous environments (Bou-Zeid et al., 2020). These circulations
61 can result in violations of common EC methodological assumptions, such as non-negligible horizontal
62 flux divergence or mean advection (Feigenwinter et al., 2012). These flows violate the assumption of one-
63 dimensional, vertical transport, which is typically used to infer surface-atmosphere exchange from EC
64 flux measurements (Aubinet et al., 2012; Burba, 2013). Diagnosing the presence of such flows can be
65 attempted, for example, with multi-level turbulent flux measurements (Yi et al., 2000). Yi et al. (2000)
66 found only modest deviations from vertical-only transport in a highly heterogeneous forested region. In
67 other locations, however, heterogeneity-induced secondary circulations have also been shown to impact
68 EC measurements in arguably less complex settings (compared to an urban setting) like agricultural fields
69 (Eder et al., 2015a) and deserts (Eder et al., 2015b), and have been linked to the lack of closure of the

70 surface energy balance endemic to EC flux measurements (Mauder et al., 2020). In summary, surface-
71 atmosphere fluxes inferred from EC flux measurements collected in heterogeneous urban environments
72 should also be treated with caution.

73
74 Mixed sources add complexity to the interpretation of urban EC flux measurements, as biological and
75 anthropogenic factors are often interwoven. The combined impacts of anthropogenic and biogenic sources
76 and sinks of CO₂ (Miller et al., 2020; Turnbull et al., 2019), sensible and latent heat (Ward et al., 2022)
77 and momentum (Kent et al., 2018) are measured by urban EC instruments. This complexity layers upon
78 underlying mixtures of fluxes within natural (e.g., respiration and photosynthesis; evaporation and
79 transpiration) and anthropogenic (vehicles and buildings; residential and industrial) systems.

80
81 None of these challenges, however, is new or unique to urban systems, and all have the potential to be
82 addressed via ongoing research. Airborne EC has been conducted over heterogeneous flux footprints for
83 decades (Desjardins et al., 1992; Oncley et al., 1997), and flux footprint decomposition methods have
84 been employed for nearly as long (Schuepp et al., 1990; Mahrt et al., 2001). Footprint decomposition has
85 been used with tower-based EC to study natural (Wang et al., 2006; Xu et al., 2017) and anthropogenic
86 (Dennis et al., 2022; Wu et al., 2022) fluxes. Biological and anthropogenic CO₂ fluxes have been
87 disaggregated in the urban environment using both statistical partitioning methods (Crawford and
88 Christen 2015; Lee et al. 2021; Menzer and McFadden 2017) and tracer ratio methods (Ishidoya et al.
89 2020; Wu et al. 2022). Complex ecosystem flux sites (e.g., Davis et al., 2003) have served as a guide for
90 flux upscaling studies (Wang et al., 2006; Xiao et al., 2014), and all AmeriFlux sites have been
91 categorized according to their degree of heterogeneity (Chu et al., 2021). Lateral flow in low turbulence
92 conditions has been recognized as a problem in all EC deployments (Barr et al., 2013). Landscape-scale
93 secondary circulations have been investigated in agricultural (Kang et al., 2007) and forested landscapes
94 (Butterworth et al., 2021). Given that urban environments are where over 55% (and rising) of the global
95 population lives (Sun et al., 2020) and given the past successes in studying complex micrometeorological
96 environments, we would like to stress the importance of understanding these complex systems and
97 moving ahead with measurements that go beyond the classic homogeneous flux tower site.

98
99 Many efforts have successfully measured fluxes using EC in the urban environment (Biraud et al., 2021;
100 Kotthaus and Grimmond, 2014; Menzer and McFadden, 2017; Vogt et al., 2006; Wu et al., 2022). Urban
101 GHG emissions are a common focus of these efforts. Urban areas are responsible for 67-72% of
102 anthropogenic CO₂ emissions globally (Lwasa et al., 2023). Many cities have pledged to reduce GHG
103 emissions in this era of anthropogenic climate change. The EC method can directly measure GHG fluxes
104 within the tower's footprint and reveal the urban metabolism. Liu et al., (2012) investigated spatial and
105 temporal variability of CO₂ fluxes in the Beijing megacity using the EC method and found weekly (e.g.,
106 traffic volume) and seasonal (e.g., domestic heating) patterns in CO₂ fluxes. Crawford and Christen
107 (2015) were able to disaggregate observed CO₂ fluxes into biogenic and anthropogenic sources by
108 modeling various sources/sinks within the turbulent source area (i.e., flux footprint) of a residential area
109 in Vancouver, Canada. Pawlak and Fortuniak (2016) assessed the temporal variability of CH₄ fluxes in a
110 populated area of Łódź, Poland, and found the city's annual emissions (17.6 g m⁻² year⁻¹) were comparable
111 to surrounding natural sources like wetlands (18 g m⁻² year⁻¹). Menzer and McFadden (2017) used
112 statistical partitioning of CO₂ fluxes over a suburban neighborhood outside Saint Paul, Minnesota, (US-
113 KUO: KUOM tower) to separate biogenic from anthropogenic sources.

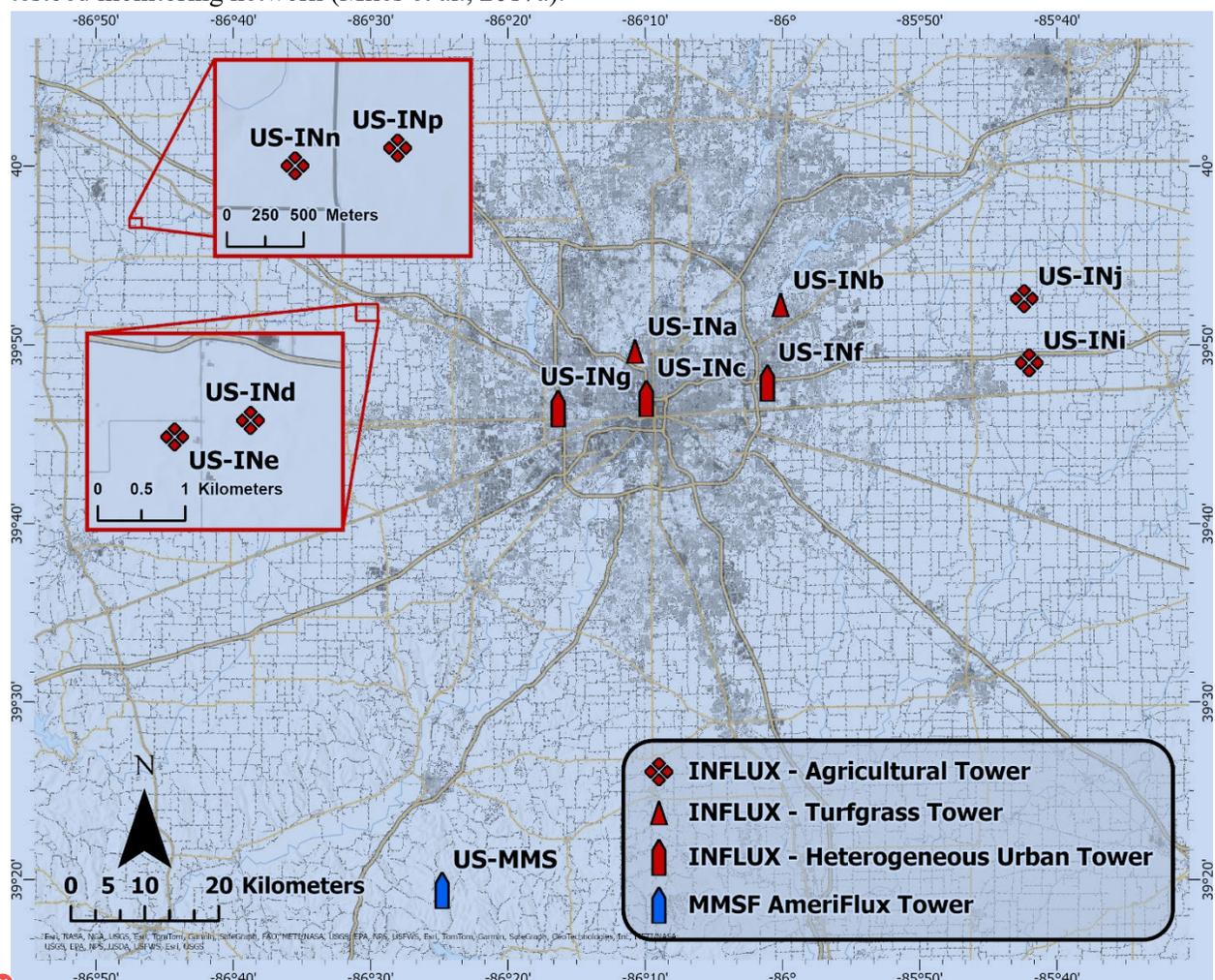
114
115 Recent studies have employed an increasing number of urban EC measurements to study surface-
116 atmosphere fluxes across multiple cities (Lipson et al., 2022; Nicolini et al., 2022; Papale et al., 2020).
117 Nicolini et al. (2022) compared thirteen EC towers in eleven different European cities to assess the
118 impacts of the COVID-19 lockdown on CO₂ emissions. They found a significant relationship between
119 factors such as the lockdown stringency index and the relative CO₂ flux change (i.e., before vs. during
120 lockdown), demonstrating the value of EC measurements in detecting both long-term and short-term
121 changes in CO₂ fluxes in real-time. The Urban-PLUMBER project (<https://urban-plumber.github.io/>)
122 gathered measurements from twenty flux towers located all over the world, creating a dataset of urban EC
123 measurements covering a spectrum of different climatic conditions and urban forms, and has used these
124 data for urban land surface model evaluation (Lipson et al., 2022).

