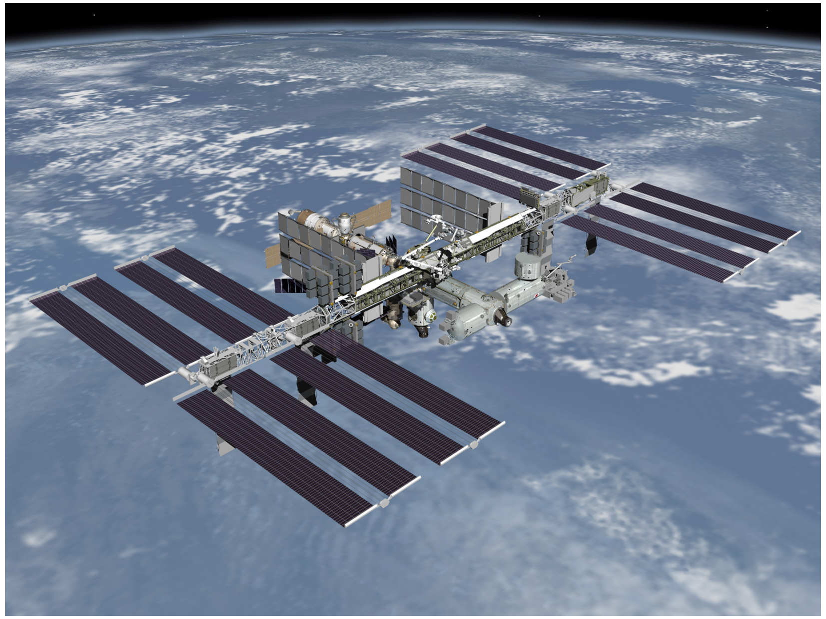
LSCE

PennState

City-scale: lessons (learned) from (some) US (and non-US) research activities

Thomas Lauvaux

Now at LSCE, France
Worked performed while at The Pennsylvania State University



Inferring trace gas emissions from urban areas

Urban areas represent 70% of the global fossil fuel emissions and 50% of the population (projected to grow to 70% by 2050)

Metropolitan regions increasingly complex as city centers merge into connected urban metabolisms

Two major projects in North America: Indianapolis and Los Angeles (also Salt Lake City and Washington D.C./Baltimore)

Indianapolis (INFLUX experiment, PennState): simple terrain, single city center, flat terrain, agricultural landscape
Collaborators: Paul Shepson, Purdue; Kevin Gurney, ASU; Colm Sweeney, NOAA GMD; Jocelyn Turnbull, GNSS

Los Angeles (LA Megacity, JPL): megacity, complex terrain (coastal basin), urban vegetation
Collaborators: Riley Duren, JPL; Paul Wennberg, Caltech; John Miller, NOAA;

Inferring trace gas emissions from urban areas: Indianapolis

Natasha Miles, Scott Richardson, Kenneth Davis, Kai Wu, Nikolay Balashov, Aijun Deng, Brian Gaudet

