Inverse estimates of greenhouse gas sources and sinks using regional measurement networks

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with contributions from many colleagues

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What's an atmospheric inversion?

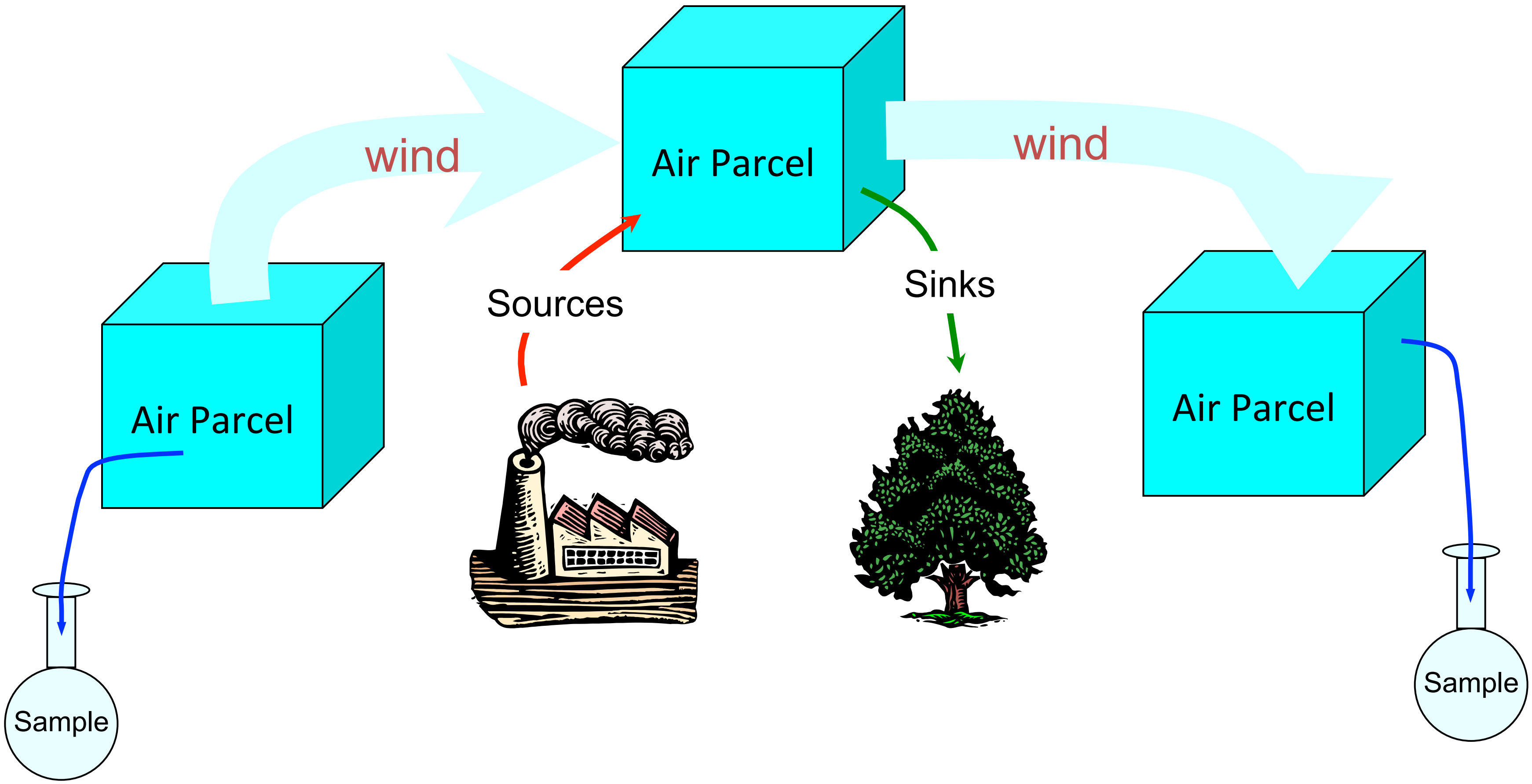


Figure courtesy A. Scott Denning, circa 2000

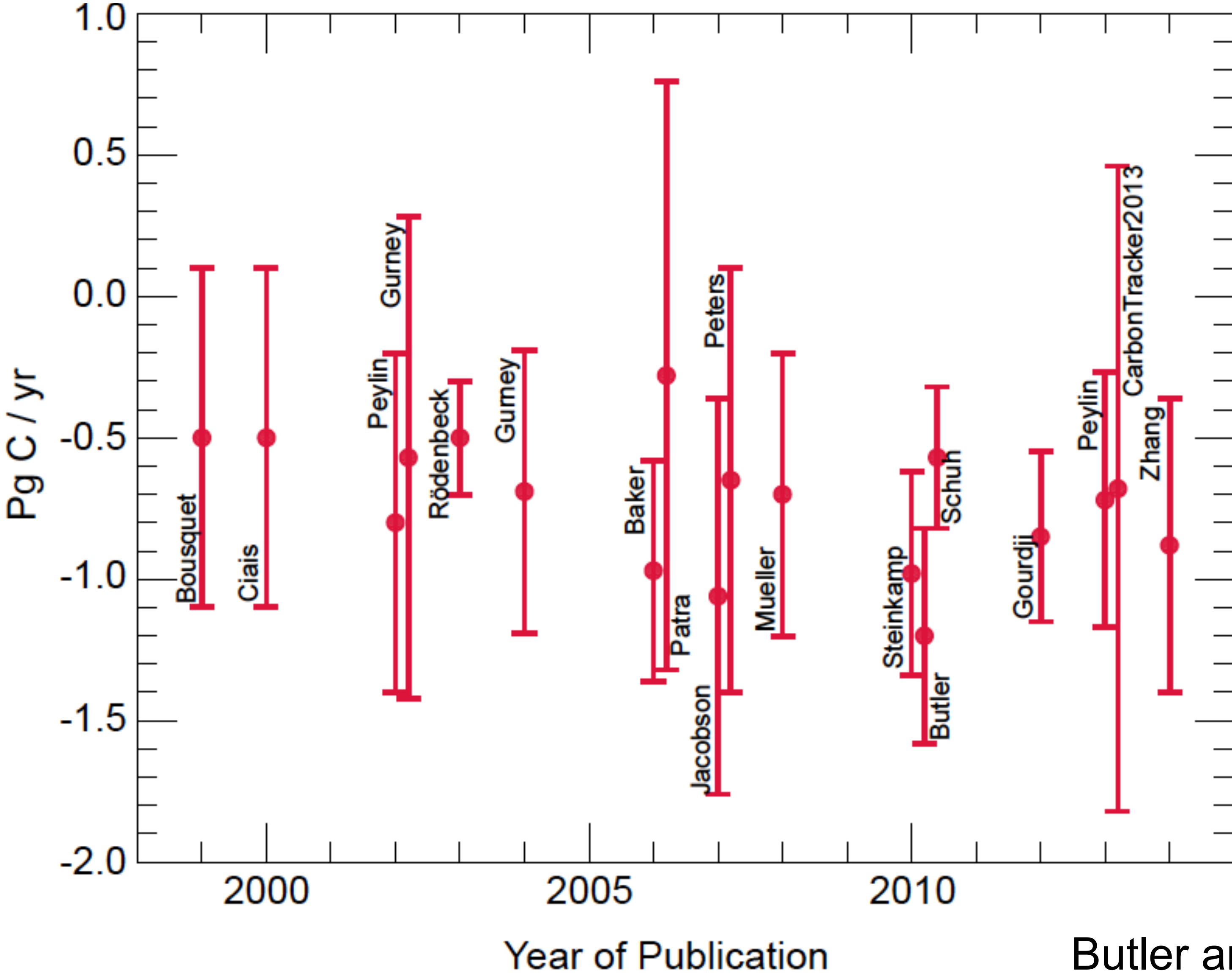
Atmospheric inversion basics

- Take a first guess at CO_2 emissions
- Transport these through the atmosphere using an atmospheric model (reanalysis)
- Compute CO_2 at measurement points
- Compare modeled and observed CO_2
- Adjust first guess of emissions to minimize the difference between observed and modeled CO_2.

A brief review of the state of regional inverse CO_2 ~~and CH_4~~ flux estimates

- Biogenic CO_2 fluxes
  - Atmospheric inversions are informative at global scale down to zonal bands
  - Continental scale inversions are only marginally informative to date. Success is limited by:
    - Limited data
    - Limited understanding of atmospheric transport errors
- Anthropogenic CO_2 fluxes
  - Previously assumed to be well known at global scales (relative to biogenic CO_2). But uncertainties are converging.
  - Global sampling network not suited for large-scale anthropogenic flux estimates.

Results from atmospheric inversions: North American terrestrial ecosystem CO_2 fluxes



This shows that there is a significant N. American terrestrial sink.

We more or less knew that in 1990.

Butler and Davis, in prep

"Top-down" and "Bottom-up" CO_2 flux estimates. Why bother with atmospheric methods?

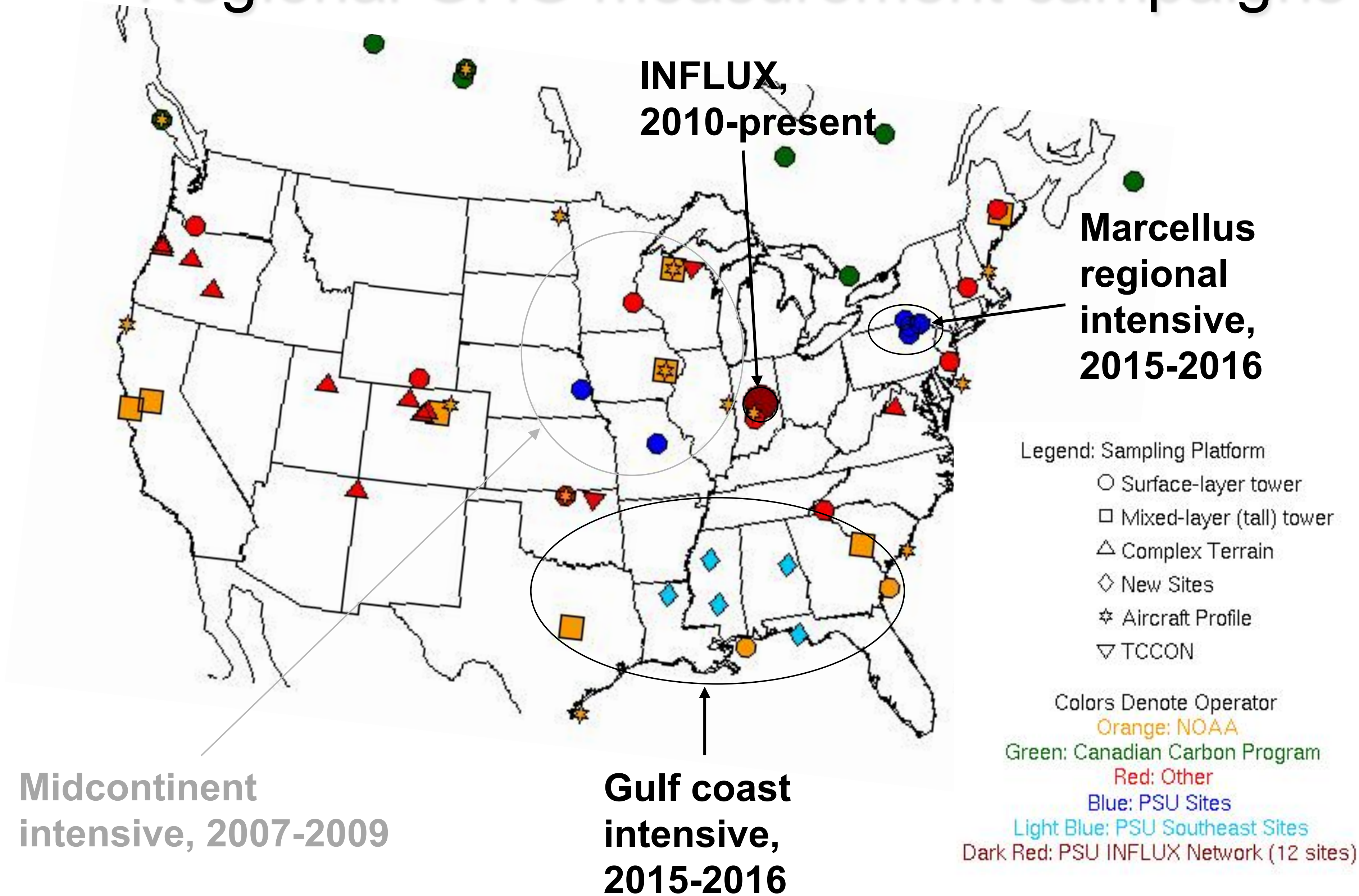
- "Bottom-up," or inventory methods
  - are rich in source sector information
  - can be very precise and accurate locally
  - are prone to systematic errors (source / sink missed)
  - errors tend to aggregate, not cancel – do not decrease a great deal as spatial domain increases
  - difficult to implement continuously - temporal resolution is limited
- "Top-down," or atmospheric inverse methods
  - capture all greenhouse gas (GHG) sources and sinks.
  - excellent temporal resolution
  - powerful independent validation of inventories
  - are difficult to use for attribution.
  - errors increase as spatial (or sectoral) resolution increases

Methods are complementary. Uncertainty estimates and comparative studies are essential.

Path(s) forwards?