125
126 Most recently, intra-urban networks have begun to emerge. Multiple towers within and outside a single
127 city enable a more detailed understanding of the urban system than could be achieved with a single flux
128 tower. For example, Nicolini et al. (2022) were able to use paired towers within the same city (e.g.,
129 residential vs. non-residential) to infer qualitative information on the dominant CO₂ driver (e.g., vehicular,
130 vegetation, etc.). Peters et al. (2011) showed the benefit of measuring turfgrass lawns using a short-stature
131 (1.35 m) tower to help interpret evapotranspiration (ET) measurements made on the KUOM tall tower (40
132 m) in Saint Paul, Minnesota. In recent years there has been an expansion of urban EC in the United States
133 through projects like the Indianapolis Flux Experiment (INFLUX, Davis et al., 2017), the Baltimore
134 Social and Environmental Collaborative (BSEC), the Coastal Rural Atmospheric Gradient Experiment
135 (CoURAGE, Davis et al., 2024), the Community Research on Climate and Urban Science (CROCUS,
136 Raut et al., 2025), and the Southwest Urban Integrated Field Laboratory (SW-IFL, 2024).

137
138 INFLUX was a contribution to the urban greenhouse gas test beds program of the National Institute of
139 Standards and Technology (Semerjian and Whetstone, 2021). This program endeavored to “improve
140 emission measurement tools to better equip decision makers and mitigation managers with capabilities to
141 chart progress in GHG emissions mitigation” ([https://www.nist.gov/greenhouse-gas-measurements/urban-
142 test-beds](https://www.nist.gov/greenhouse-gas-measurements/urban-test-beds)). The INFLUX project was the longest-running test bed in this program. Atmospheric inversions
143 were the primary technological approach employed for urban GHG emissions estimates in the test bed
144 program (Karion et al., 2023; Lauvaux et al., 2020; Yadav et al., 2023), given their ability to encompass
145 emissions from the entirety of an urban area. Atmospheric inversions struggle, however, to infer the
146 spatial structure of emissions within a city (e.g. Lauvaux et al., 2020). EC flux towers, long used to study
147 fluxes at a spatial resolution more accessible to local-scale, process-based model evaluation, have been
148 deployed in INFLUX to complement whole-city atmospheric inversions.

149
150 The INFLUX EC flux towers measured CO₂, H₂O, energy, and momentum fluxes in and around
151 Indianapolis. The network included EC flux observations from eleven locations (Fig. 1), comprising over
152 a decade and a half of observation site years (Table 1, Fig. 2). These tower locations range from
153 agricultural sites in the croplands surrounding Indianapolis to towers in the cities’ interior over turfgrass,
154 suburban forests, residential areas, and heavily developed urban regions (Fig. 1). This multiplicity of flux
155 sites was achieved by moving instrumentation from site to site as deemed necessary to sample the
156 variability in fluxes in and around this urban landscape. A subset of the flux measurements (Table 1) have

157 been co-located with mole fraction observations (Richardson et al., 2017) from the INFLUX urban GHG
 158 testbed monitoring network (Miles et al., 2017a).



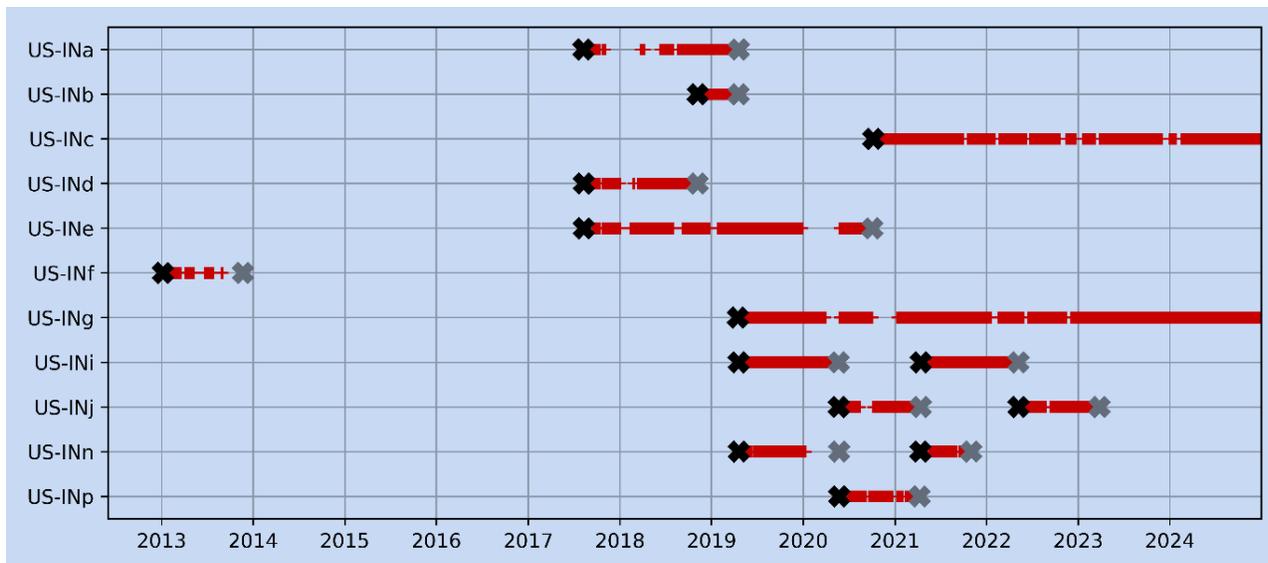
159 **Figure 1.** Locations of INFLUX eddy covariance towers in and around Indianapolis, IN. Specific flux
 160 tower site locations (i.e., latitude and longitude) are included in the site metadata file with the processed
 161 data files. The gray shading represents the 2023 impervious surface cover from the National Land Cover
 162 Database (doi.org/10.5066/P9JZ7A03). Major roadways are depicted using orange lines, and waterways
 163 are shown in light blue. The Morgan-Monroe State Forest (MMSF) AmeriFlux tower is also included for
 164 spatial reference. Service layer credits go to City of Indianapolis, Marion County, Esri, TomTom,
 165 Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, USFWS, and GeoTechnologies Inc.

167 **Table 1.** Site identification in FLUXNET format, deployment period, and a short description of each site.
 168

Site – Category	Time Start	Time End	Site Description
US-INa – Turfgrass	August 2017	April 2019	Pioneer Cemetery in Crown Hill Cemetery tower measured a minimally managed turfgrass lawn. Primarily cool-season C3 grass species.

US-INb – Turfgrass	November 2018	April 2019	The Fort Golf Resort tower measured a heavily managed turfgrass lawn. Primarily cool-season C3 grass species.
US-INc – Heterogeneous Urban	October 2020	May 2025	The downtown Indianapolis tower measured an urbanized, heterogeneous area and is also mole fraction site 03*.
US-INd – Agricultural	August 2017	November 2018	An agricultural tower near Pittsboro measured a mixture of corn and soy.
US-INe – Agricultural	September 2017	October 2020	An agricultural tower near Pittsboro measured corn (2018 and 2020) and soy (2019).
US-INf – Heterogeneous Urban	January 2013	November 2013	The tower at East 21st St measured a heterogeneous commercial and residential area, and also corresponds to the mole fraction site 02*.
US-ING – Heterogeneous Urban	April 2019	May 2025	Wayne Twp Comm tower measures a heterogeneous residential and commercial area and is also mole fraction site 07*.
US-INi – Agricultural	April 2019	May 2022	The agricultural tower measured soy (2019) and corn (2021). Located near mole fraction site 09*.
US-INj – Agricultural	May 2020	March 2023	The agricultural tower measured corn during both growing seasons (2020 and 2022). Located near mole fraction site 09*.
US-INn – Agricultural	April 2019	October 2021	Agricultural tower measured corn during 2019 and 2021. Located near mole fraction site 14*.
US-INp – Agricultural	May 2020	April 2021	The agricultural tower measured a mixture of corn and turfgrass in 2020. Located near mole fraction site 14*.

169 * Mole fraction towers and their numbers are described in Miles et al. (2017a).



170
 171 **Figure 2:** Data availability at each site through 2024. Each half-hour data point is indicated by a red "+",
 172 flux instrumentation deployment dates are indicated by black x's, and flux instrumentation
 173 decommissioning dates are indicated by gray x's. Any missing data between the deployment and
 174 decommissioning dates is due to power loss or instrument malfunction.

175 This paper documents the urban EC measurements undertaken as part of the INFLUX project. We discuss
 176 methods for quality-controlling the INFLUX EC measurements and describe the groups of EC flux sites
 177 within the INFLUX project (i.e., agricultural, turfgrass, and heterogeneous urban towers). We present the
 178 data processing required to interpret the data within this urban network and document the availability of
 179 data products.

180 **2 INFLUX Eddy Covariance Tower Network**

181 **2.1 General Climate**

182
 183 The INFLUX project is based in and around Indianapolis, IN, USA. The city of Indianapolis and the
 184 surrounding area are on the boundary of two Köppen climate classifications, Dfa and Cfa (Kottek et al.,
 185 2006) at an elevation of approximately 220m above sea level. We reference data from the National
 186 Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information
 187 (NCEI) to provide averages for the period between 1991 and 2025. Indianapolis receives, on average,
 188 approximately 111 cm of liquid precipitation and 65 cm of snowfall (depth) annually. The annual average
 189 daily high and low temperatures are 17°C and 7°C, respectively.