Department of Meteorology, Pennsylvania State University

Colm Sweeney

ESRL/NOAA GMD, CIRES, Boulder

Anna Karion, Kim Mueller

NIST

Jocelyn Turnbull

GNS Science, New Zealand

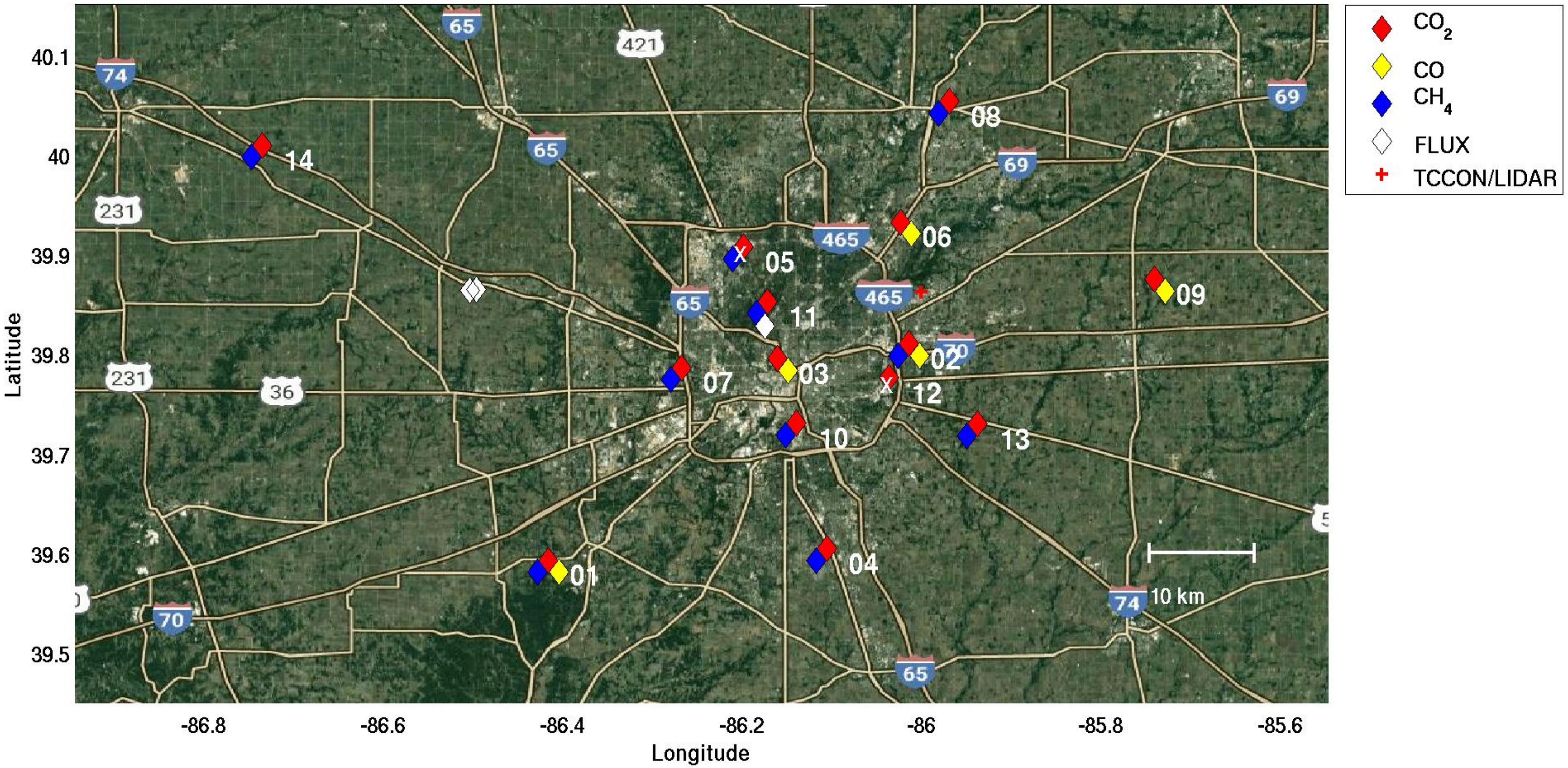
Paul Shepson, Obie Cambaliza,

Purdue University

Jon Wang, Lucy Hutyra

University of Boston

Inferring trace gas emissions from urban areas: Indianapolis



The INFLUX observing network

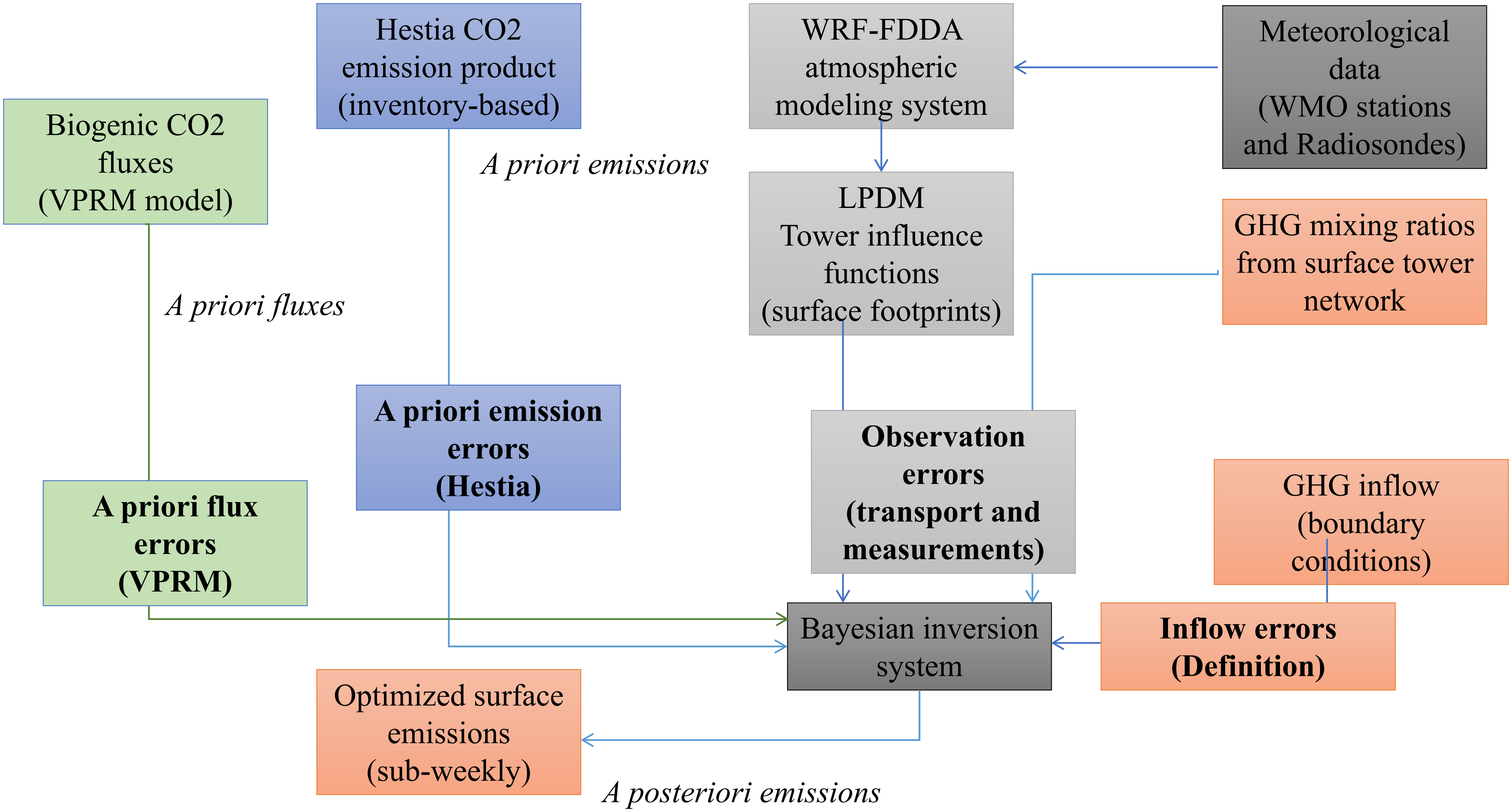
- 12 towers (CO_2/CH_4/CO)
- 5 NOAA flask samplers
- 3 eddy-flux towers
- 1 Doppler lidar