- High density regional CO_2 and CH_4 measurement networks
  - In situ
  - Remote
- High resolution, regional atmospheric transport models with sophisticated meteorological data assimilation and uncertainty quantification

Regional GHG measurement campaigns



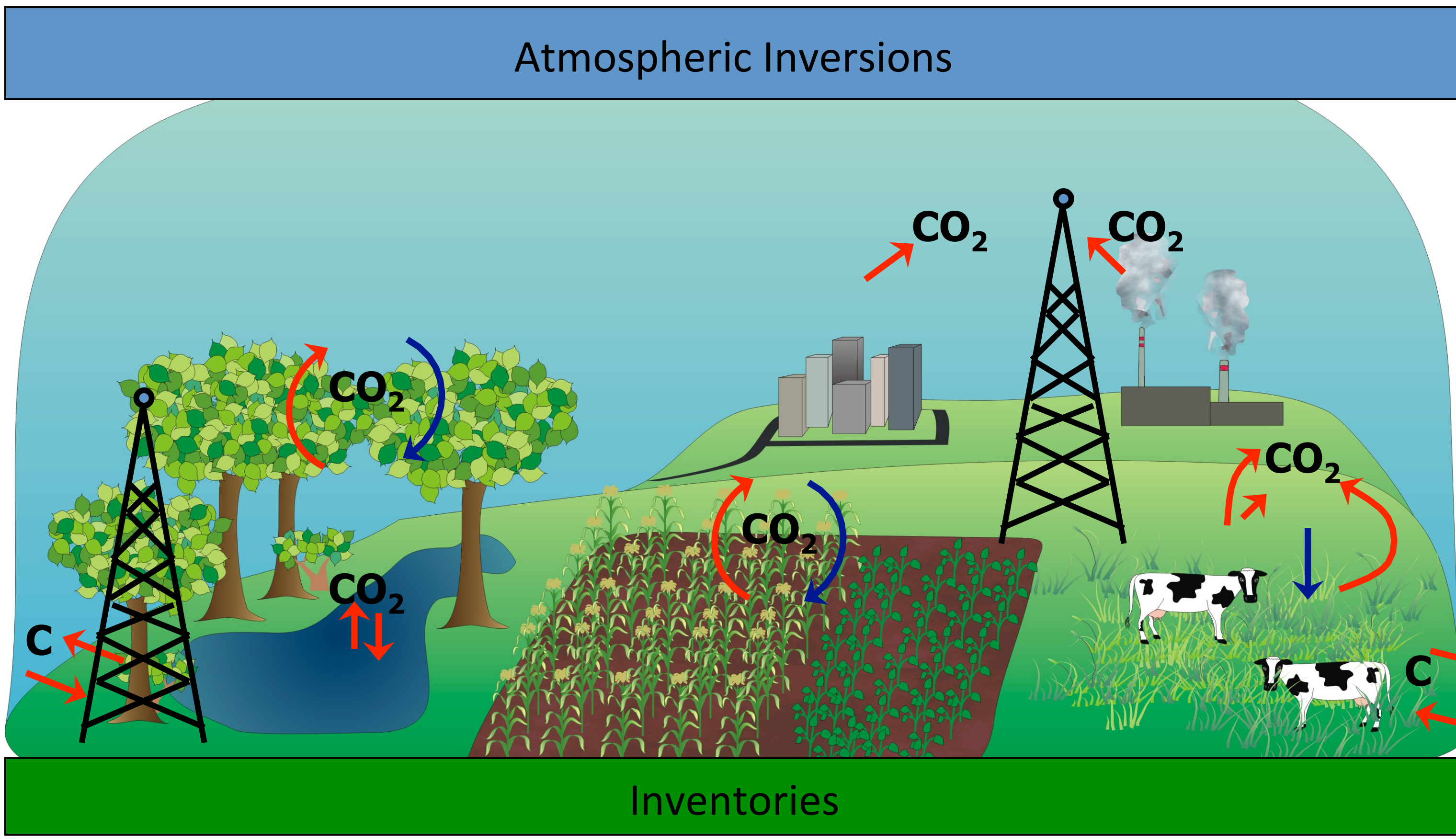
Examples:

North American Carbon Program Midcontinent Intensive (NACP MCI)

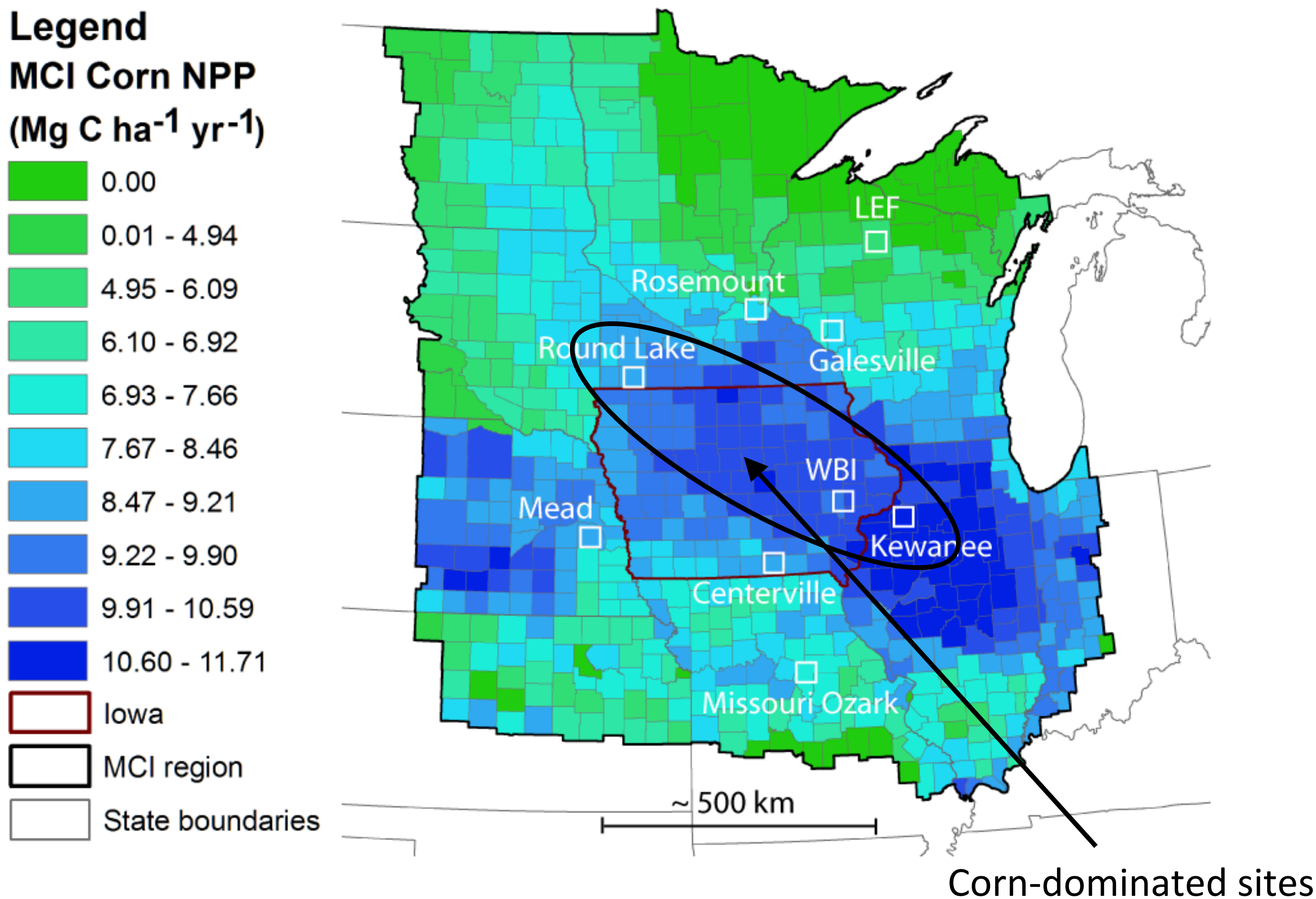
Indianapolis Flux Experiment (INFLUX)

NACP Midcontinent Intensive (MCI)

- To what degree can we demonstrate convergence in regional flux estimates using top-down and bottom-up methods?

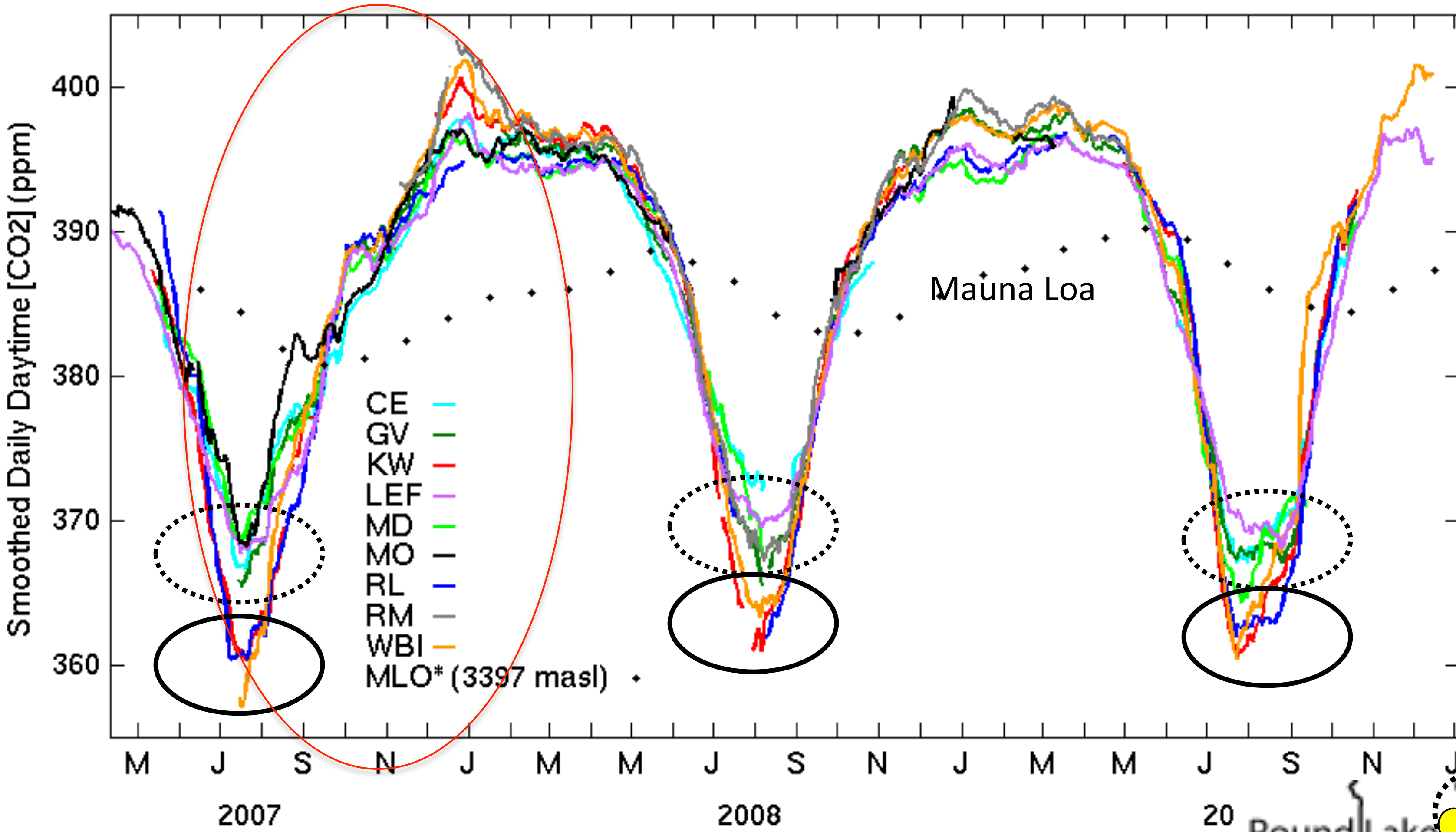


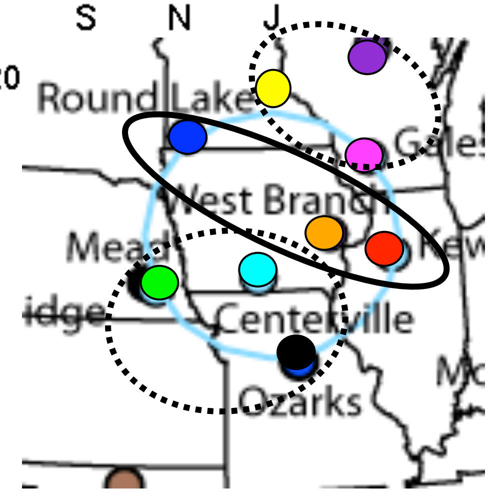
MidContinent Regional Intensive Tower-Based CO_2 Observational Network



Miles et al, 2012, JGR-B

MCI 31 day running mean daily daytime average CO2

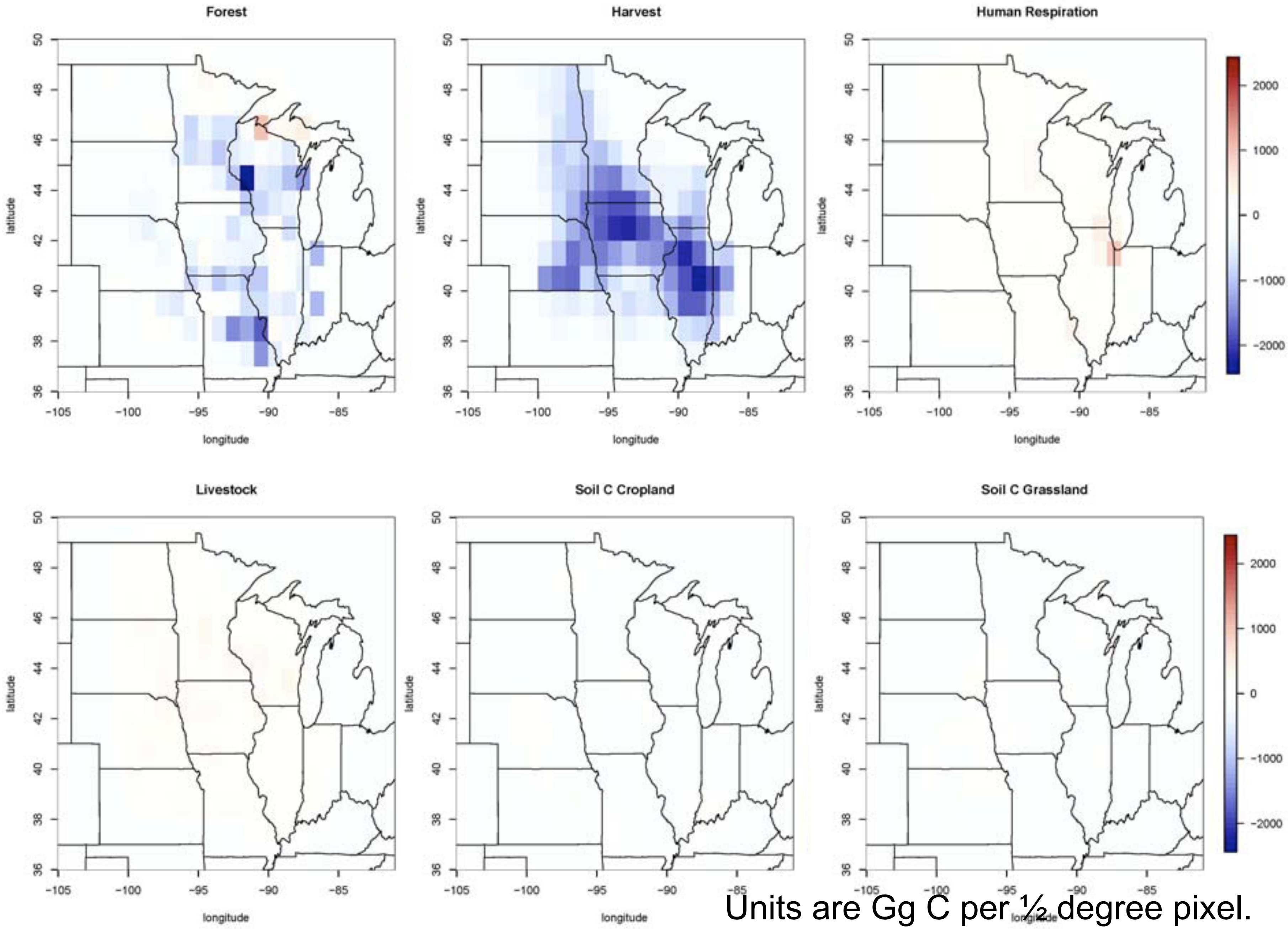




- Large differences in seasonal drawdown of CO_2
- 2 groups: 33-39 ppm drawdown and 24 – 29 ppm drawdown. Tied to density of corn.