191 **2.2 Flux tower sites and site categories**

192
 193 The INFLUX flux towers can be subdivided into heterogeneous (US-INc, US-ING, US-INF) and
 194 homogeneous sites. Within the homogeneous grouping, we further subdivide the towers into agricultural
 195 (US-INd, US-INE, US-INi, US-INj, US-INn, US-INp) and turfgrass (US-INa, US-INb) categories. Each
 196 site is equipped with a sonic anemometer, either a Gill WindMaster (WindMaster, Gill Instruments,
 197 Lymington, UK) or CSAT3 (CSAT3, Campbell Scientific, Logan, UT, USA), and an infrared gas

198 analyzer (LI-7500DS or LI-7500A, LI-COR Biosciences, Lincoln, NE, USA) collecting data at 10Hz
 199 frequency (Table 2). The low-stature towers are also equipped with a temperature and humidity probe
 200 (HMP155, Vaisala Oyj, Vantaa, Finland), and a subset of them are equipped with photosynthetically
 201 active radiation (PAR) sensors (LI190R, LI-COR Biosciences, Lincoln, NE, USA) (Table 2). US-INc and
 202 US-INg were equipped with 4-way net radiometers (CNR4, Kipp and Zonen, Delftechpark, Netherlands)
 203 in October 2023 and March 2024, respectively. In addition to the INFLUX EC towers, the AmeriFlux
 204 Core Site US-MMS (Fig. 1), located in the Monroe-Morgan State Forest, is approximately seventy
 205 kilometers to the southwest of Indianapolis (Dragoni et al., 2011; Schmid et al., 2000).

206
 207 **Table 2.** Measurement heights of deployed eddy covariance instruments and flux instruments for each
 208 site.

Site Category	EC measurement height AGL	Infrared gas analyzer	Sonic anemometer	Temperature/ Humidity	PAR	Net Radiation	Arable
US-INa – Turfgrass	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	-	-	-
US-INb – Turfgrass	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	-	-	-
US-INc – Mixed Urban	43 m	Licor LI-7500A	Campbell CSAT3	-	-	Kipp & Zonen CNR4 (10/2023)	-
US-INd – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	-	-	-
US-INe – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	-	-	Yes
US-INf – Mixed Urban	30 m	Licor LI-7500A	Campbell CSAT3	-	-	-	-
US-INg – Mixed Urban	41 m	Licor LI-7500DS	Gill WindMaster	-	-	Kipp & Zonen CNR4 (03/2024)	-
US-INi – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	Licor LI190R	-	-
US-INj – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	Licor LI190R	-	Yes
US-INn – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	Licor LI190R	-	-
US-INp – Agricultural	3 m	Licor LI-7500A	Campbell CSAT3	Vaisala HMP155	-	-	Yes

209
 210 **2.3 Data acquisition and organization**
 211

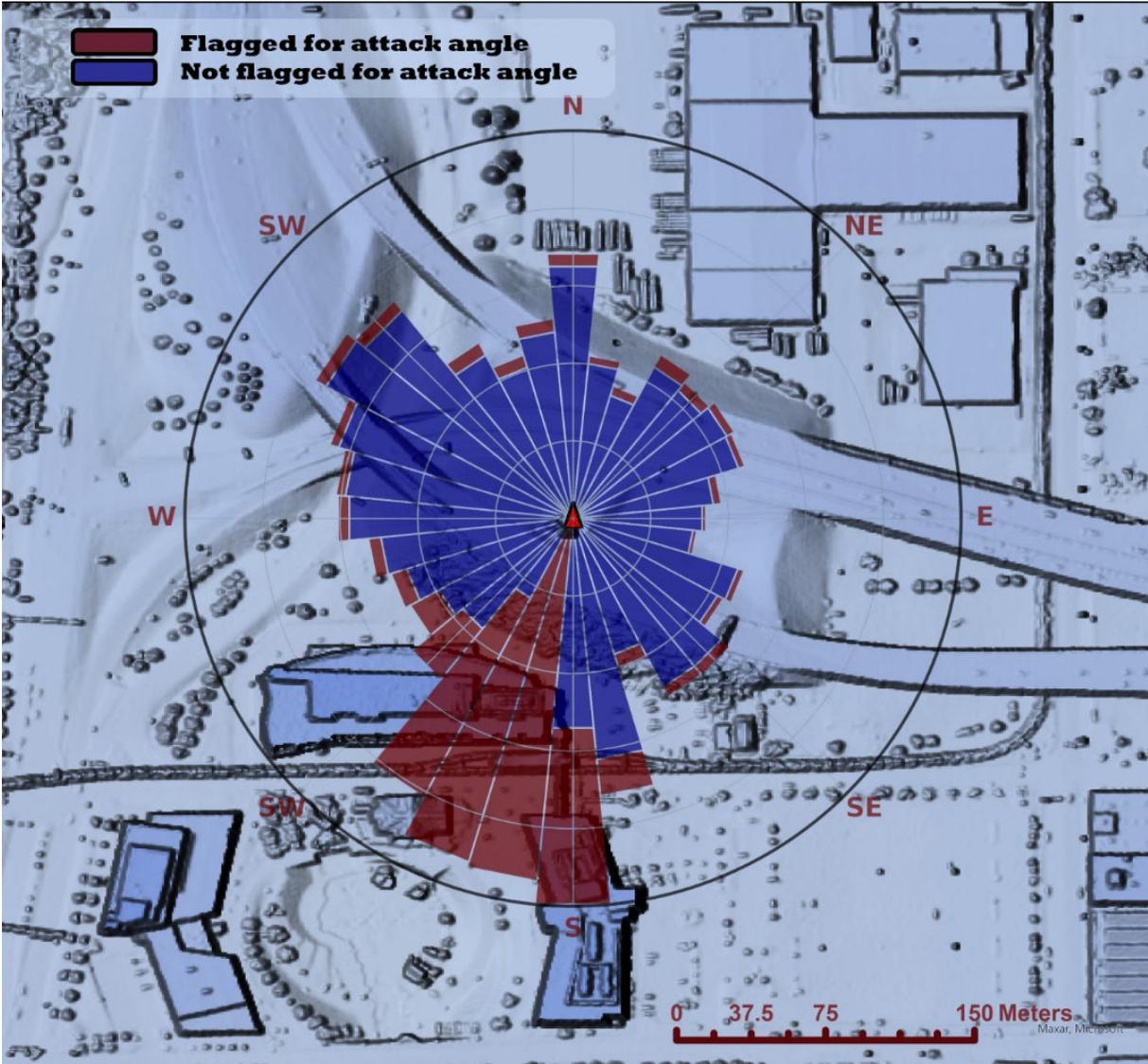
212 The INFLUX EC instruments produce 10 Hz GHG data files, each containing thirty minutes of
213 continuous data; 48 files per day. The GHG file is then transferred from the logger to a Linux server using
214 the Secure Socket Shell (SSH) file transfer protocol. Each instrument has a unique incoming directory
215 where the files are stored. Every night, a set of shell scripts checks to see if all 48 files have been
216 delivered. Furthermore, every night, GHG files are copied to an archive while the data files are checked
217 for (i) readability for further processing (occasionally some files are corrupt), (ii) monotonically time
218 increase of recorded data (will be automatically corrected if possible), (iii) any non-ASCII characters
219 which could cause problems during further scientific processing), (iv) incomplete data rows. Emails are
220 automatically generated if any fault is recognized, while copies of the automatically modified and
221 corrected data files are saved. Each step is captured in a log file. Missing data, errors, and file
222 modifications due to errors trigger an email notification. These checks test file integrity and data
223 completeness. Once the integrity tests are completed, the data is automatically processed and analyzed
224 using EddyPro (LI-COR, 2021) and Python scripts. Graphics of the processed data (a two-week data
225 window) are automatically updated online, allowing for manual monitoring of the incoming data and
226 quick identification and resolution of issues. This allows researchers to quickly determine whether the
227 instruments produce reasonable results or require immediate attention.

228 229 2.4 Flux processing and quality control

230
231 The complete time series of fluxes is calculated separately from the automatic processing script using a
232 set of distinct post-processing steps and the EddyPro software package. For a comparison between
233 EddyPro and other commonly used software (e.g., TK3 and eddy4R) when processing fluxes at
234 heterogeneous urban flux towers, please see Lan et al. (2024). For every thirty minutes, we apply a block-
235 averaging detrending (Foken, 2008; Lee et al., 2004) and planar fit coordinate rotation (Lee et al., 2004;
236 Paw U et al., 2000; Wilczak et al., 2001). The Vickers and Mahrt (1997) despiking procedure is done
237 before calculating fluxes, spikes are removed, and the number of spikes is reported. As the molar
238 densities are measured by open-path sensors (LI-7500A or LI-7500DS), we apply the Webb, Pearman,
239 and Leuning correction for density fluctuations (Lee and Massman, 2011; Paw U et al., 2000; Webb et al.,
240 1980) following the iterative methodology employed in EddyPro. The cospectra are corrected (high and
241 lowpass) via the analytical methods of Moncrieff et al. (1997), which is based on the methods of Moore
242 (1986) using the similarity-based cospectral models from Kaimal et al. (1972). For each averaging period,
243 using the methods of Vickers and Mahrt (1997), a set of flags is generated based on the high-frequency
244 measurements. The deployment at US-INf was a preliminary effort that did not follow these same
245 procedures. We employed a locally written EC code (Shi et al., 2013) that includes planar fit rotation and
246 Vickers and Mahrt (1997) despiking algorithms. Due to differences in the data acquired for this system,
247 we were unable to apply the data processing used for the remaining INFLUX towers. The US-INf data are
248 described in more detail in Sarmiento et al. (2017) and Wu et al. (2022).