Operational since 2010 (full network in 2012)

Aircraft mass-balance flights

High-resolution data product (Hestia, *Gurney et al., 2012*)

Inferring trace gas emissions from urban areas: Indianapolis



Multi-species assimilation to identify economic sectors

- Sector-level emissions require disaggregation of atmospheric signals

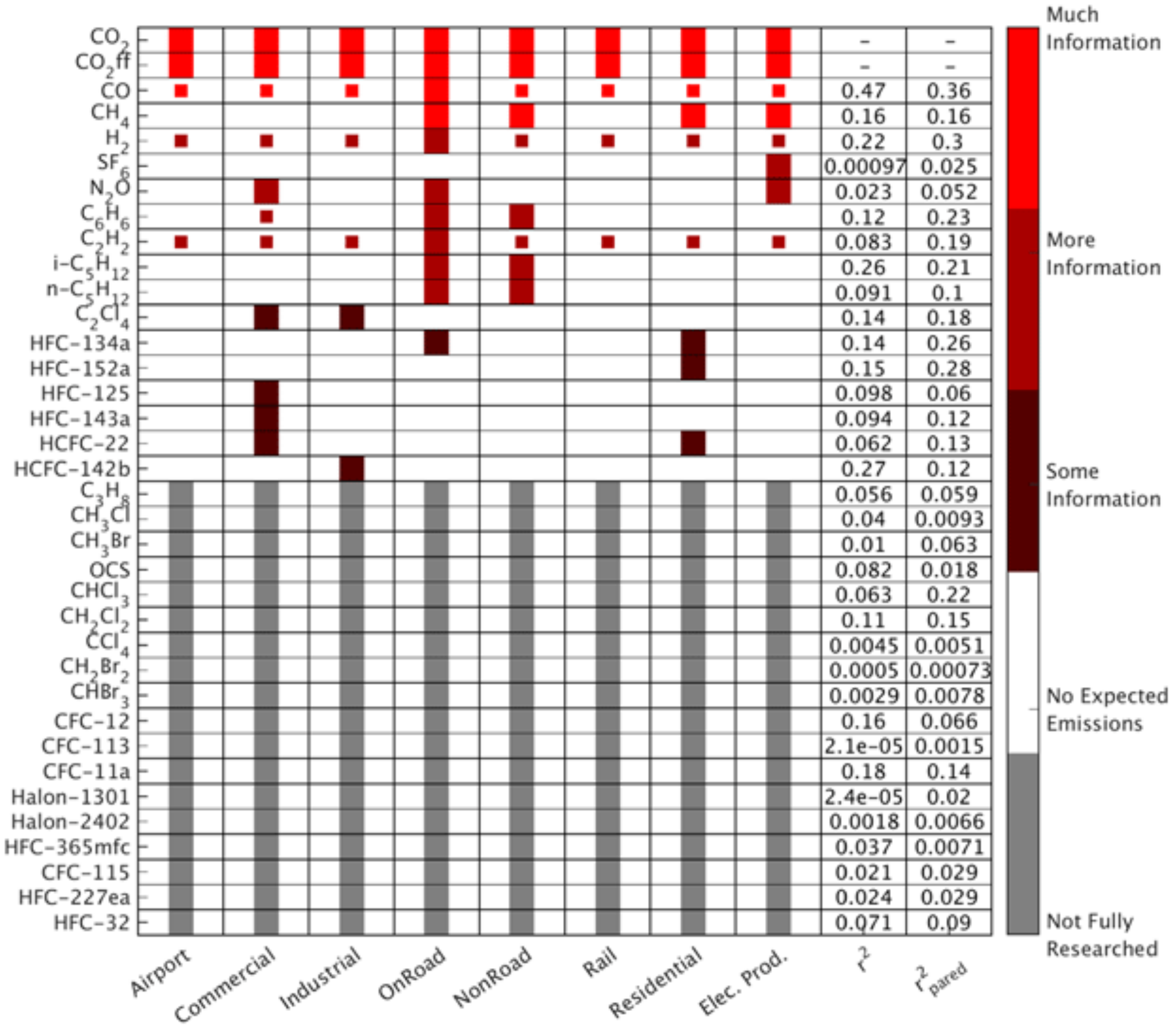
- Additional data are required to disentangle contributors from mixed plumes