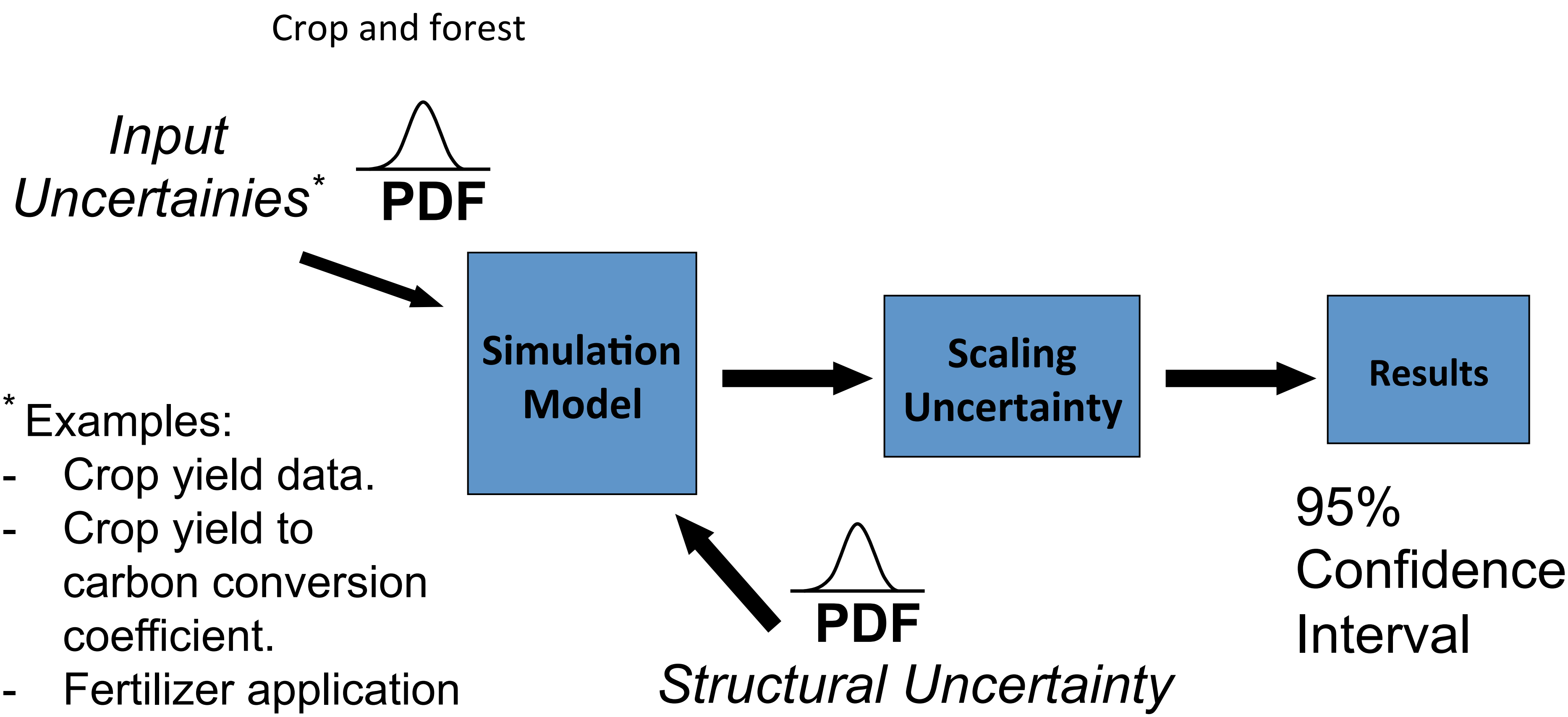
Miles et al, 2012, JGR-B

MCI inventory estimates: Forest and crop yield dominate



Units are Gg C per ½ degree pixel.

Inventory Uncertainty Assessment



* Examples:

- Crop yield data.
- Crop yield to carbon conversion coefficient.
- Fertilizer application rate.

Spatial correlations embedded.

Ogle et al., Global Change Biology, 2010

Regionally and time integrated C flux uncertainty assessment: Sensitivity to assumptions in the inversion

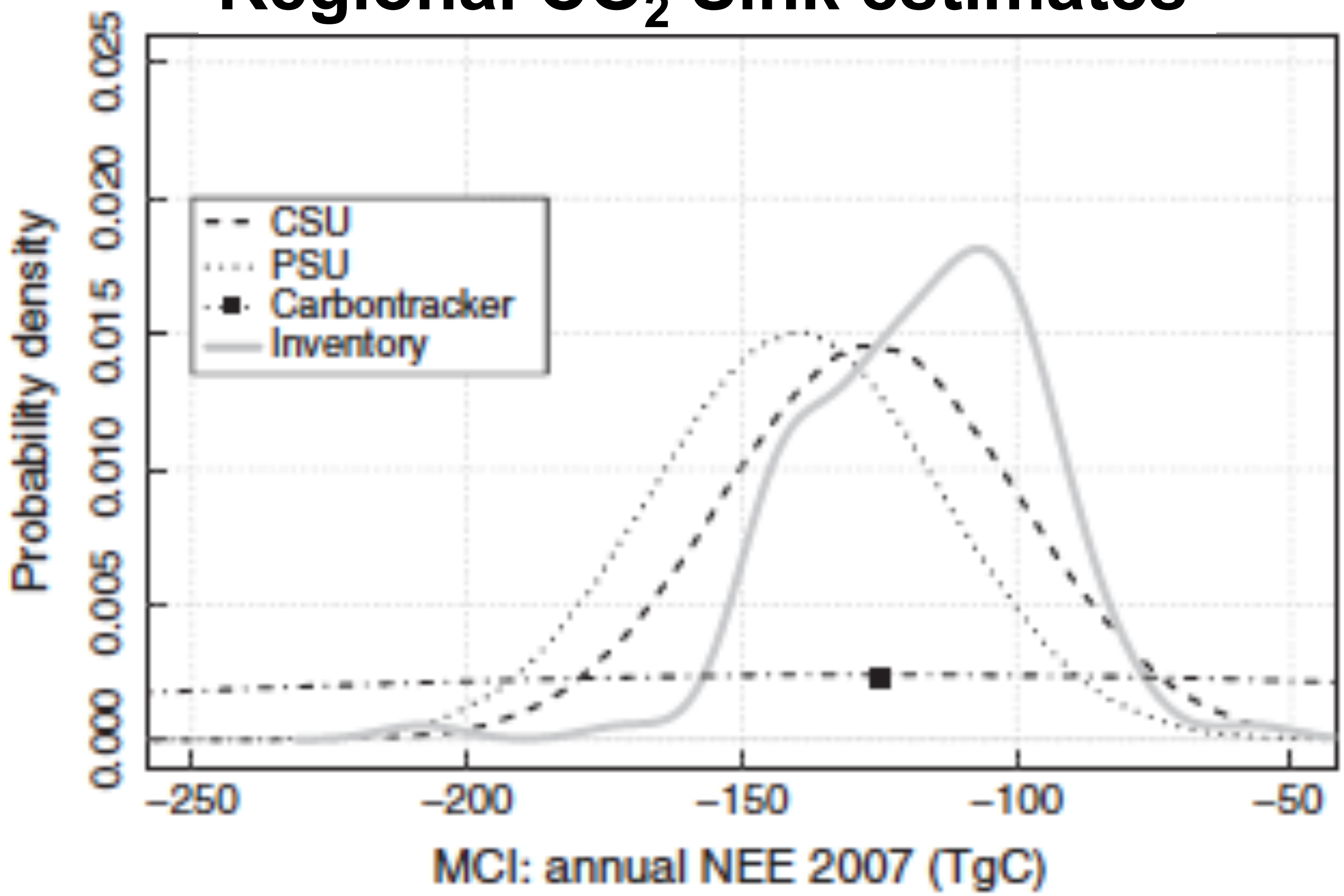
	prior	post	large σ_B	low σ_R^{night}	low σ_R^{day}	$\rho(t) \neq 0$	T_{bc} =90h	$\rho_B = f(L)$
SiBcrop	-109	-194	-190	-149	-195	-153	-178	-179
CT_{v09}	-198	-215	/	/	/	-182	/	/

Table 1. Regional CO_2 flux balance from June to December 2007 in TgC over the MCI using Sibcrop and CarbonTracker2009 as prior fluxes in the reference setup (prior and posterior), then assuming larger uncertainties in the prior (= larger σ_B), more confidence in nighttime data *i.e.* 10ppm instead of 100ppm (=lower σ_R^{night}), more confidence in daytime data *i.e.* 2ppm instead of 3ppm for the lower limit (=lower σ_R^{day}),temporal correlations in hourly observation errors between the hour t with the following n hours (= $\rho_{(X_t,X_{t+n})} \neq 0$ or $\rho(t) \neq 0$), a longer time period to correct for boundary influence (= T_{bc} =90h), and prior error correlations based on distance only ($\rho_B = f(L)$)

Formal posterior from a Bayesian matrix inversion also computed. About 30 TgC.

Lauvaux et al, 2012a, ACP

Regional CO_2 Sink estimates



Schuh et al, 2013, GCB

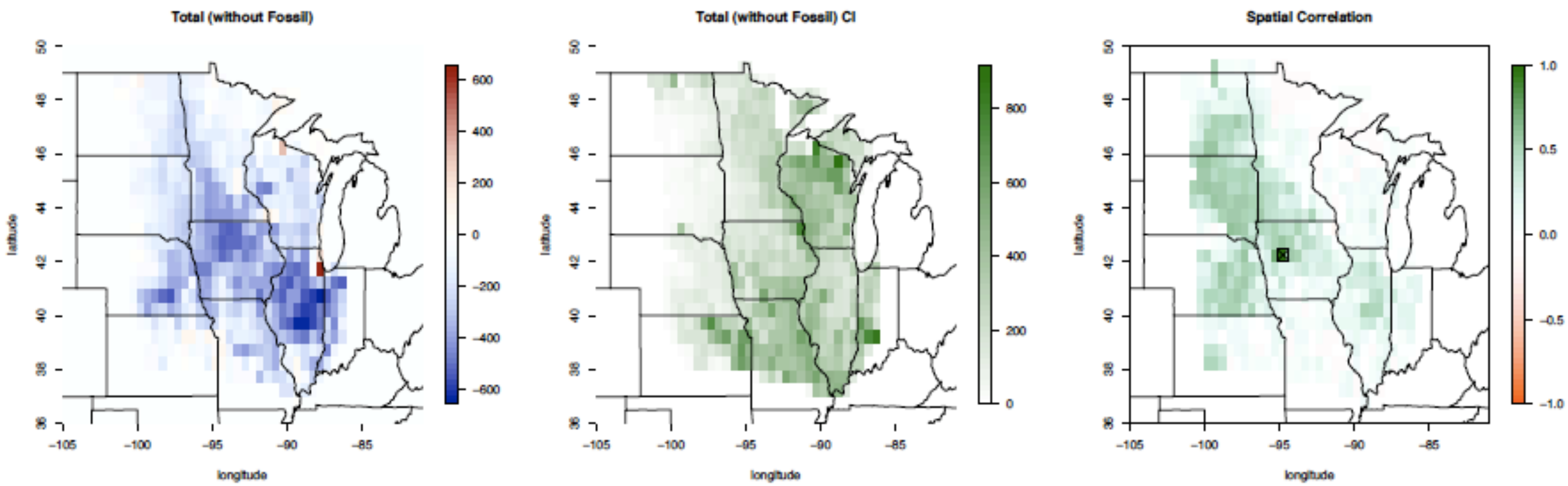
Atmospheric inversions and agricultural inventory agree.

Regional inversions and inventory have similar uncertainty bounds!

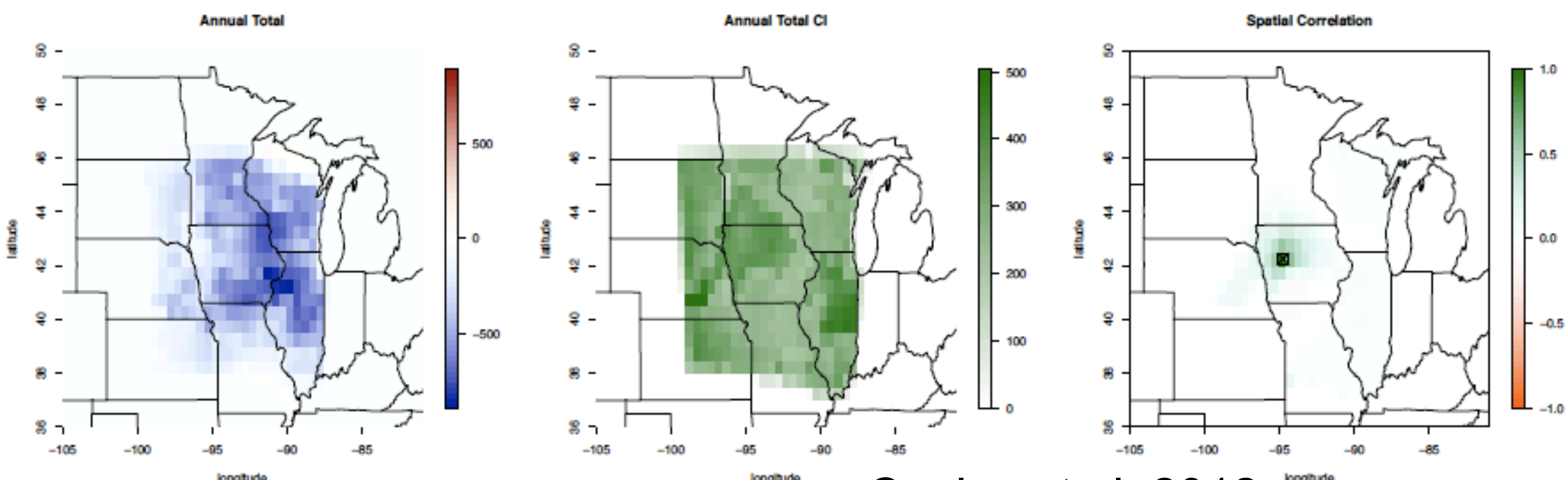
Atmospheric inversions have great potential for carbon balance inference given suitable data density.