249
250 Flux data are flagged for violating an angle of attack test if $>10\%$ of the wind vectors exceed an attack
251 angle of $>|30^\circ|$ for the averaging period. In the urban environment, the attack angle can be used to
252 examine the impact of wake turbulence generated by roughness elements (RE) within the tower's
253 footprint. For example, wind directions from the southwest ($180\text{--}225^\circ$) of US-INc (Fig. 3) are flagged \geq
254 30% of the time, detecting wake turbulence generated by a 30 m tall building 100 m southwest of the

255 tower. From these impacted wind directions, the measured fluxes are not within the inertial sublayer (i.e.,
256 the constant flux layer), where traditional EC assumptions are potentially valid.



257
258 **Figure 3.** Percent of total data (i.e., all wind directions) flagged (radial) as a binary attack angle flagging
259 (red/blue) vs. wind direction (angular) at US-INc (Oct 2020 – Jan 2023). Radial scales show 1.1, 2.2, 3.3,
260 4.4, and 5.6 percent of the total data moving from the inner to the outer ring, respectively. The red triangle
261 represents the location of US-INc. The base map is a digital surface map generated using 2016 Indiana
262 Statewide 3DEP LiDAR Data Products for Marion County (USDA, 2016). Service layer credits go to
263 Maxar and Microsoft.

264
265 Fluxes are also flagged using a suite of quality control tests available through EddyPro, which are
266 commonly used in EC research. Stationarity tests are conducted for each half-hour using the methodology
267 of Foken and Wichura (1996) and Vickers and Mahrt (1997). Modeled integral turbulence characteristics
268 from flux variance similarity theory are compared to measured variances of winds and scalars using the
269 methods of Foken and Wichura (1996). Depending on the degree of nonstationarity and deviation from
270 flux similarity theory, as determined by the Foken and Wichura (1996) tests, each averaging period is

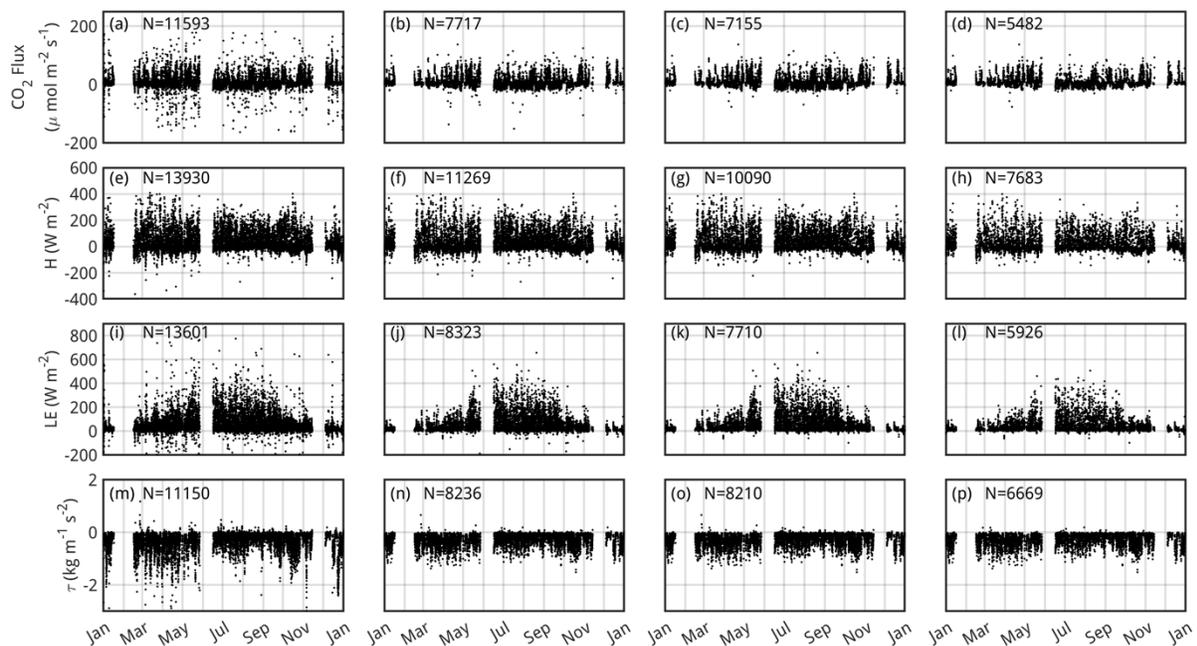
271 assigned a value (1-9) based on the scheme of Mauder and Foken (2004). When comparing measurements
272 made at the heterogeneous urban towers to similarity predictions, it is worth noting that aerodynamic
273 parameters, such as displacement height, are often directionally dependent (Kent et al., 2018). Thus, the
274 similarity-based relationship should scale differently depending on the wind direction. Subtle details, such
275 as these, are not included in the current version of EddyPro, but the software's default flags, generated (as
276 discussed here), can still guide users in interpreting the data.

277
278 For two agricultural sites, US-INn and US-INp, periods of the high-frequency data were lost, and only a
279 version of the processed thirty-minute data using the default EddyPro settings was recovered. At US-INn,
280 the period is from April 21, 2019, 00:00 UTC to January 10, 2020, 03:30 UTC, and at US-INp, it is from
281 May 23, 2020, 21:30 UTC to December 22, 2020, 16:00 UTC. For these periods, a double rotation rather
282 than a planar fit is used, and fluxes are flagged based on a simplified version of the 1-9 scheme, as
283 outlined in the Spoleto agreement of 2004 for CarboEurope-IP, as described in Mauder and Foken (2004).
284 These periods of missing high-frequency data have been combined with those where the high-frequency
285 data is available, resulting in a mixture of flagging schemes and coordinate rotation in some columns.

286
287 After calculating half-hourly fluxes, additional screening methods generate flags based on periods with
288 weak gas analyzer signals, extreme flux values, or inadequate mechanical mixing during nocturnal
289 periods. The data are flagged if the signal strength reported by the gas analyzer for a half-hour period falls
290 below the mean signal strength for a moving window of two weeks. Nighttime data (i.e., periods when the
291 solar altitude is $\leq 0^\circ$) are flagged during low turbulent intensities based on the methods of Goulden et al.
292 (1996). We acknowledge that the use of friction velocity filters in urban areas is still under question
293 (Papale et al., 2022); a consensus has not been reached. We assert that this remains a valuable screening
294 tool that we apply to this dataset. Finally, the flux data are flagged based on a threshold of N standard
295 deviations from the mean, where N is a site-specific number chosen to keep flux magnitudes within
296 geophysical limits.

297
298 We provide processed, half-hourly flux datasets for each of the eleven INFLUX sites through Penn State
299 Data Commons and Ameriflux (See Section 3). Included with these data are metadata files with
300 information on details such as flagging thresholds (e.g., friction velocity threshold) or site geographic
301 coordinates. We do not remove data based on the generated flags for the data set available on Penn State
302 Data Commons; instead, we leave the filtering decisions to the users. For most use cases, we do not
303 recommend eliminating all points flagged using the quality control flags provided by the methods of
304 Vickers and Mahrt (1997) and Mauder and Foken (2004), as a large proportion of physically reasonable
305 data is flagged. We give an example of four different quality control flag combinations for CO₂, latent
306 heat, sensible heat, and momentum fluxes using observations at Site US-INg in Fig. 4. The four quality
307 control flag combinations for each of these fluxes are summarized in Table 3. We recommended at
308 minimum filtering the data according to friction velocity and CO₂ flux standard deviation flags for
309 analysis of CO₂ fluxes, sensible heat standard deviations flags for analysis of sensible heat fluxes, latent
310 heat standard deviation flags for analysis of latent heat fluxes, and removing wind directions from which
311 the measurement is impacted by distortion due to the tower (for Site US-INg, observations from wind
312 directions 30-135° should be removed) for momentum fluxes (Set 1 in Table 3). From wind directions
313 where the towers distort the flow, we do not observe a clear impact on scalar fluxes; thus, we leave the
314 decision for removal to the data user. To remove additional outlier points, we suggest filtering by Sets 2 or

315 3 (Table 3) as shown in Fig. 4b and Fig. 4c for CO₂ fluxes, Fig. 4f and Fig. 4g for sensible heat fluxes,
 316 Fig. 4j and Fig. 4k for latent heat fluxes, and Fig. 4n and Fig. 4o for momentum fluxes. Given the
 317 significant reduction of overall data points, we do not suggest the flagging combination of Set 4, as shown
 318 in Fig. 4d, h, l, and p, unless the application of the data requires the strictest turbulence screening, which
 319 is appropriate only if the most idealized conditions for EC flux measurements are needed. At the
 320 heterogeneous urban flux towers (US-INc and US-INg), we recommend not removing scalar flux data
 321 based on the Vickers and Mahrt (1997) higher-moment statistics (i.e., skewness and kurtosis), as these
 322 flags commonly target realistic data at these sites (Järvi et al., 2018). This is due to the spatial and
 323 temporal heterogeneity of the urban environment, which can cause the distribution of high-frequency
 324 scalar measurements for a single period often to exceed the default skewness or kurtosis thresholds in
 325 EddyPro.