Example: trace gas measurements from discrete flask samples with 55 atmospheric species from NOAA PFP's

Can we attribute signals to specific sectors of the economy?

Options for the INFLUX project:
- CO from incomplete combustion (traffic)
- C_2H_2 from traffic and industries
- HFC-134a from air conditioning
- Alkanes for methane attribution

Still large gaps in our knowledge – and technology changes rapidly



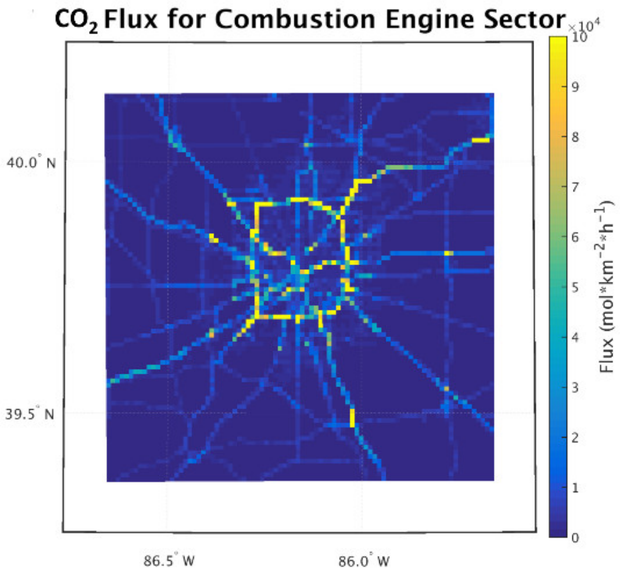
Sectoral attribution of trace gases measured in NOAA flask samples.

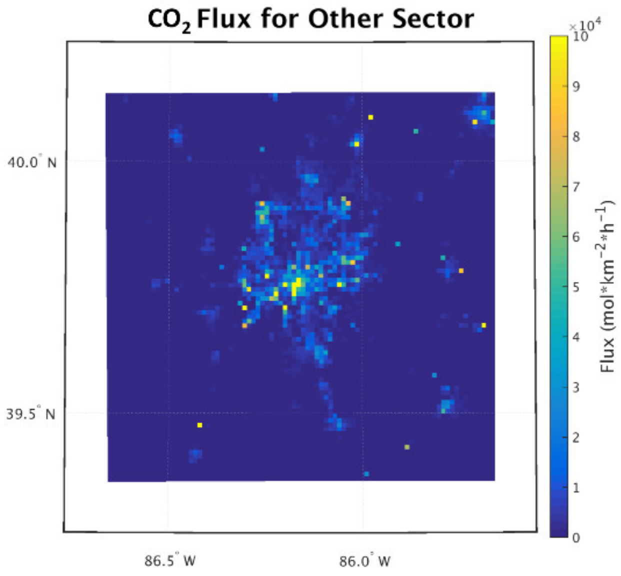
Multi-species assimilation to identify economic sectors

Assimilation of multiple sectors of the economy:

- Atmospheric CO_2 mixing ratios only: Requires balanced uncertainties *(dichotomy problem)*

- Atmospheric CO and CO_2 mixing ratios: Uncertainties of the sectors should be balanced by the sensitivities of the trace gases





Two activity sectors used in the inversion system:

- Combustion Engine (traffic & non-road)

- Other sectors
(Res & Ind & Utility & Com & Airport & Rail)

Nathan et al., accepted JGR-Atmos.

Render to Caesar the things that are Caesar's

Dr. Brian Nathan

Now Post-doctoral researcher, at Aix-Marseille University, France

Current project: Aix-Marseille Carbon (AMC) Project, studying CO_2 emissions and behavior in the South France/Coastal Mediterranean region (P.I.: Dr. Irène Xueref-Rémy)