Total Inventory/PSU Inversion Annual Total

Inventory

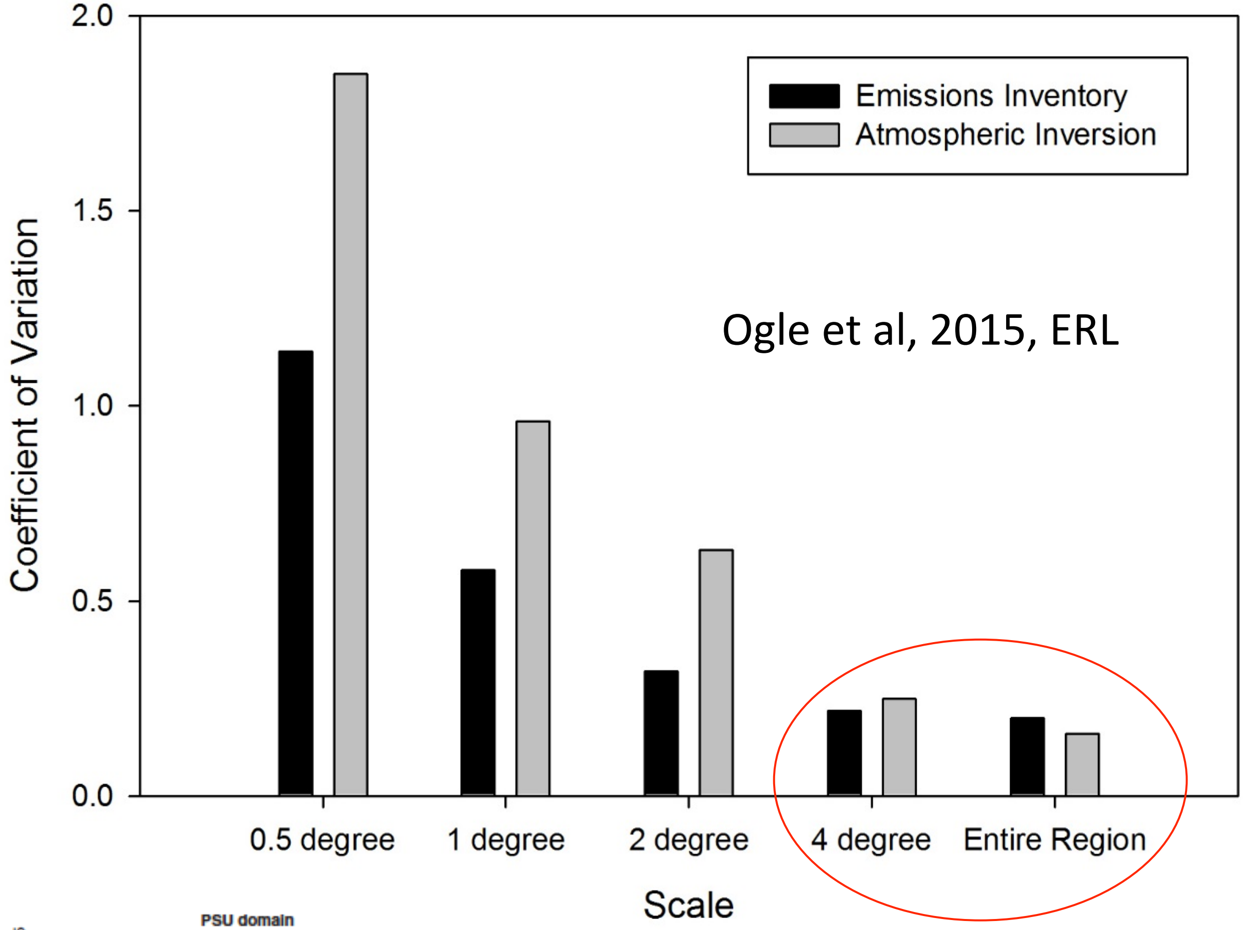


Inversion



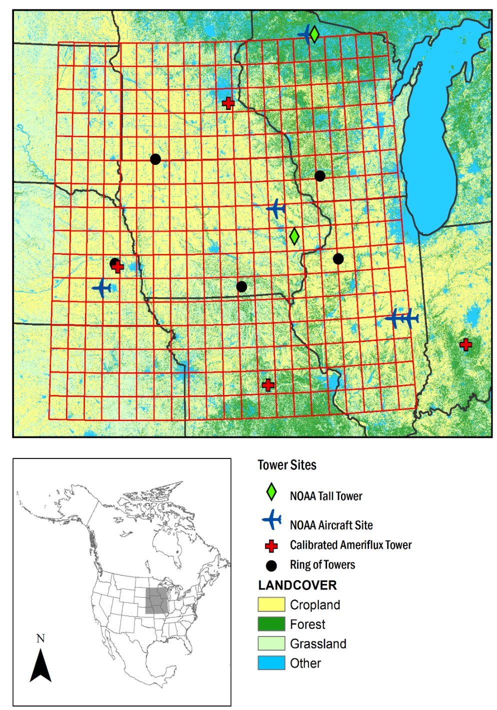
Cooley et al, 2012

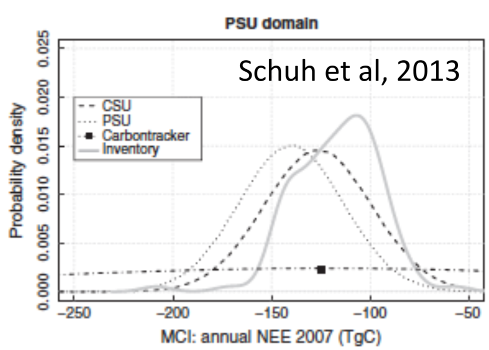
Cross-over point? Inversion vs. inventory



Atmospheric inversions provide great insights at global scale. Emissions inventories are very informative at small scales. Can we bridge the gap?

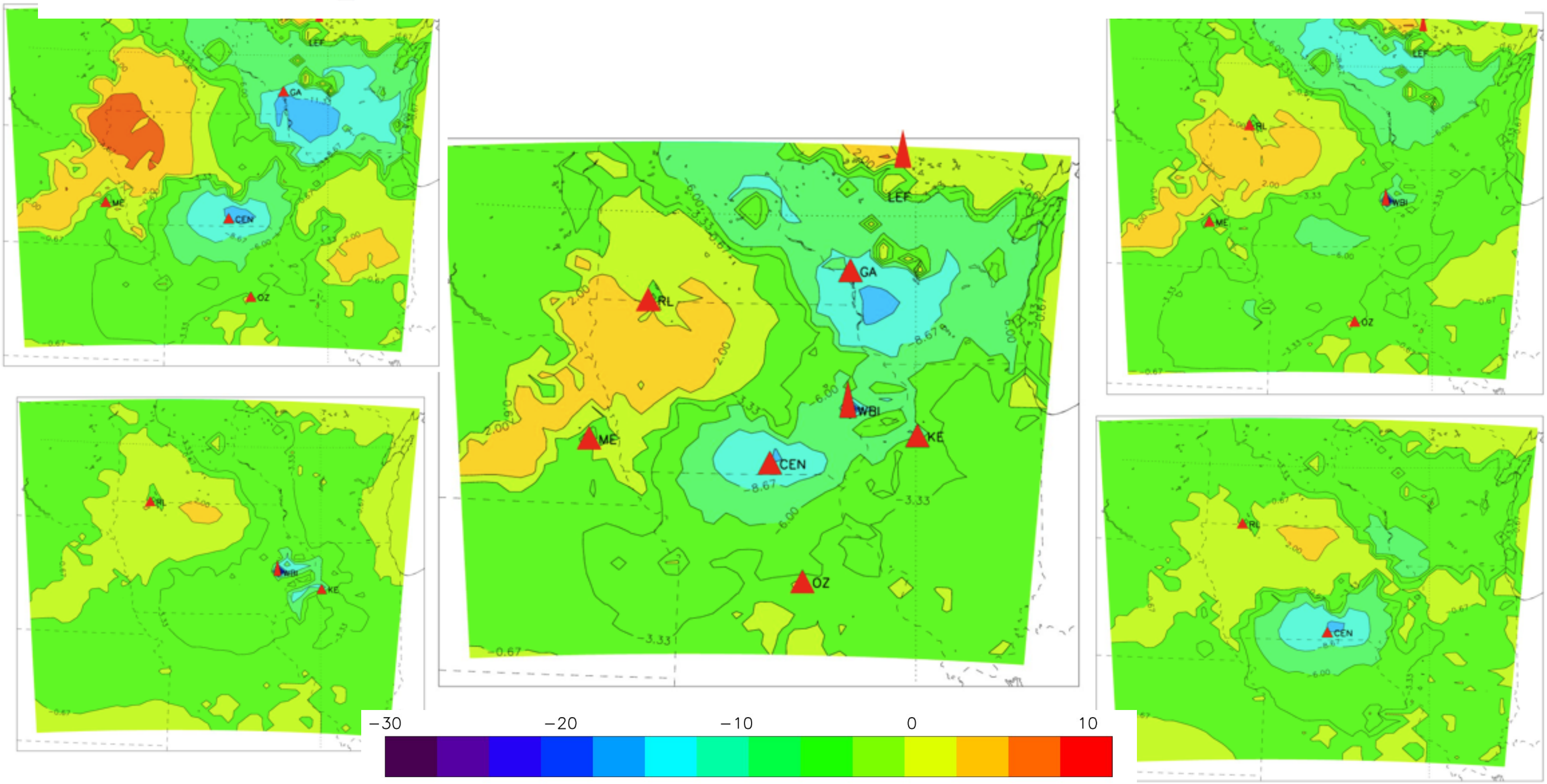
Midcontinent Intensive study area





MCI results suggest that uncertainty in an atmospheric inversion equals the uncertainty in an agricultural inventory at (several 100 km)^2 resolution for this inventory and these atmospheric data

How many towers are needed to capture the correct spatial distribution of the fluxes?



Flux correction using the entire tower network (in TgC.deg^{-2})

Areal integral doesn't change much.

Lauvaux et al, 2012b, Tellus

INFLUX motivation and goals

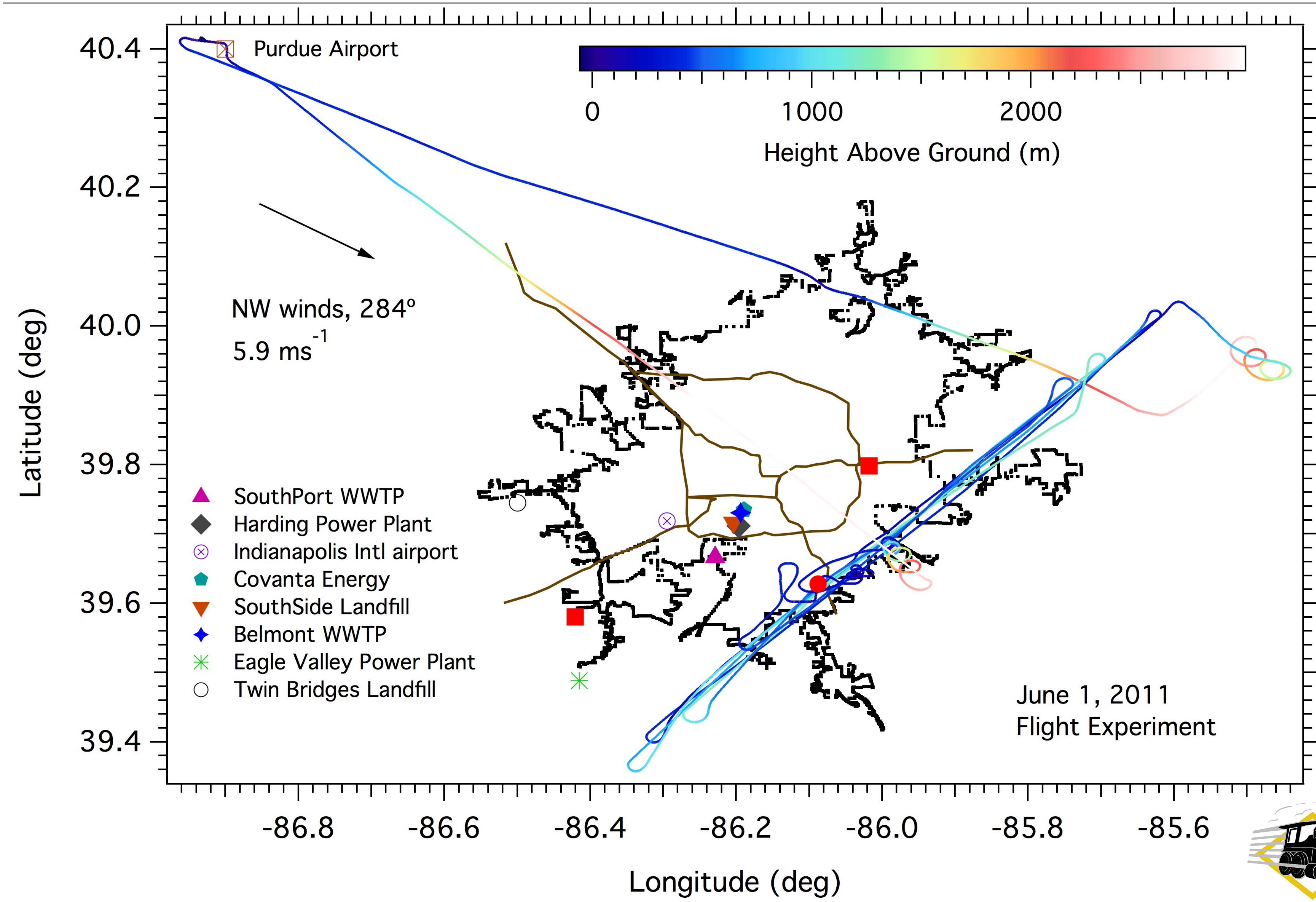
Indianapolis Flux Experiment (INFLUX) – influx.psu.edu

- Motivation
  - Anthropogenic greenhouse gas (GHG) emissions are uncertain at local / regional scales, where emissions mitigation will happen.
  - Validation of emissions mitigation will require independent measurements.
  - Atmospheric GHG measurements have the potential to provide such independent emissions estimates.
- Goals
  - Develop and assess methods of quantifying GHG emissions at the *urban scale*, using Indianapolis as a test bed.
  - Determine whole-city emissions of CO_2 and CH_4
  - Measure emissions of CO_2 and CH_4 at 1 km^2 spatial resolution and weekly temporal resolution across the city
  - Distinguish biogenic vs. anthropogenic sources of CO_2
  - Quantify and reduce uncertainty in urban emissions estimates