326
 327 **Figure 4.** CO₂ fluxes (panels (a)-(d)), sensible heat fluxes (H) (panels (e)-(h)), latent heat fluxes (LE)
 328 (panels (i)-(l)), and momentum fluxes (τ) (panels (m)-(p)) at Site US-INg for 2022 with different quality
 329 control flags applied. From left to right, the filtering sets 1, 2, 3, and 4 (see Table 3 for full set
 330 descriptions) are shown for each of the fluxes, representing a range of filtering choices from least to most
 331 stringent. The number of points remaining in the dataset after removing quality control flags is indicated
 332 on each panel. With no filtering applied, there are 13,779 CO₂ flux data points, 13,969 sensible heat data
 333 points, 13,697 latent heat flux data points, and 13,969 momentum flux data points. For filtering Sets 1, 2,
 334 3, and 4, respectively, 84.1%, 56.0%, 51.9%, and 39.7% of the total CO₂ flux data are preserved, 99.7%,
 335 80.6%, 72.2%, and 55.0% of sensible heat flux data are preserved, 99.2%, 60.7%, 56.2%, and 43.2% of
 336 latent heat flux data are preserved, and 79.8%, 58.9%, 58.7% and 47.7% of momentum flux data are
 337 preserved.

338 **Table 3:** Description of quality control flag combinations considered for CO₂, sensible heat (H), latent
 339 heat (LE), and momentum (τ) fluxes. The hard flag is abbreviated as 'hf' in the table.

Flux	Set 1	Set 2	Set 3	Set 4
------	-------	-------	-------	-------

CO₂ 	Friction velocity	Friction velocity	Friction velocity	Friction velocity
	CO ₂ flux standard deviation	CO ₂ flux standard deviation	CO ₂ flux standard deviation	CO ₂ flux standard deviation
		Spike hf w	Spike hf w	Spike hf w
		Amplitude resolution hf w	Amplitude resolution hf w	Amplitude resolution hf w
		Drop out hf w	Drop out hf w	Drop out hf w
		Absolute limits hf w	Absolute limits hf w	Absolute limits hf w
		Discontinuities hf w	Discontinuities hf w	Skewness and kurtosis hf w
		Spike hf CO ₂	Spike hf CO ₂	Discontinuities hf w
		Amplitude resolution hf CO ₂	Amplitude resolution hf CO ₂	Spike hf CO ₂
		Drop out hf CO ₂	Drop out hf CO ₂	Amplitude resolution hf CO ₂
		Absolute limits hf CO ₂	Absolute limits hf CO ₂	Drop out hf CO ₂
		Discontinuities hf CO ₂	Discontinuities hf CO ₂	Absolute limits hf CO ₂
		Signal strength	Signal strength	Discontinuities hf CO ₂
			CO ₂ QC greater than 5	Signal strength
			CO ₂ QC greater than 5	
			Attack angle hf	
			Nonsteady wind hf	
H	H standard deviation	H standard deviation	H standard deviation	H standard deviation
		Spike hf w	Spike hf w	Spike hf w
		Amplitude resolution hf w	Amplitude resolution hf w	Amplitude resolution hf w
		Drop out hf w	Drop out hf w	Drop out hf w
		Absolute limits hf w	Absolute limits hf w	Absolute limits hf w
		Discontinuities hf w	Discontinuities hf w	Skewness and kurtosis hf w
			H QC greater than 5	Discontinuities hf w
			H QC greater than 5	
			Attack angle hf	
			Nonsteady wind hf	
LE	H ₂ O flux standard deviation	H ₂ O flux standard deviation	H ₂ O flux standard deviation	H₂O flux standard deviation 
		Spike hf w	Spike hf w	Spike hf w
		Amplitude resolution hf w	Amplitude resolution hf w  	Amplitude resolution hf w 
		Drop out hf w	Drop out hf w	Drop out hf w
		Absolute limits hf w	Absolute limits hf w	Absolute limits hf w
		Discontinuities hf w	Discontinuities hf w	Skewness and kurtosis hf w
		Spike hf H₂O	Spike hf H ₂ O	Discontinuities hf w
		Amplitude resolution hf H₂O	Amplitude resolution hf H ₂ O	Spike hf H ₂ O

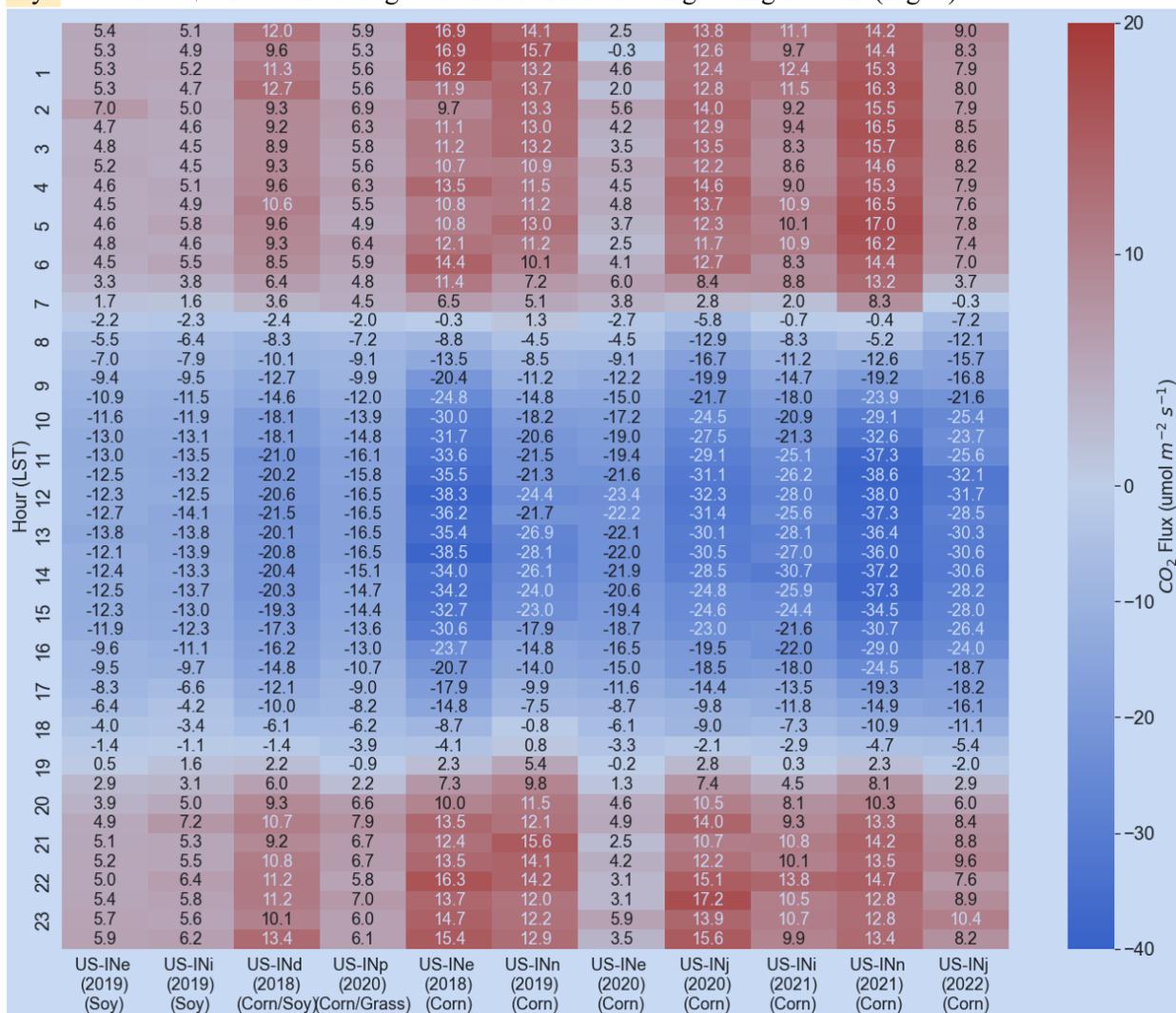
		<p>Drop out hf H₂O</p> <p>Absolute limits hf H₂O</p> <p>Skewness and kurtosis hf H₂O</p> <p>Signal strength</p>	<p>Drop out hf H₂O</p> <p>Absolute limits hf H₂O</p> <p>Skewness and kurtosis hf H₂O</p> <p>Signal strength</p> <p>LE QC greater than 5</p>	<p>Amplitude resolution hf H₂O</p> <p>Drop out hf H₂O</p> <p>Absolute limits hf H₂O</p> <p>Skewness and kurtosis hf H₂O</p> <p>Signal strength</p> <p>LE QC greater than 5</p> <p>Attack angle hf</p> <p>Nonsteady wind hf</p>
τ	Wind directions impacted by tower distortion	<p>Wind directions impacted by tower distortion</p> <p>Spike hf w</p> <p>Amplitude resolution hf w</p> <p>Drop out hf w</p> <p>Absolute limits hf w</p> <p>Discontinuities hf w</p> <p>Spike hf v</p> <p>Amplitude resolution hf v</p> <p>Drop out hf v</p> <p>Absolute limits hf v</p> <p>Discontinuities hf v</p> <p>Spike hf u</p> <p>Amplitude resolution hf u</p> <p>Drop out hf u</p> <p>Absolute limits hf u</p> <p>Discontinuities hf u</p> <p>Attack angle hf</p>	<p>Wind directions impacted by tower distortion</p> <p>Spike hf w</p> <p>Amplitude resolution hf w</p> <p>Drop out hf w</p> <p>Absolute limits hf w</p> <p>Discontinuities hf w</p> <p>Spike hf v</p> <p>Amplitude resolution hf v</p> <p>Drop out hf v</p> <p>Absolute limits hf v</p> <p>Discontinuities hf v</p> <p>Spike hf u</p> <p>Amplitude resolution hf u</p> <p>Drop out hf u</p> <p>Absolute limits hf u</p> <p>Discontinuities hf u</p> <p>QC τ greater than 5</p> <p>Attack angle hf</p>	<p>Wind directions impacted by tower distortion</p> <p>Spike hf w</p> <p>Amplitude resolution hf w</p> <p>Drop out hf w</p> <p>Absolute limits hf w</p> <p>Skewness and kurtosis hf w</p> <p>Discontinuities hf w</p> <p>Spike hf v</p> <p>Amplitude resolution hf v</p> <p>Drop out hf v</p> <p>Absolute limits hf v</p> <p>Skewness and kurtosis hf v</p> <p>Discontinuities hf v</p> <p>Spike hf u</p> <p>Amplitude resolution hf u</p> <p>Drop out hf u</p> <p>Absolute limits hf u</p> <p>Skewness and kurtosis hf u</p> <p>Discontinuities hf u</p> <p>QC τ greater than 5</p> <p>Attack angle hf</p> <p>Nonsteady wind hf</p>