Sectoral atmospheric inversion framework

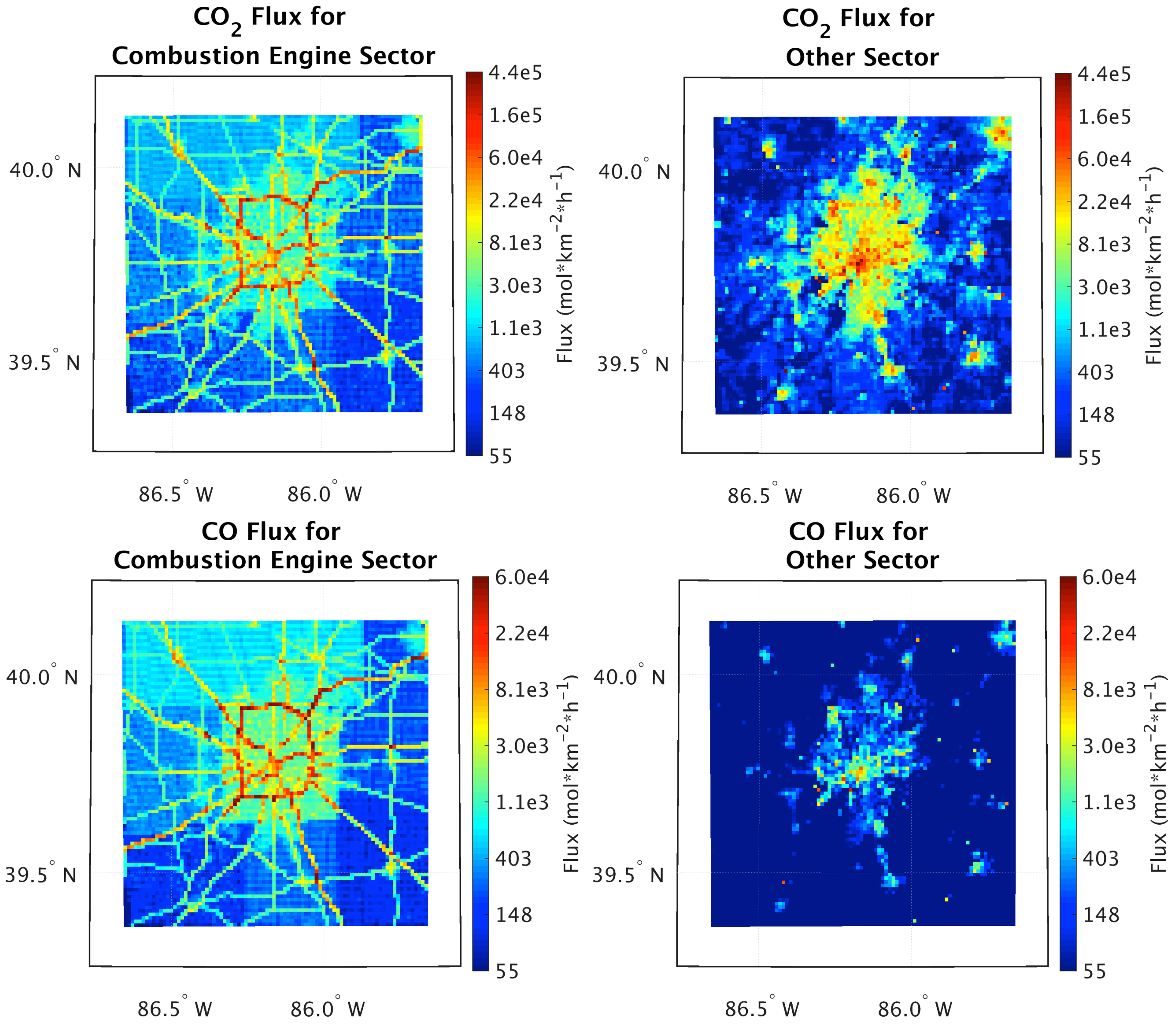
The definition of emission sectors needs to address:

- *attribution* problem: balancing error variances
- *orthogonality*: maximize the information from gas-to-gas ratios (e.g. commercial and residential sectors are nearly identical in terms of $CO:CO_2$ ratios)

For Indianapolis:

- Sector 1: On-road and off-road sectors (about 50% of the total emissions) – High $CO:CO_2$ ratio
- Sector 2: Everything else – Low $CO:CO_2$ ratio

Sectoral emissions of CO and CO_2



Couple notes:

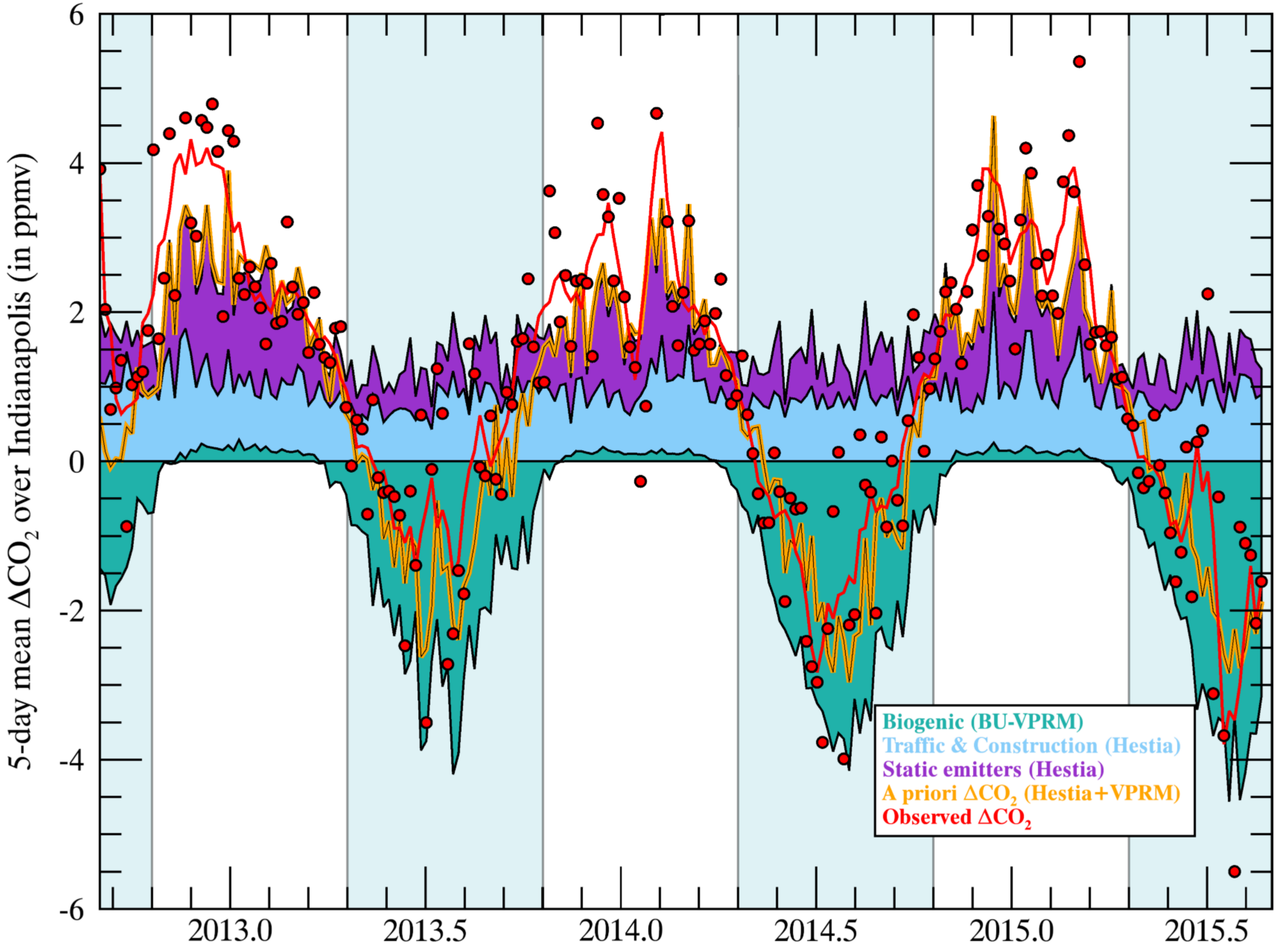
- *Combustion Engine* has a high sensitivity to CO = the balance in CO error variances is not optimal

- Other Sector shows larger point sources = error variances will be even larger (squares of large peaks are even larger)