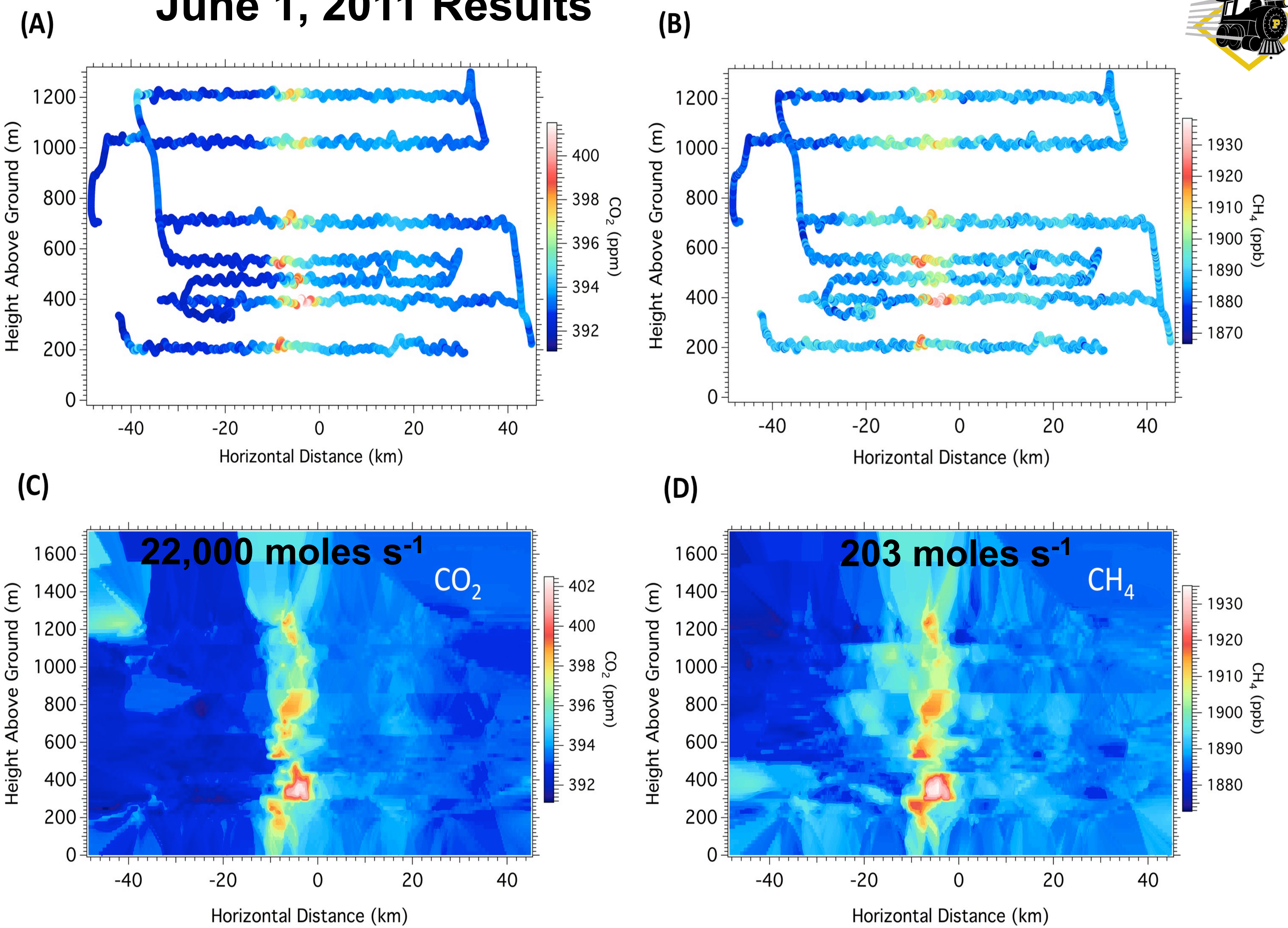
INFLUX methodology

- Atmospheric observations: 12 GHG Towers (CO_2, CH_4, CO); periodic aircraft flights (GHG, met, flasks); Doppler lidar; 4 eddy covariance flux towers; 6 flask samplers ($^{14}CO_2$, other trace gases).
- Emissions products: Vulcan (10km, hourly resolution, U.S.), Hestia (250m resolution, Indianapolis), ODIAC (1km resolution, global).
- Modeling system: WRF-Chem, 1km, nested, with meteo data assim. Lagrangian Particle Dispersion Model. Bayesian matrix inversion. Modeled and directly observed GHG lateral boundary conditions.

Example INFLUX Experiment, June 1, 2011 Flight path



June 1, 2011 Results



Cambaliza et al., 2014a; 2014b

Ground-based observations

Towers

Flasks

CO_2, CH_4, CO, $^{14}CO_2$, $^{13}CO_2$,
Halocarbons, Hydrocarbons

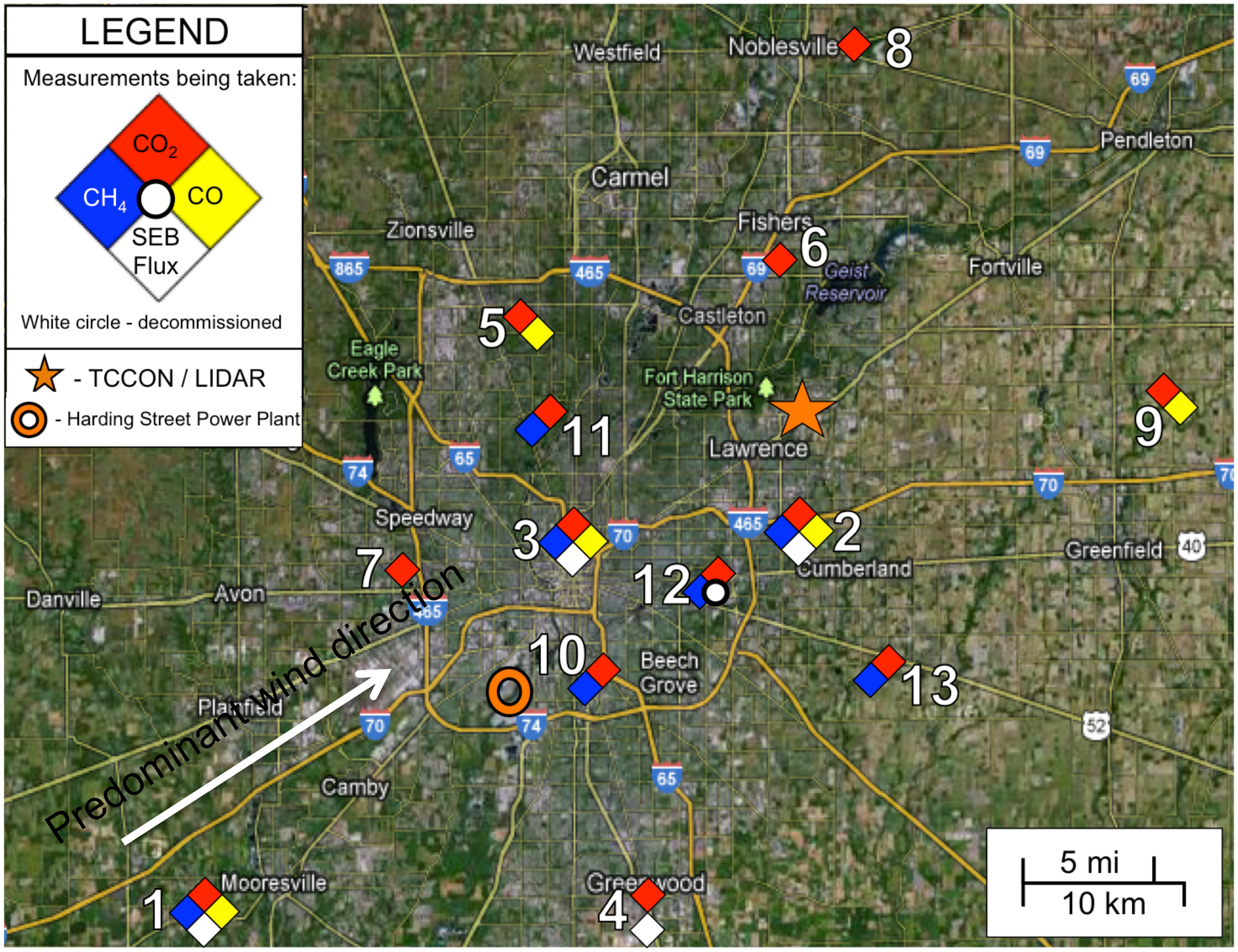
Attribution

In situ measurement

CO_2, CH_4, CO

Quantification

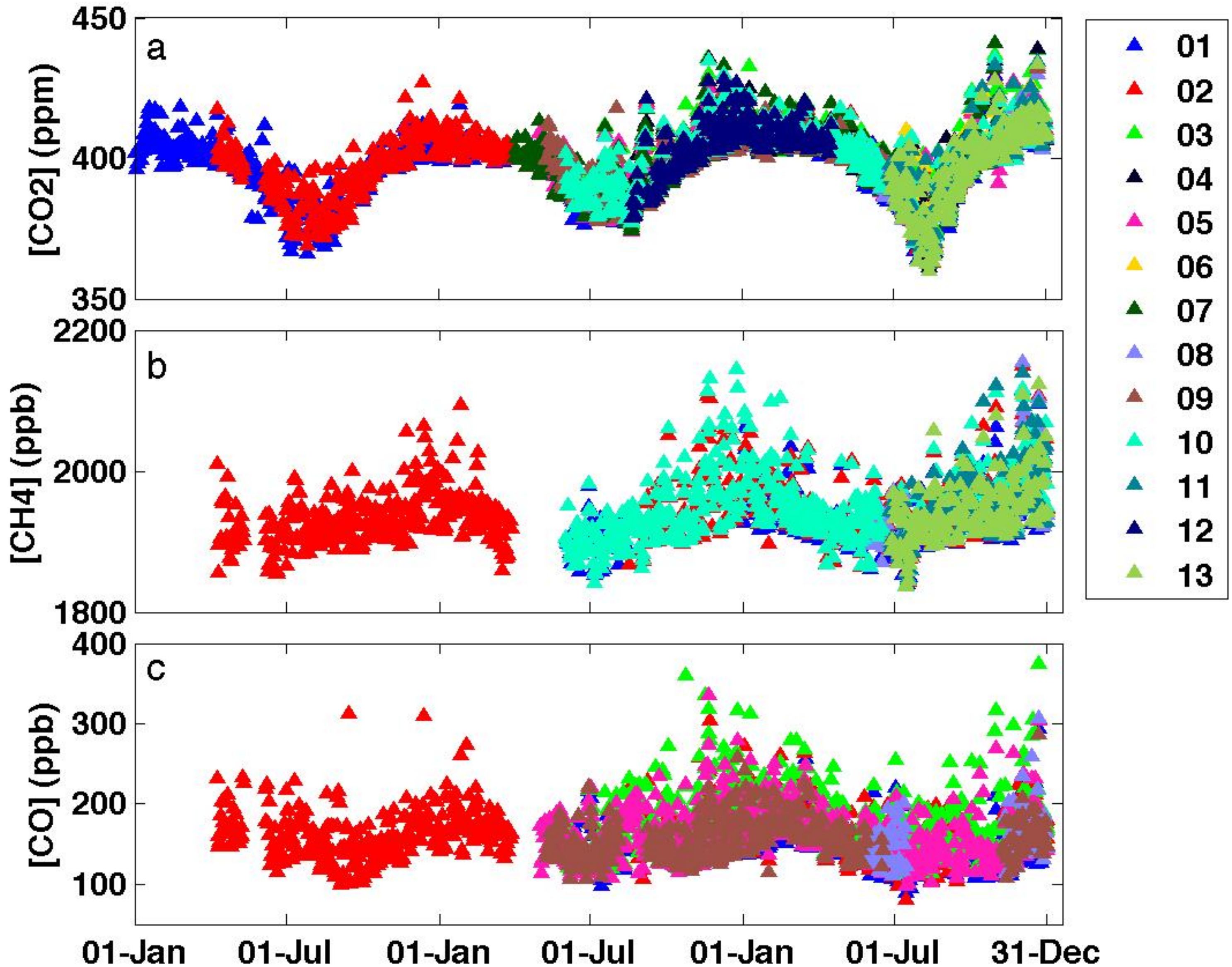
INFLUX GROUND-BASED NETWORK



- Communications towers ~100 m AGL
- Picarro, CRDS sensors
- 12 measuring CO2, 5 with CH4, and 5 with CO

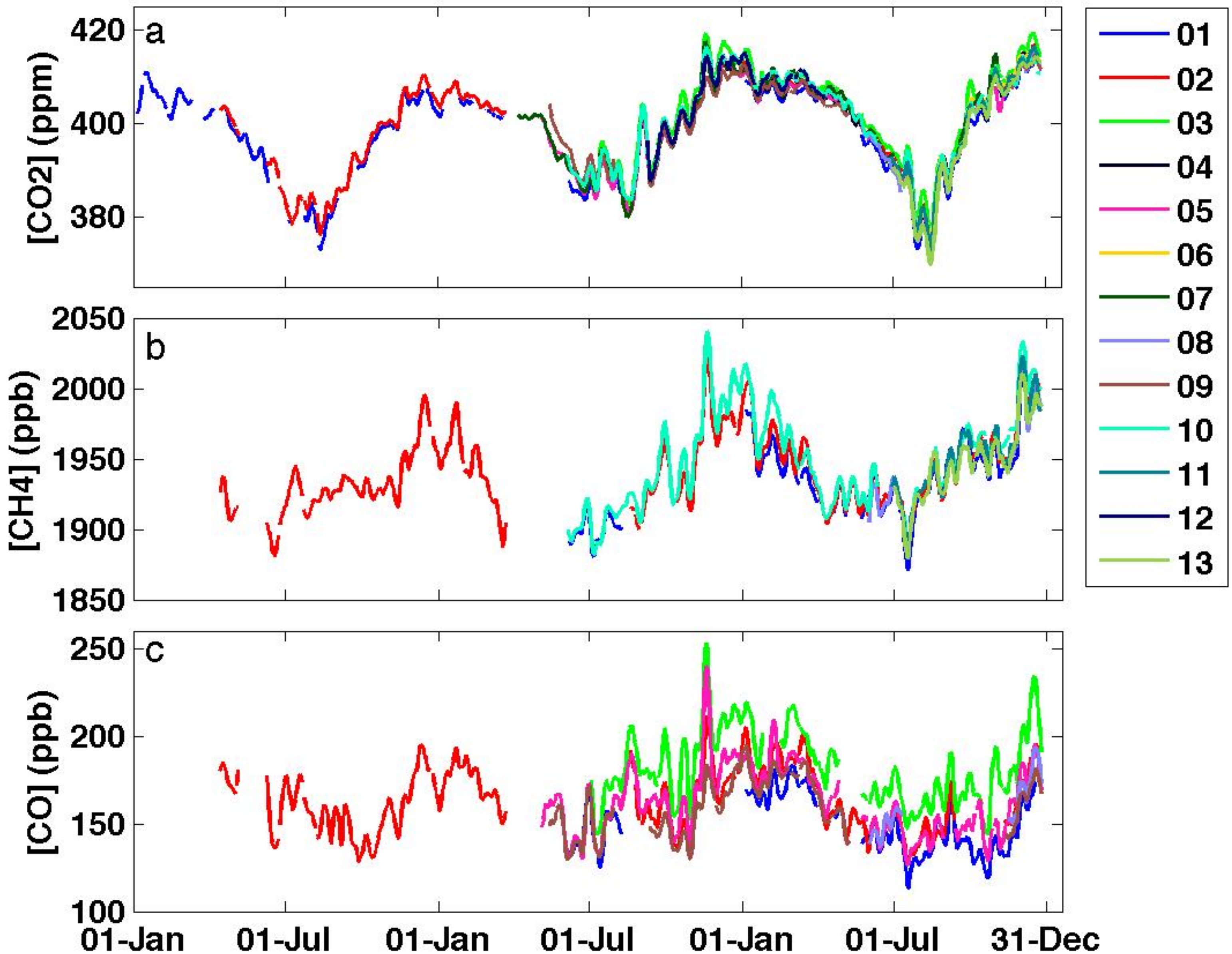
- NOAA automated flask samplers
- NOAA LIDAR
- Eddy flux at 4 towers