340

341 **2.5 Agricultural Sites**

342

343 Understanding the boundary layer dynamics and CO₂ fluxes surrounding a city is important for
 344 understanding measurements collected within the city. The area surrounding Indianapolis is mainly
 345 composed of agricultural fields planted with a rotation of corn and soybeans. We deployed short-stature
 346 (~3-m AGL) flux towers at six locations in agricultural fields within 30-60 km of downtown Indianapolis
 347 (Fig. 1). The instrumentation for the agricultural sites was, in most cases, relocated annually to sample a
 348 variety of fields (specifically US-INd, US-INe, US-INn, US-INp). Each location was given a different site
 349 key. We collected data at the six agricultural sites for eleven growing seasons (Fig. 5).



350 **Figure 5.** The average summer (JJA) diel cycle of CO₂ fluxes for each agriculture site-year. Each column
 351 is also labeled with the surrounding vegetation. The numbers indicate the average value for each half-hour
 352 flux corresponding to the underlying color. Text color is for visual purposes only.

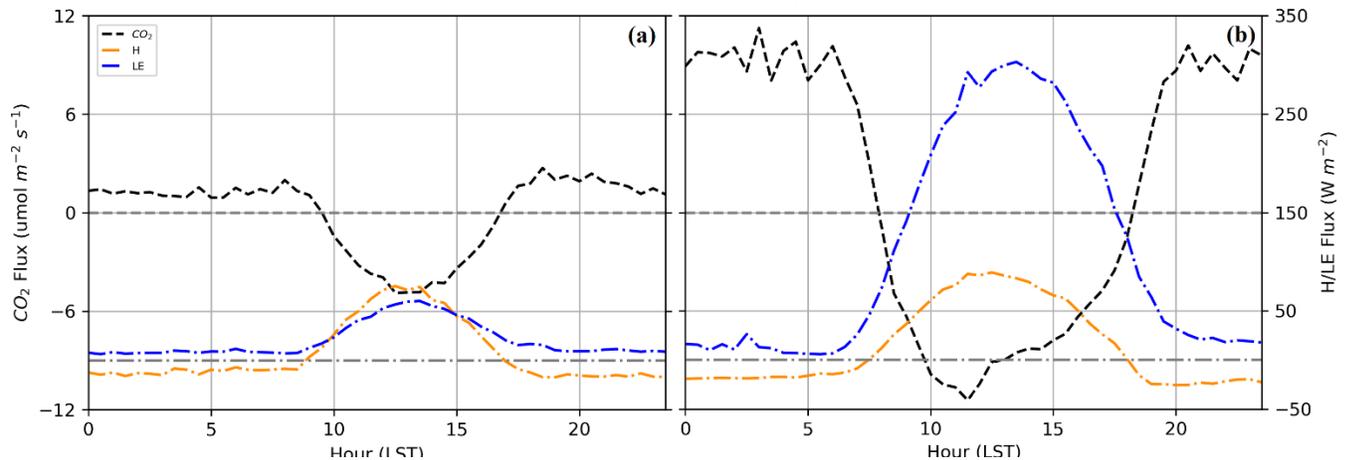
354 Flux footprint analyses are used to identify averaging periods when these agricultural towers may
 355 have been strongly influenced by vegetation other than the crops to be sampled. These conditions arise
 356 from the practical need to place the flux towers close to, but not directly within, the actively managed
 357 crop fields. The fractional coverage of the agricultural crop of interest (corn or soybean) within the
 358 estimated tower footprint was calculated for each agricultural flux site in the INFLUX network. The
 359 calculated fractional coverage values allow a data user to select thresholds for which they would consider

360 the half-hourly flux value representative of the vegetation of interest. The Flux Footprint Prediction (FFP)
361 model, developed by Kljun et al. (2015), is utilized to calculate the vegetation fraction for each point in
362 the data record. Atmospheric boundary layer heights for input into the FFP come from ERA5 reanalysis
363 (Hersbach et al., 2023). Imagery from Google Earth and ArcGIS Pro software is used to visually select
364 areas covered with the vegetation of interest. Areas with the vegetation type of interest are assigned a
365 value of one, while other areas are assigned a value of zero. For all half hours during which the required
366 input data are available, the FFP climatology function simulates footprints at a 1 m grid spacing for a 501
367 m by 501 m domain. The site map distinguishing landcover types and the footprint estimate is multiplied
368 to obtain a gridded map representing only the footprint attributable to the vegetation of interest. For every
369 possible half hour, two values are computed using the predicted footprints: a value representing the
370 footprint attributable to the vegetation of interest and a value for the total footprint. The former is
371 calculated by summing over the footprint attributable to the vegetation of interest, and the latter by
372 summing the footprint over the entire domain. The ratio of these values represents the fraction of the
373 footprint attributable to the vegetation of interest.

374
375 The agricultural EC measurements have been used to evaluate the background conditions for the city.
376 Murphy et al. (2025) evaluated the accuracy and precision of a simple carbon flux model used to describe
377 ecosystem CO₂ fluxes surrounding the city. Ongoing work is evaluating the latent and sensible heat fluxes
378 simulated by numerical weather prediction (NWP) models. These models are necessary for conducting
379 urban climate and GHG inversion studies.

380 381 **2.6 Turfgrass Sites**

382
383 Turfgrass is a common urban land cover (Milesi et al., 2005). Only a handful of towers have previously
384 been deployed to measure turfgrass lawns (i.e., mixed species low-stature vegetation often artificially
385 managed through irrigation, fertilization, and/or mowing) (Ng et al., 2015; Pahari et al., 2018; Pérez-Ruiz
386 et al., 2020; Peters and McFadden, 2012) despite these lawns being an abundant vegetative community in
387 urban areas (Horne et al., 2025). We deployed two flux towers (US-INa and US-INb) to monitor turfgrass
388 lawns. The two INFLUX turfgrass towers captured different levels of management intensity. US-INa
389 measured fluxes over a cemetery lawn (Fig. 6) with lower intensity management (i.e., infrequent mowing,
390 no fertilization, and no irrigation), and US-INb measured fluxes over a golf course (i.e., frequent mowing,
391 fertilization, and irrigation). These towers were of low stature and sited to minimize contributions to the
392 flux footprint from anything other than turfgrass. We have used the CO₂ flux data from these two turfgrass
393 towers to evaluate the Vegetation Photosynthesis and Respiration Model (VPRM) performance at
394 reproducing seasonal turfgrass fluxes, finding that these lawns require a unique representation in the
395 VPRM (Horne et al., 2025). These towers are also being used in ongoing analyses of the sensible and
396 latent heat fluxes in NWP models.



397
 398 **Figure 6.** The average winter (DJF) (a) and summer (JJA) (b) diel cycle of latent heat (LE), sensible heat
 399 (H), and CO₂ fluxes for US-INa (cemetery lawn). Data for averaging are taken from the periods over the
 400 site deployment (Aug 2017 – April 2019). The dashed and dashed-dot horizontal lines indicate zero
 401 crossings for the CO₂ or sensible and latent heat flux, respectively.

402

403 2.7 Heterogeneous Footprint (Mixed) Urban Flux Towers

404

405 Three communications towers with EC instrumentation at 30 to 43 m AGL were instrumented to measure
 406 fluxes from the complex, mixed land cover typical of urban environments. These higher-altitude
 407 measurements are necessary to measure fluxes above the trees and buildings commonly found throughout
 408 the metropolitan area. As mentioned, these towers host flux instrumentation and mole fraction
 409 measurements that are part of the INFLUX urban GHG testbed monitoring network (Miles et al., 2017a;
 410 Davis et al., 2017). In addition, publicly available high-resolution data, although not included here, are
 411 available and can complement specific investigations, aiding users in interpreting measurements.