- Lack of spatial resolution in off-road emissions

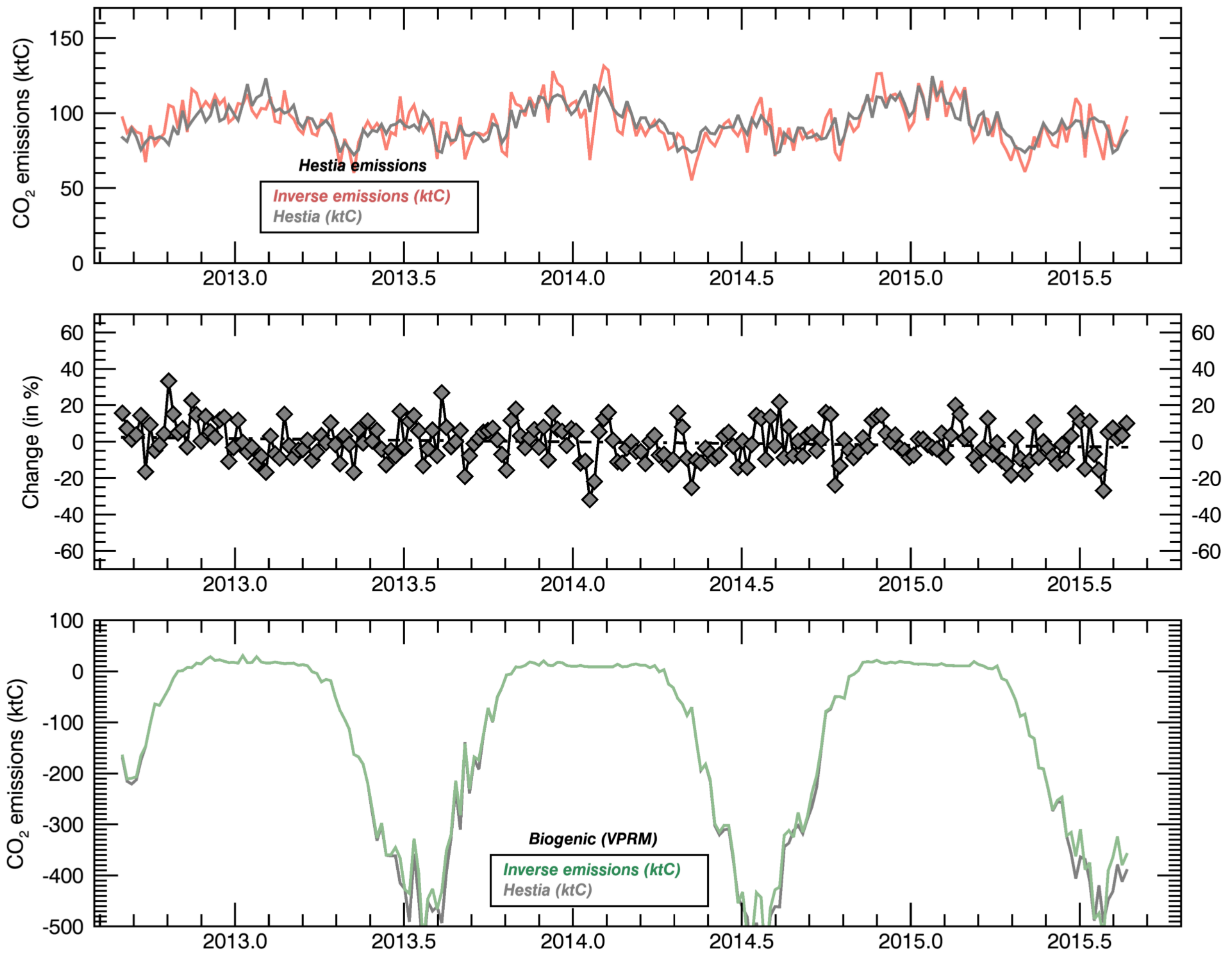
- Inversion only optimizes CO_2 emissions ($CO:CO_2$ ratios used to propagate CO innovations into CO_2 flux space)