INFLUX afternoon average GHG ABL mole fractions



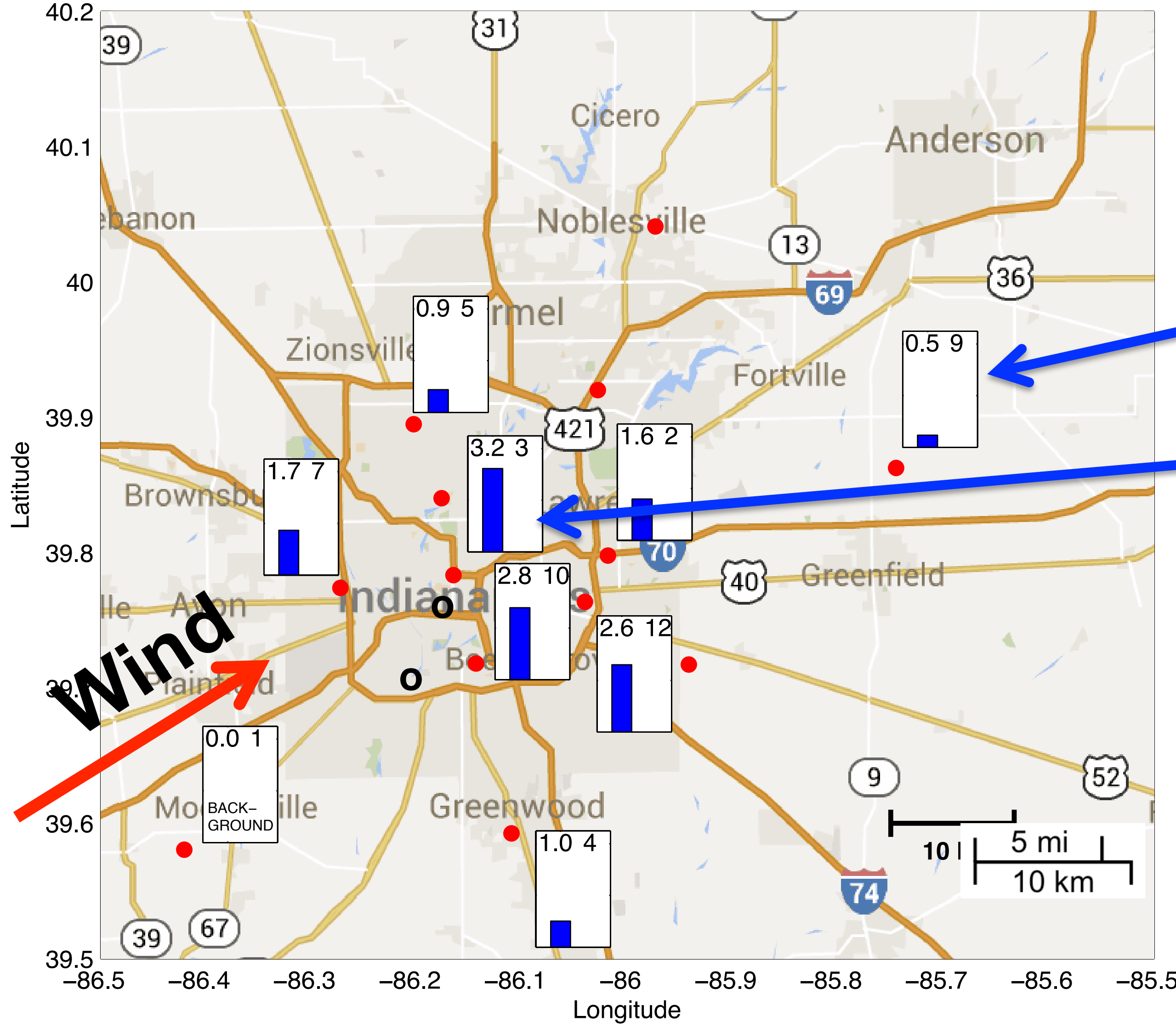
Miles et al, in prep

INFLUX afternoon average 15 day running mean GHG ABL mole fractions



Miles et al, in prep

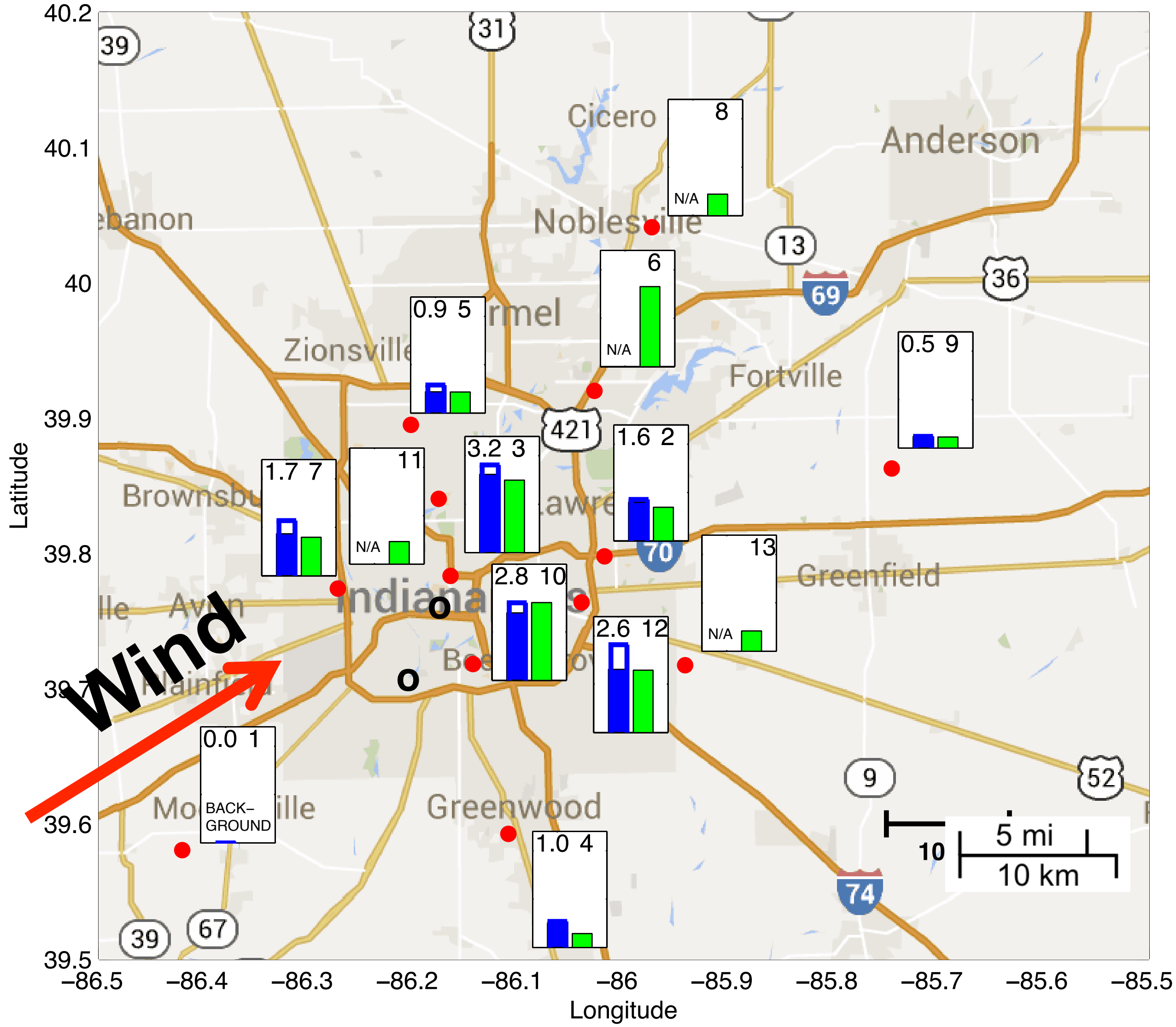
Observed spatial structure of urban CO_2



- Observed CO_2: afternoon values, averaged Jan-April 2013
- Site 09: 0.5 ppm larger than Site 01
- Site 03: measures larger $[CO_2]$ by 3.2 ppm

Miles et al, in prep

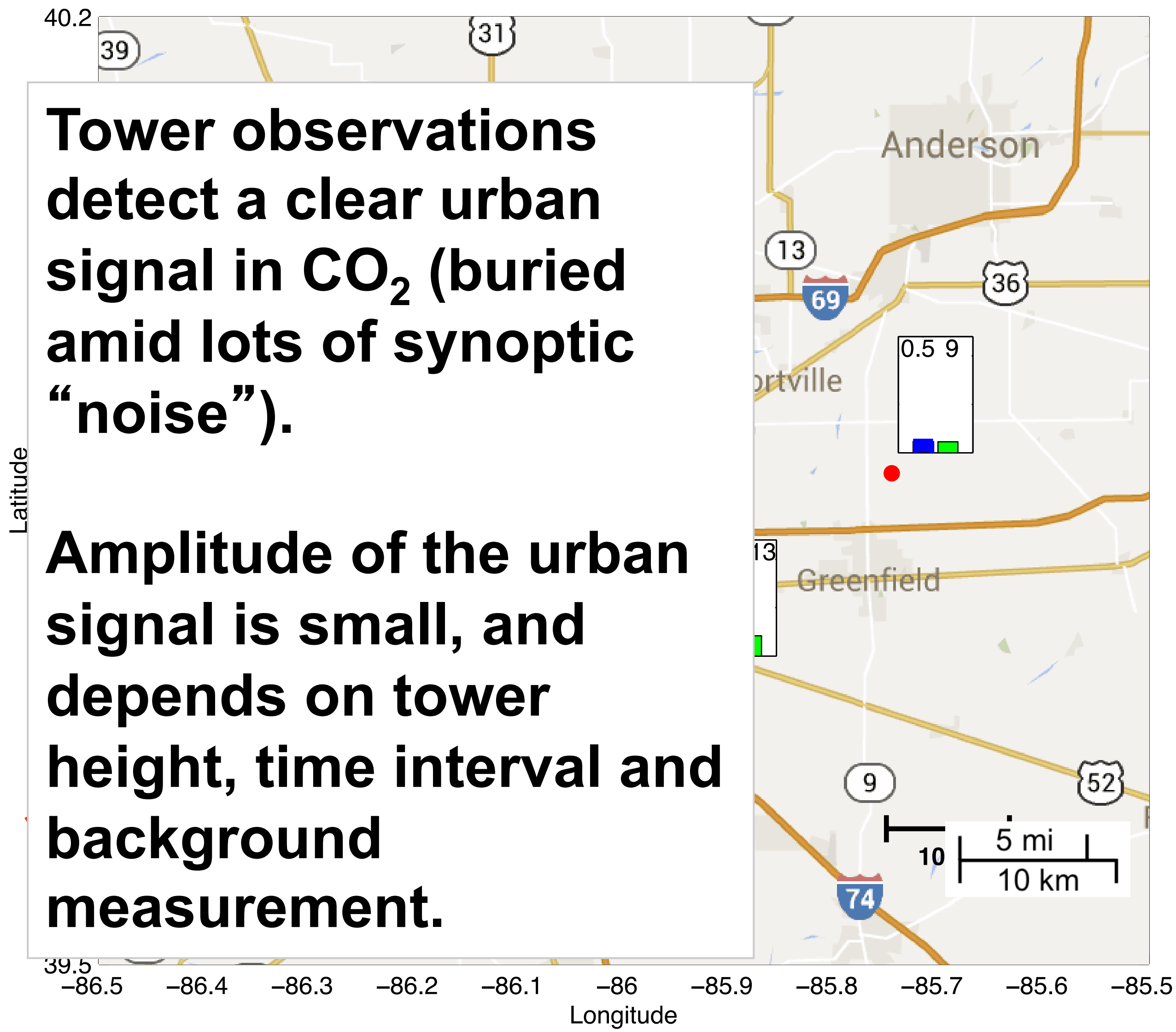
Spatial structure of urban CO_2: observed and modeled



- Observed CO_2: afternoon values, averaged Jan-April 2013
- Modeled CO_2 using LPDM footprints and Hestia emissions
- Overall, the spatial structure is similar

Miles et al, in prep

Spatial structure of urban CO_2: observed and modeled



Tower observations detect a clear urban signal in CO_2 (buried amid lots of synoptic "noise").

Amplitude of the urban signal is small, and depends on tower height, time interval and background measurement.

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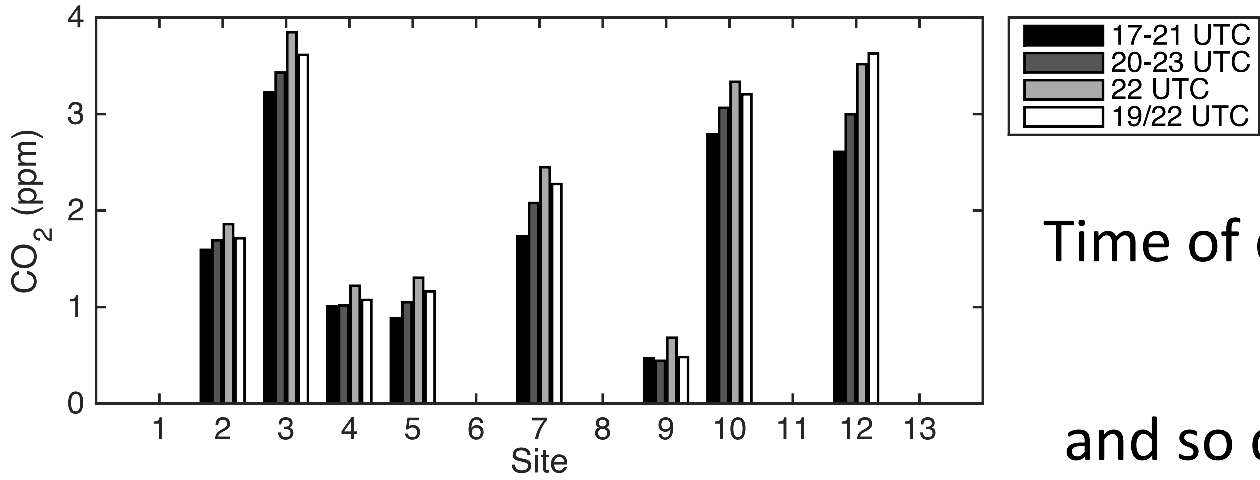
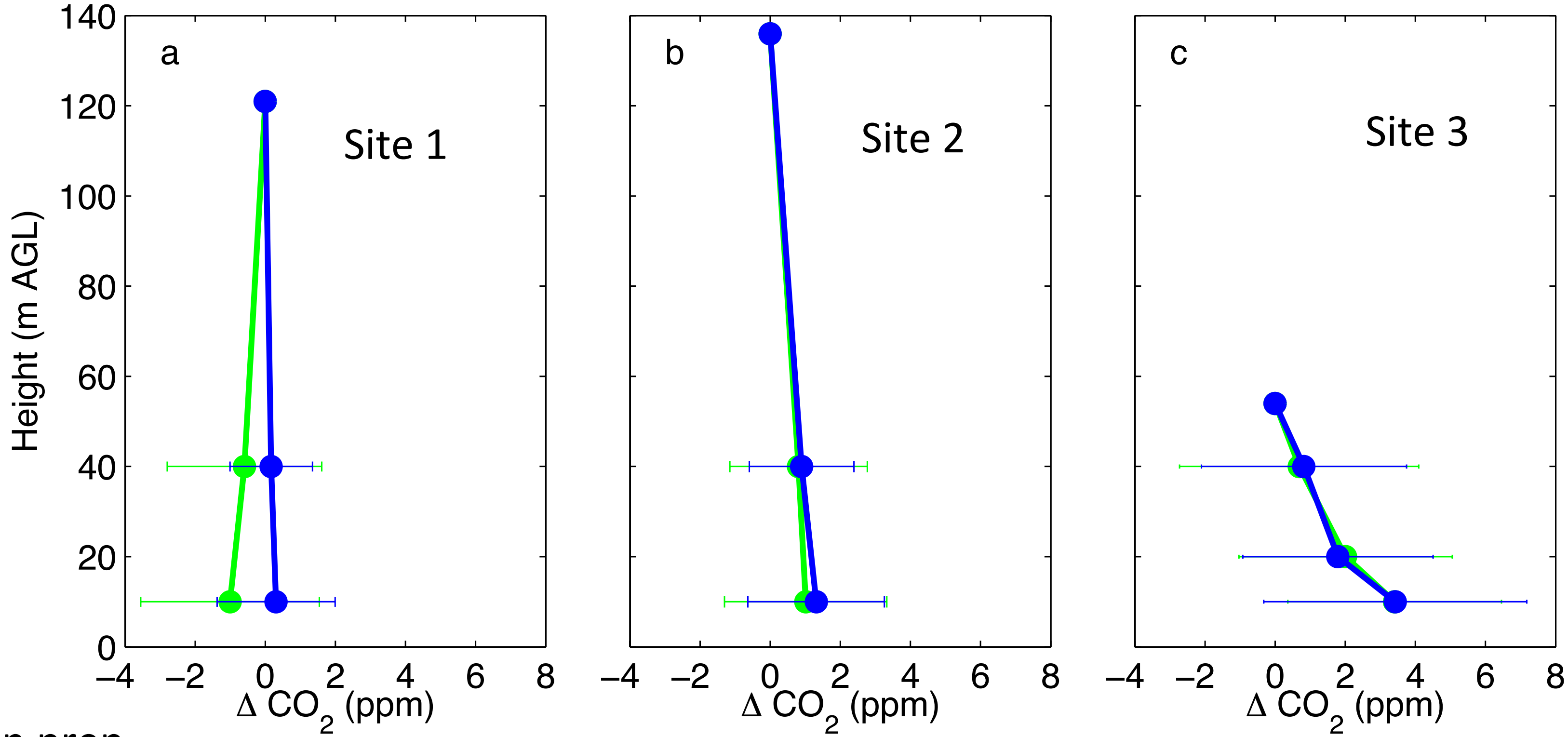
- Overall, the spatial structure is similar