412 Footprint climatologies generated using the Kljun et al. (2015) FFP model for the INFLUX mixed urban
 413 flux towers are shown in Figs. 7. We include footprint climatologies for these sites alone to show the level
 414 of heterogeneity at each site and the estimated area measured by these towers. These footprint
 415 climatologies guide our characterization of the regions sampled by these towers. We describe broad
 416 characteristics of the urban landscapes in their flux footprints following the example of the Urban-
 417 PLUMBER project (<https://urban-plumber.github.io/>, Lipson et al., 2022). Table 4 provides metadata for
 418 the area surrounding the three heterogeneous urban flux towers (US-INc, US-INf, US-INg). In Table 4,
 419 values for roughness length (z_0) and displacement height (z_d) are provided. These length scales are
 420 simultaneously fitted using the logarithmic wind profile and isolating measurement periods during near-
 421 neutral conditions ($|z/L| < 0.05$, where z is the height of the EC measurement and L is the measured
 422 Obukhov length), where the tower frame does not impact the measurement. These provided z_d and z_0
 423 values serve as a reasonable first-order estimate for use in a flux footprint model. It should be noted that
 424

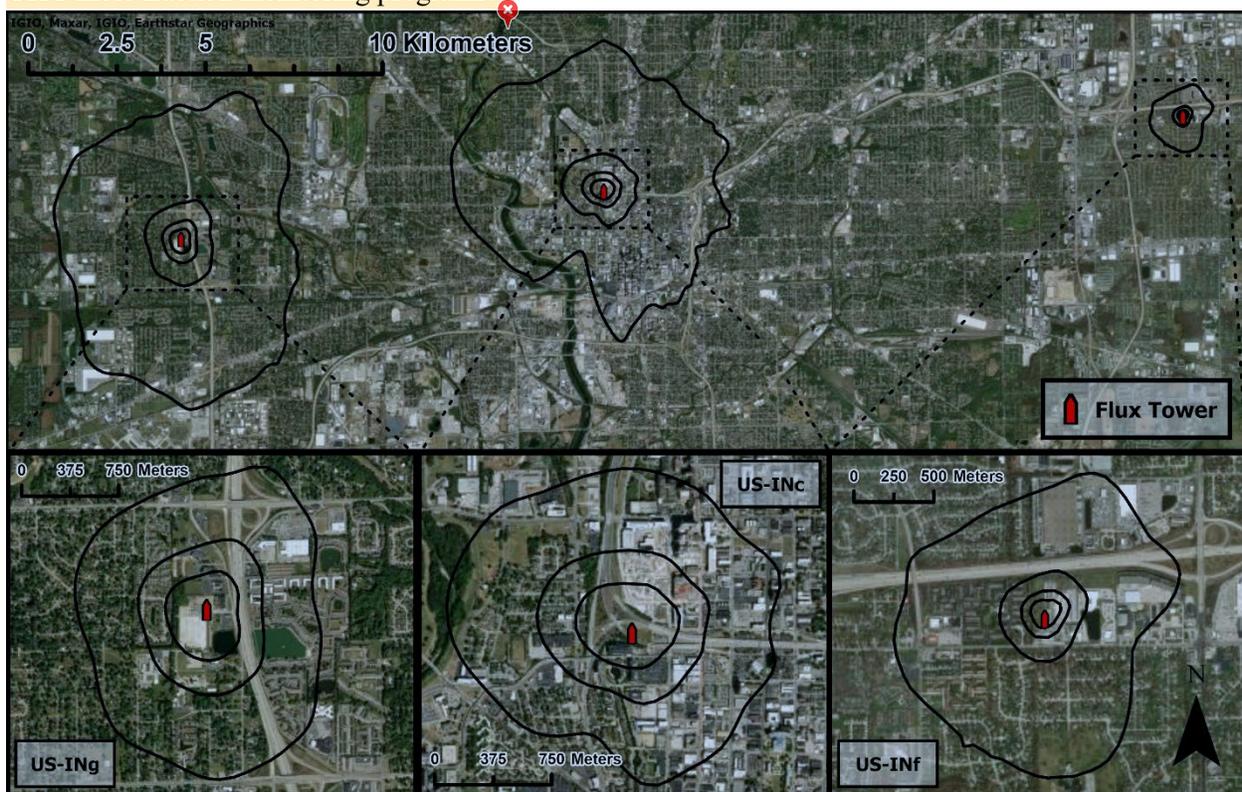
425 **Table 4.** Metadata for the surrounding land cover at the three heterogeneous flux towers. We include
 426 values of roughness length (z_0) and displacement height (z_d) for each of the towers. The domain is 4 km²
 427 centered around the respective tower and separated into quadrants NE [0-90°), SE [90-180°), SW [180-
 428 270°), and NW [270-360°) to capture heterogeneity surrounding the tower. Data for percent impervious

429 and canopy fractions come from the National Land Cover Database (NLCD) using data for 2021 (US-INc
 430 and US-INg) and 2013 (US-INF) (doi.org/10.5066/P9JZ7AO3). LiDAR data used to estimate roughness
 431 elements (RE) (buildings and trees $\geq 2\text{m}$) characteristics comes from the 2016 Indiana Statewide 3DEP
 432 LiDAR Data Products for Marion County (USDA, 2016). Roughness element density is the ratio of
 433 surface area occupied by REs to total surface area (i.e., planar area index).

Site	Quadrant	Local Climate Zone (LCZ)	Percent		Planar density ($\text{m}^2 \text{m}^{-2}$)	Mean RE height (m)	RE standard deviation (m)	Maximum RE height (m)
			Percent impervious (%)	tree cover (%)				
US-INc (43m AGL)	NE	LCZ 8 (Large low-rise)	86	1	0.29	10.6	8.9	53
z_0 : 0.33m	SE	LCZ 8 (Large low-rise)	85	2	0.32	9.4	8.7	57
z_d : 2m	SW	LCZ 6 (Open low-rise)	69	5	0.33	6.9	5.2	36
	NW	LCZ 6 (Open low-rise)	58	6	0.23	5.8	3.7	25
US-INF (30m AGL)	NE	LCZ 8 _{Bc} (Large low-rise with scattered trees)	67	4	0.27	6.1	2.7	30
z_0 : 0.17m	SE	LCZ 6 (Open low-rise)	41	12	0.31	5.1	2.4	25
z_d : 4m	SW	LCZ 6 (Open low-rise)	41	14	0.43	5.2	2.4	31
	NW	LCZ 6 (Open low-rise)	49	11	0.35	5	2.1	23
US-INg (41m AGL)	NE	LCZ 8 _B (Large low-rise with scattered trees)	64	4	0.19	5.4	2.1	25
z_0 : 0.11m	SE	LCZ 6 (Open low-rise)	50	6	0.22	5.4	2.2	22
z_d : 1.5m	SW	LCZ 6 (Open low-rise)	35	12	0.33	5.4	2.6	34
	NW	LCZ 6 (Open low-rise)	42	15	0.33	4.9	2.2	22

434
 435 data from these towers have been employed in multiple previous studies. Wu et al. (2022) demonstrated a
 436 method of disaggregation using INFLUX EC data and mole fraction measurement profiles available at the
 437 three INFLUX mixed urban flux towers (Richardson et al., 2017; Miles et al., 2017a), as well as tracer

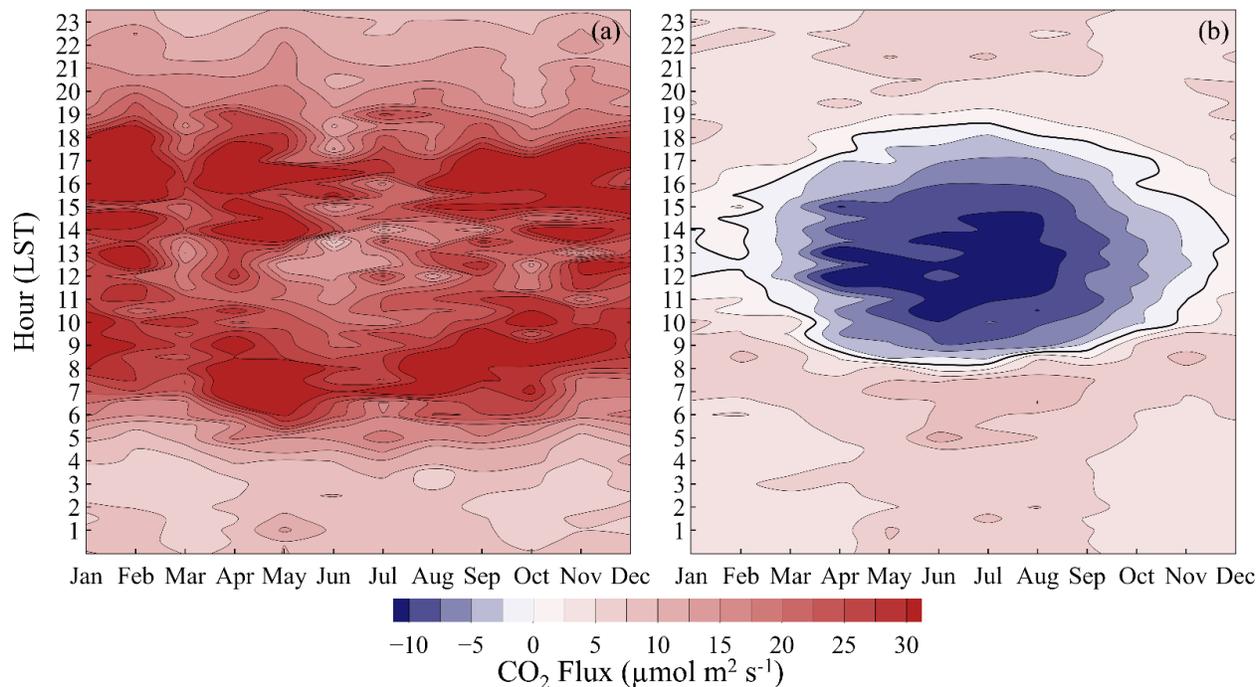
438 ratio methods. This methodology estimates the fossil fuel component of the CO₂ flux by combining
 439 carbon monoxide (CO) flux estimates with measurements of the CO to CO₂ flux ratio from fossil fuel
 440 combustion (Turnbull et al., 2015). The biogenic CO₂ flux is then determined by subtracting the fossil
 441 fuel flux from the total CO₂ flux measured via EC. Vogel et al. (2024) applied this methodology to the
 442 flux record from US-INg to study changes in emissions caused by the COVID-19 lockdown. Both Wu et
 443 al. (2022) and Vogel et al. (2024) employed flux footprint and tracer decomposition methods in
 444 conjunction to compare the EC measurements with the Hestia urban emissions inventory (Gurney et al.,
 445 2012). Kenion et al. (2024) used US-INc EC flux data to demonstrate our ability to infer local-scale urban
 446 GHG fluxes using flux-gradient and flux-variance methods. These approaches can be applied to mole
 447 fraction measurement sites that are relatively abundant across the NIST urban test beds and other urban
 448 GHG mole fraction monitoring programs.



449 **Figure 7.** Flux footprint climatologies for all three heterogeneous urban flux towers are shown. Footprint
 450 climatologies are created using the Kljun et al. (2015) flux footprint prediction (FFP) model and available
 451 data from 2022 (US-INc and US-INg) or 2013 (US-INF). Boundary layer height data for FFP are provided
 452 by ERA5 reanalysis. The outermost climatology boundary represents 90% of the area, and extents moving
 453 towards the respective tower represent a 20% decrease in climatological area (i.e., 70%, 50%, 30%).
 454 Wind directions impacted by the building wake (Fig. 2) at US-INc are removed. Zoomed-in maps of the
 455 area around each tower are provided, with their extent shown by the dashed outlines on the upper plot.
 456 Service layer credits go to Earthstar Geographics, IGIO, and Maxar.

458
 459 Two mixed urban flux towers, US-INF and US-INg, can each be interpreted as two distinct flux tower
 460 sites. We describe these differences in terms of building and vegetation cover (Table 4) and local climate
 461 zones (LCZ) (Stewart and Oke, 2012). The EC instruments at US-INg, for example, are set between a
 462 highway (LCZ E – Bare rock or paved) and commercial buildings (LCZ 8_B – Large low-rise with

463 scattered trees) to the east and a forested residential neighborhood (LCZ 6 - Open low-rise) to the west.
 464 The two sectors exhibit dissimilar diel patterns of CO₂ fluxes (Fig. 8). To the west, we observe a
 465 photosynthetic drawdown from the suburban forest during the growing season. To the east, we can
 466 observe two distinct peaks in net emissions, corresponding to morning and evening rush-hour traffic
 467 (Vogel et al., 2024). We suggest interpreting these sectors independently, potentially thought of as two
 468 distinct flux towers. Similarly, the footprint at US-INf is divided roughly into northerly and southerly
 469 sectors (Table 4), with highway and commercial areas to the north and residences to the south. Multiple
 470 INFLUX studies (Vogel et al., 2024; Kenion et al., 2024; Wu et al., 2022) have shown that the results are
 471 highly interpretable using this simple wind direction interpretation.



472
 473 **Figure 8.** Isopleths of measured CO₂ flux at US-ING (April 2019 - January 2023) as a function of time of
 474 year (x-axis) and time of day (y-axis) for a) westerly wind directions (180 - 360°) and b) easterly wind
 475 directions (0 - 180°). Positive values indicate net emissions of CO₂; negative values indicate a net uptake
 476 of CO₂.

477 We have not divided the flux data from US-INf and US-ING into two distinct records, nor have we posted
 478 flux footprint data sets to accompany each flux tower. However, the flux tower records contain all the
 479 data needed to subdivide the datasets and produce flux footprints, except for the atmospheric boundary
 480 layer height, which can be obtained from reanalysis products such as ERA5 (Hersbach et al., 2023). We
 481 note that urban systems frequently violate the assumptions implicit in the surface layer similarity theory
 482 and, consequently, the current flux footprint models (e.g., homogeneous turbulence forcing within the
 483 flux footprint). We, along with others, such as Feigenwinter et al. (2012), argue that existing footprint
 484 models (e.g., Kljun et al., 2015) remain quite helpful in interpreting these datasets. However, more
 485 research into the sensitivity of these models to complex urban systems is warranted.

486 3 Data availability

487

488 Unprocessed 10Hz data and processed INFLUX data are available on Penn State Data Commons (Table
 489 5). This version contains all the processed data with flagging, but no data has been removed based on
 490 flagging. This processed data also included a metadata file describing the naming convention of variables
 491 and flagging. Data from all agricultural sites includes calculated fractional coverage and data collected
 492 using the Arable sensors on-site.
 493

494 **Table 5.** Citations for each INFLUX tower. The raw data collected directly from the instruments, a
 495 processed version of the data available on Ameriflux, and a processed version with no flagged data
 496 removed are available through Penn State Data Commons.

Site	10Hz Data/full processed dataset	Ameriflux
	Richardson et al. (2023a) - https://doi.org/10.26208/CJTC-KS26	
US-INa	Horne et al. (2025b) - https://doi.org/10.26208/BV87-RP98	Davis (2023a) - https://doi.org/10.17190/AMF/2001300
	Richardson et al. (2023a) - https://doi.org/10.26208/CJTC-KS26	
US-INb	Horne et al. (2025b) - https://doi.org/10.26208/BV87-RP98	Davis (2023b) - https://doi.org/10.17190/AMF/2001301
	Richardson et al. (2023b) - https://doi.org/10.26208/fsy8-h855	
US-INc	Horne et al. (2025c) - https://doi.org/10.26208/E8CE-ZH47	Davis (2023c) - https://doi.org/10.17190/AMF/1987603
	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	
US-INd	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	Davis (2023d) - https://doi.org/10.17190/AMF/2001302
	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	
US-INe	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	Davis (2023e) - https://doi.org/10.17190/AMF/2001303
	Sarmiento and Davis (2017) - https://doi.org/10.17190/AMF/2001304	
US-INF	Richardson et al. (2023b) - https://doi.org/10.26208/fsy8-h855	Davis (2023f) - https://doi.org/10.17190/AMF/2001304
	Horne et al. (2025c) - https://doi.org/10.26208/E8CE-ZH47	
US-ING	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	Davis (2023g) - https://doi.org/10.17190/AMF/2001305
	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	
US-INi	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	Davis (2023h) - https://doi.org/10.17190/AMF/2001306
	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	
US-INj	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	Davis (2023i) - https://doi.org/10.17190/AMF/2001307

	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	
US-INn	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	Davis (2023j) - https://doi.org/10.17190/AMF/2001308
	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	
US-INp	Richardson et al. (2023c) - https://doi.org/10.26208/2NT2-RS82	Davis (2023k) - https://doi.org/10.17190/AMF/2001309
	Horne et al. (2025d) - https://doi.org/10.26208/900V-YJ22	

497
498 In addition, all INFLUX EC datasets are available through the Ameriflux network
499 (<https://ameriflux.lbl.gov/>, Table 5). As of May 2025, the operation of all INFLUX flux towers has
500 concluded. Data collected in 2025 at US-ING and US-INc sites will be processed, updated, and made
501 available through all datasets in Table 5.

502
503 These flux measurements were a component of a broader research effort, the Indianapolis Flux
504 Experiment (INFLUX). Multiple additional measurements and model data sets exist, creating a more
505 complete experimental data set to assess urban greenhouse gases in Indianapolis, IN. These include mole
506 fraction measurements (Miles et al., 2017b), flask measurements
507 (<https://gml.noaa.gov/dv/site/?stacode=INX>), Doppler lidar measurements
508 (<https://csl.noaa.gov/projects/influx/>), anthropogenic emissions inventories (Gurney et al., 2018), aircraft
509 measurements (<https://influx.psu.edu/influx/data/flight/>), Vegetation Photosynthesis and Respiration
510 Model (VPRM) simulations (Horne and Davis, 2024; Murphy et al., 2024), and Weather Research and
511 Forecast (WRF) Reanalysis (Deng et al., 2020), which are not described in detail here. For more
512 information concerning the INFLUX Project and the data collected, please visit <https://influx.psu.edu>.
513 Most of these complementary data sets can be found at Penn State's Data Commons.

514 4 Conclusions

515
516 The INFLUX EC network has become a vital component of the multivariate INFLUX data set.
517 Micrometeorological methods like EC can bridge the gap between land surface modeling and atmospheric
518 inverse methods used to quantify urban GHG fluxes. The INFLUX EC flux data expands the growing
519 database of urban flux measurements. Data representative of the range of land-atmosphere fluxes
520 encountered in this region was obtained by deploying multiple sites representative of the land cover of the
521 city and its surroundings. We hope the data availability will support cross-collaboration between projects
522 involving urban environments.

523
524 **Author contributions.** NM, SR, and KD conceived and coordinated the INFLUX project. KD
525 conceptualized the EC flux measurement strategies for INFLUX. SR and NM installed the
526 instrumentation, and SR, NM, and BA worked on maintaining the currently deployed instruments. BJH
527 oversaw the development and implementation of the data acquisition and monitoring system, and BJH
528 and JH collaborated to create it. BA, HK, SM, and JH oversee data processing and quality control. JH led

529 the writing of this document, and all authors contributed to its editing and review. SM and JH helped
530 create footprint climatologies for heterogeneous urban towers.

531

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533

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