Miles et al, in prep

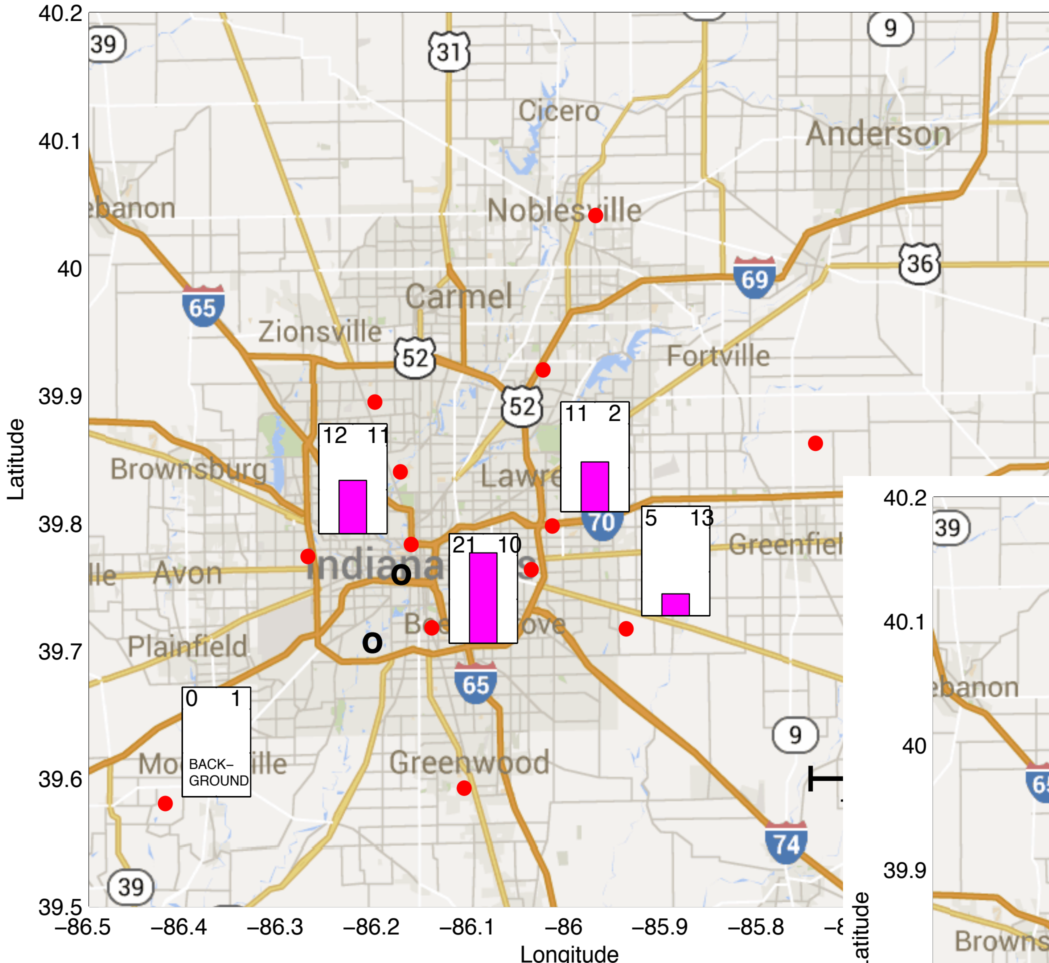


Time of day chosen matters

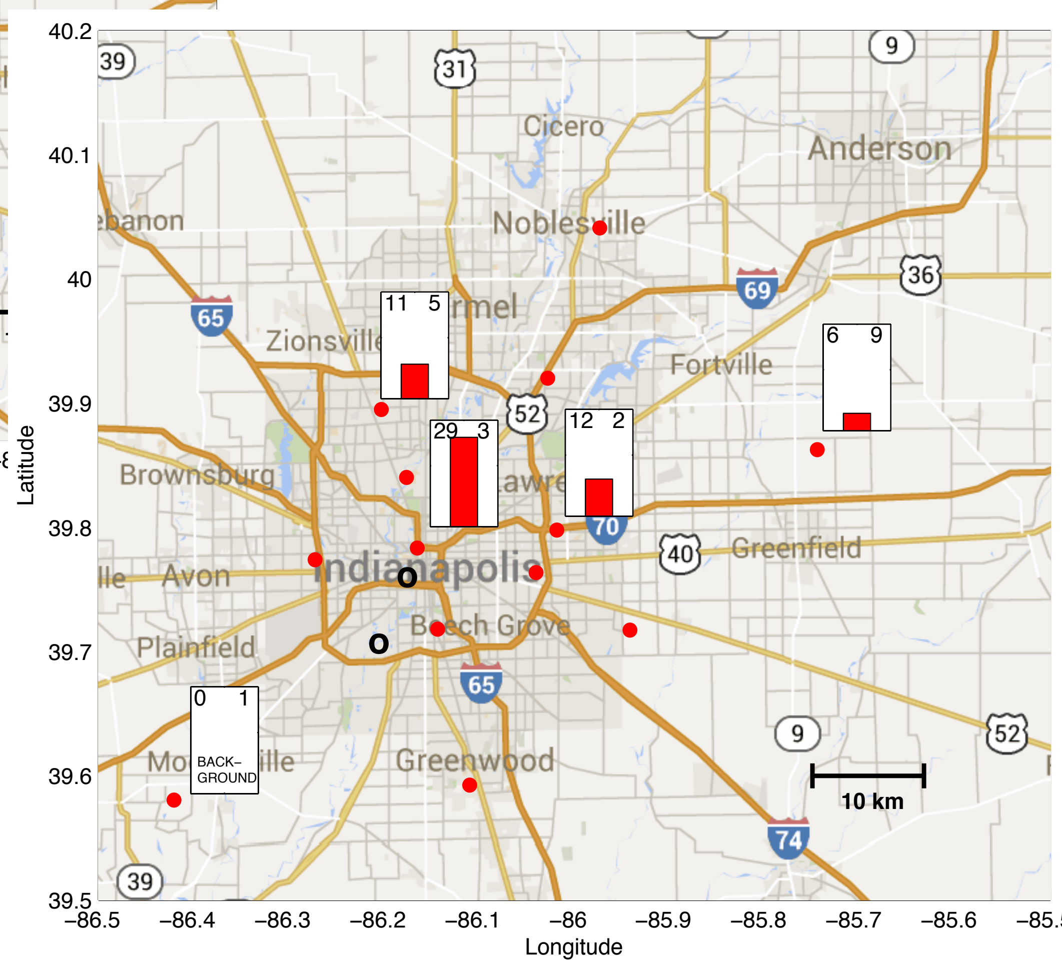
and so does measurement altitude.



Miles et al, in prep



CO

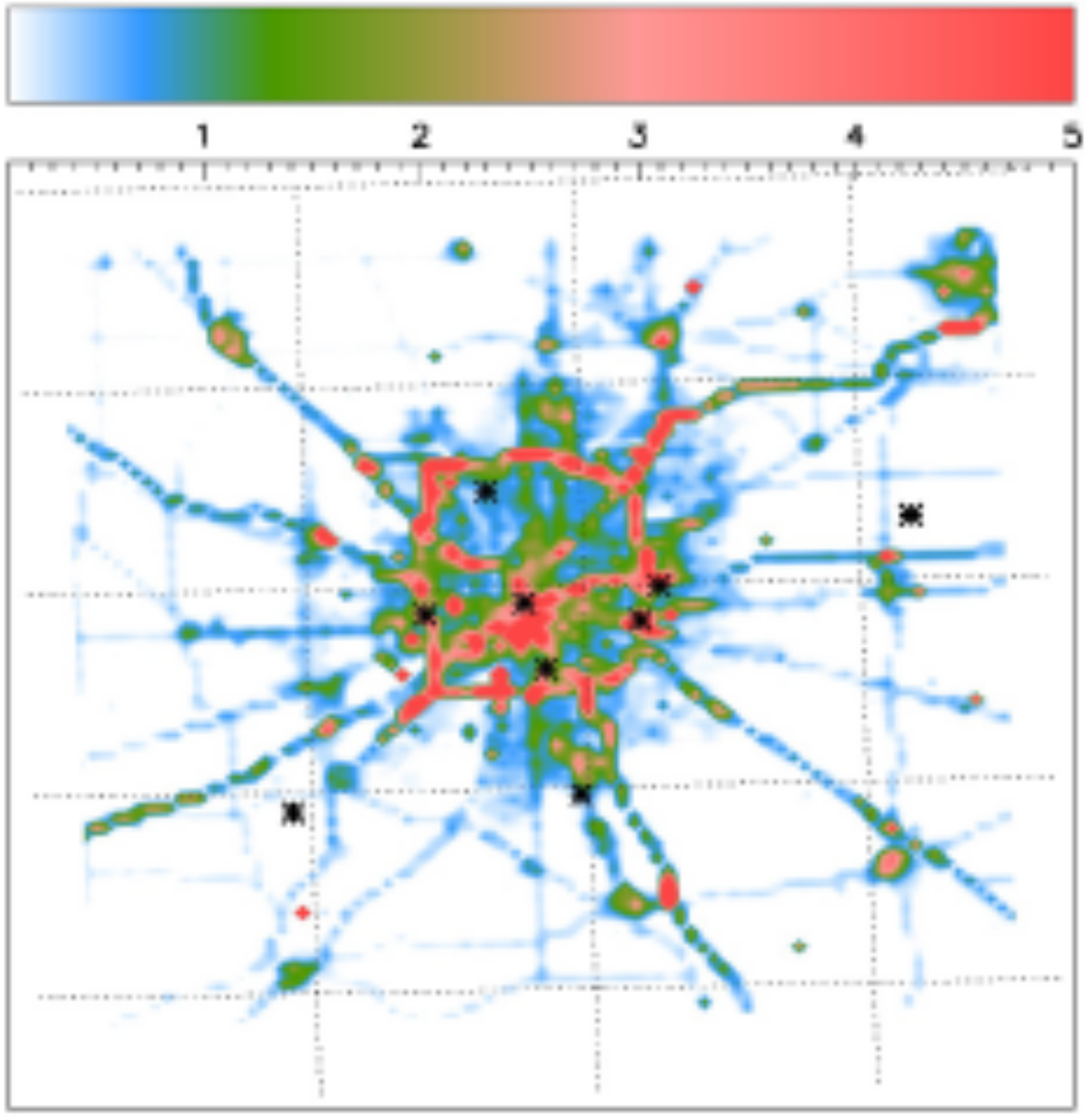


CH_4

Miles et al, in prep

INFLUX inverse CO_2 flux estimates

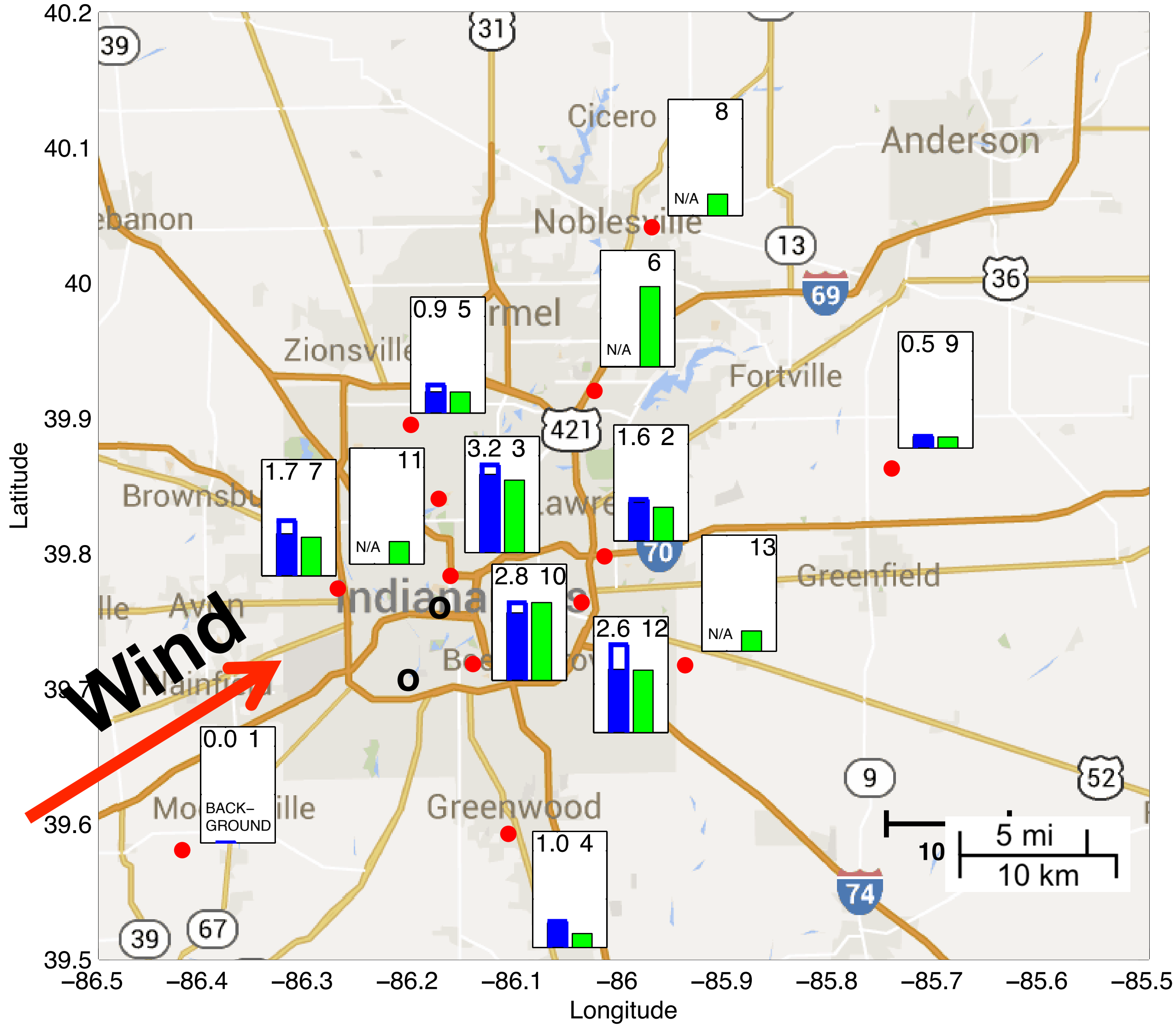
Hestia “bottom-up” CO_2 flux estimates



Micromoles per square meter per second

Lauvaux et al, in preparation

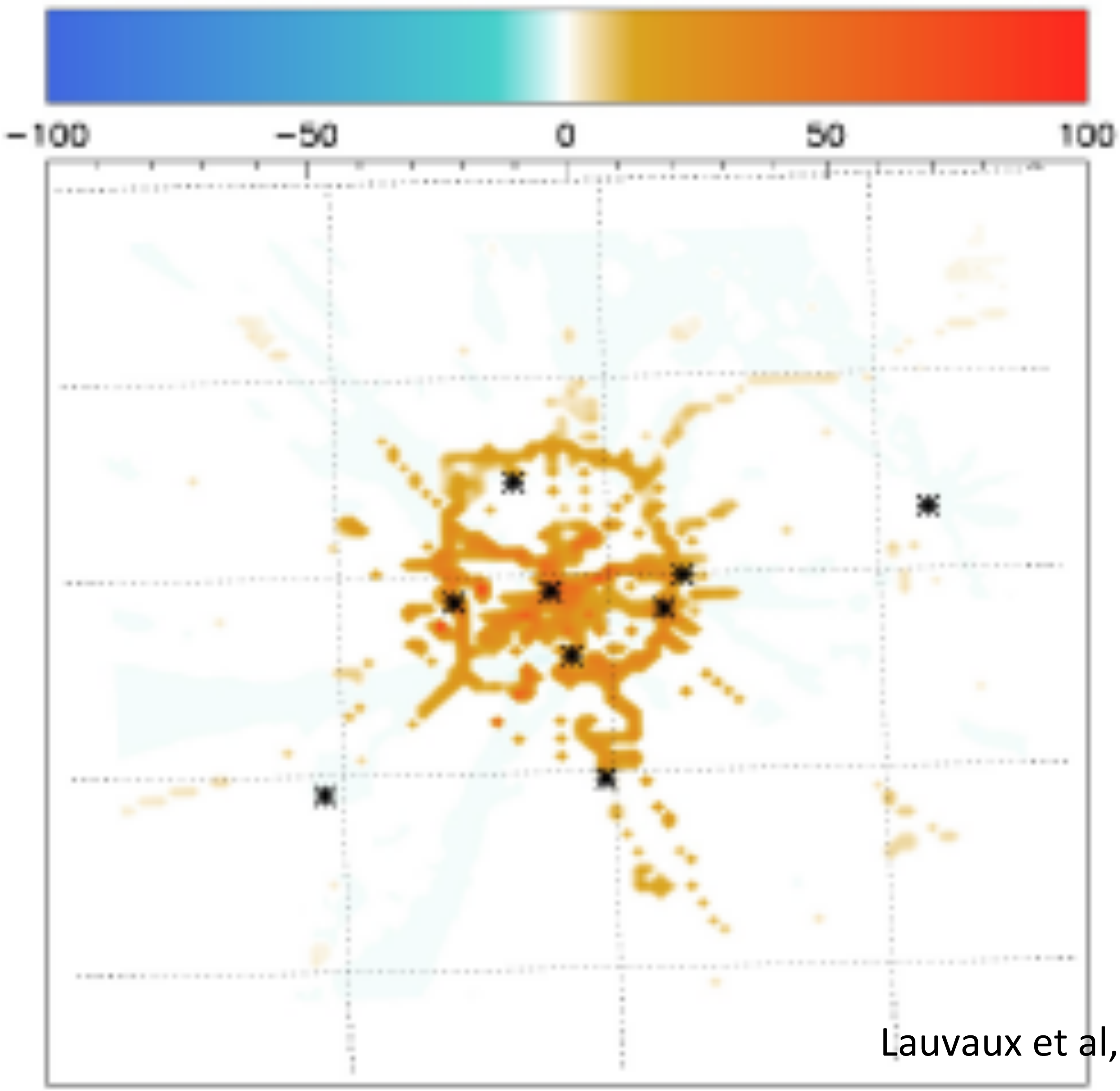
Spatial structure of urban CO_2: observed and modeled



- Observed CO_2: afternoon values, averaged Jan-April 2013
- Modeled CO_2 using LPDM footprints and Hestia emissions
- Overall, the spatial structure is similar

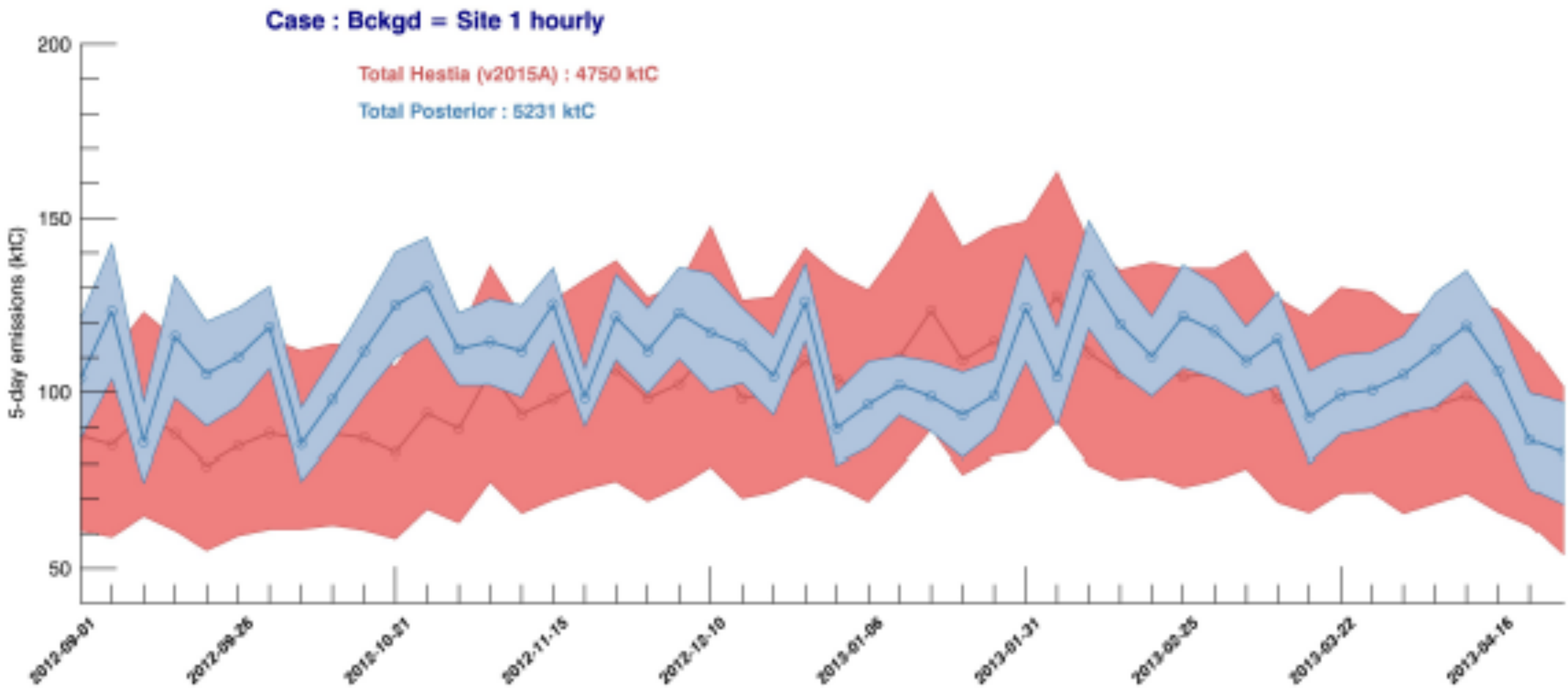
Miles et al, in prep

Percent flux change from prior



Lauvaux et al, in preparation

Inverse CO_2 flux estimates over time



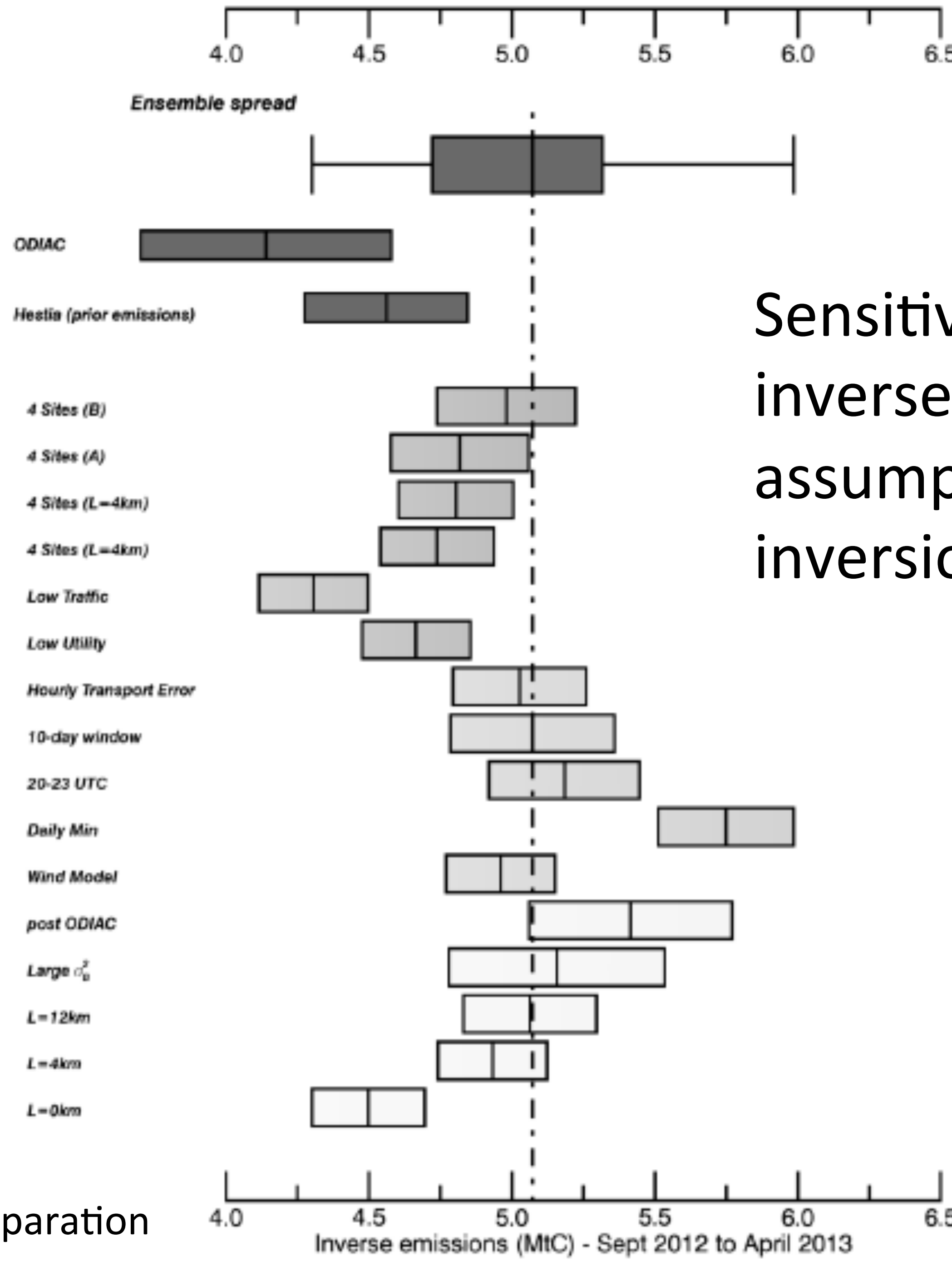
Lauvaux et al, in preparation

Sensitivity of inverse results to assumptions in the inversion system.

Case	L=12km	Low traffic	Low utility	Large σ_B^2	ODIAC	4 Sites (A)	4 Sites (B)	L=4km
Prior	4.56	3.73	4.2	4.56	4.14	4.56	4.56	4.56
Posterior	5.06	4.31	4.66	5.16	5.41	4.82	4.98	4.93
Case	Wind model	Daily Min	10 days	$\lambda.\varepsilon$	20-23UTC	4 Sites A (L=4km)	4 Sites B (L=4km)	L=0km
Prior	4.56	4.56	4.56	4.56	4.56	4.56	4.56	4.56
Posterior	4.96	5.75	5.07	5.03	5.18	4.74	4.8	4.5

Table 2. Prior and posterior emissions from the various inversion configurations referred as the initial inversion case (L=12km), a decrease of 40% in the a priori traffic emissions (Low traffic), a decrease of 40% in emissions from the a priori energy production sector (Low utility), using large prior emission variances (Large σ_B^2), using ODIAC as prior emissions (ODIAC), assimilating only 4 sites out of 9 (4 Sites (A) and 4Sites (B)), assimilating only 4 sites out of 9 with a lower correlation length of L=4km (4 Sites A (L=4km) and 4 Sites B (L=4km)), varying the correlation length L in the prior emissions errors (L=0km and L=4km), varying the definition of the background conditions using the wind direction (Wind model) or the minimum of the day (Daily Min), assimilating over a 10-day time window instead of 5 days (10 days), filtering hourly observations using wind model errors ($\lambda.\varepsilon$), and varying the afternoon window for observations (20-23UTC)

Lauvaux et al, in preparation



Sensitivity of inverse results to assumptions in the inversion system.

Lauvaux et al, in preparation

INFLUX work underway

- Adaptation of the inversion system to separate fossil fuel CO_2 from total CO_2.
- Multi-model evaluation of atmospheric transport simulations compared to multiple data sources.
- Quantification of the impact of meteorological data assimilation on the atmospheric inverse flux estimates.

Conclusions

- Atmospheric inversions provide a potent means of measuring GHG sources and sinks give sufficient high-quality atmospheric data.
- Urban GHG emissions are clearly detectable in the atmosphere but small, and could be masked by factors like tower height, background site and time sampling.
- The INFLUX atmospheric modeling system reproduces the urban GHG enhancements very well outside of summer.
- INFLUX inverse flux estimates are fairly robust, but dependent at ~10% variability on a number of assumption within the inverse system.
- Uncertainties in emissions inventories are essential for carefully assessing the relative strengths of each approach.

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