Inferring trace gas emissions from urban areas: Indianapolis

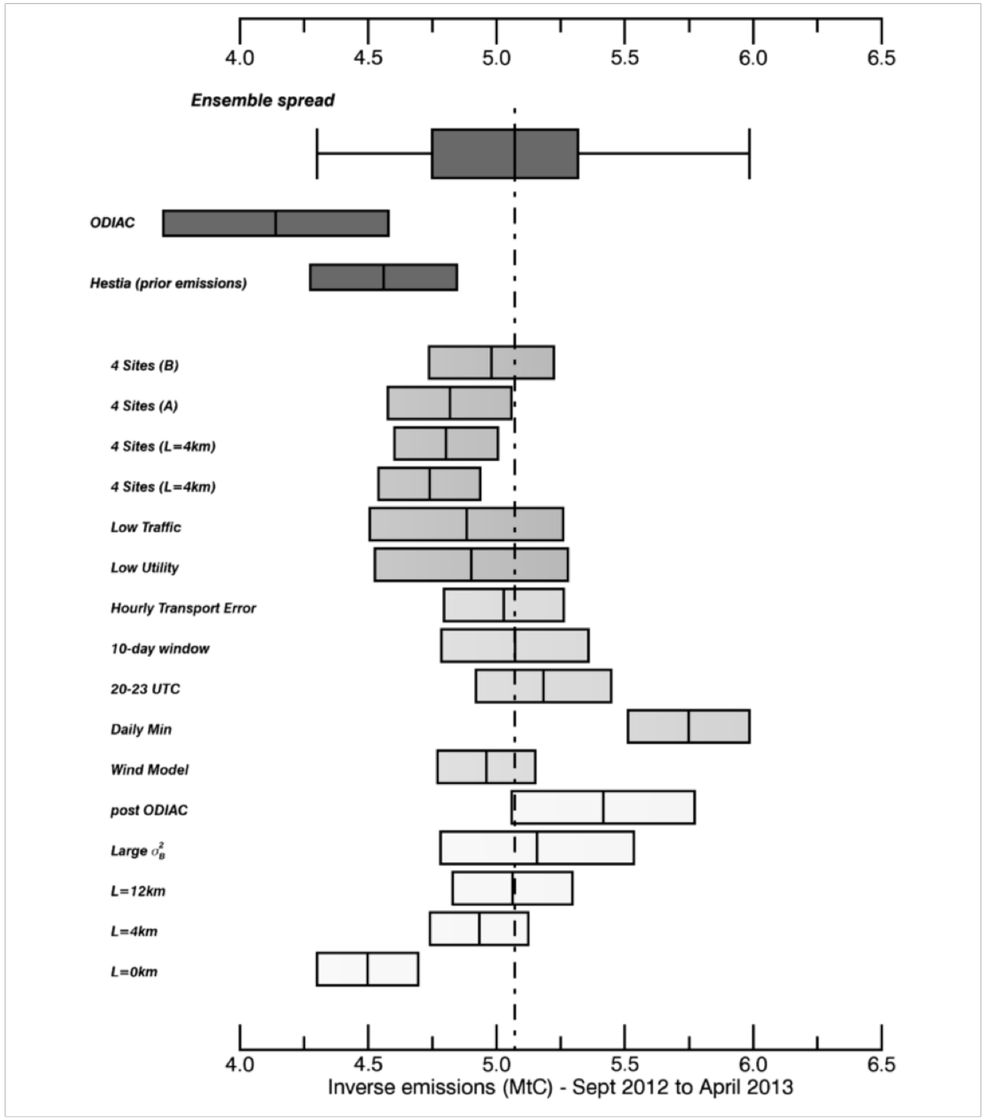


Atmospheric CO_2 mixing ratios simu;lated by WRF-LPDM for each sector (traffic and others) and biogenic fluxes from VPRM (2012-2015) compared to observed gradients (downwind minus background) averaged over 5 day periods.

Inferring trace gas emissions from urban areas: Indianapolis

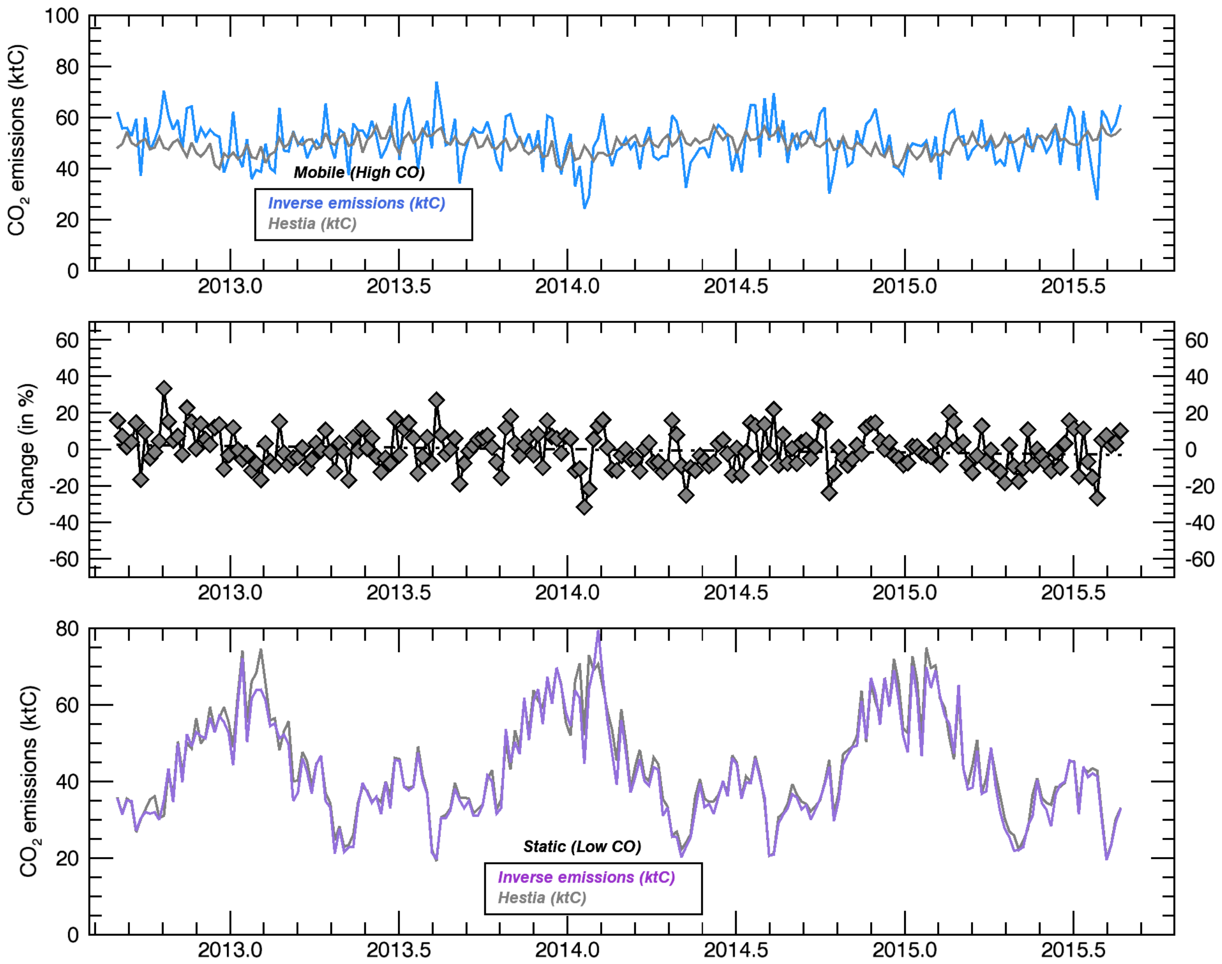


Total CO_2 emissions and biogenic fluxes (2012-2015) and overall emission trend before and after inversion (1km resolution)

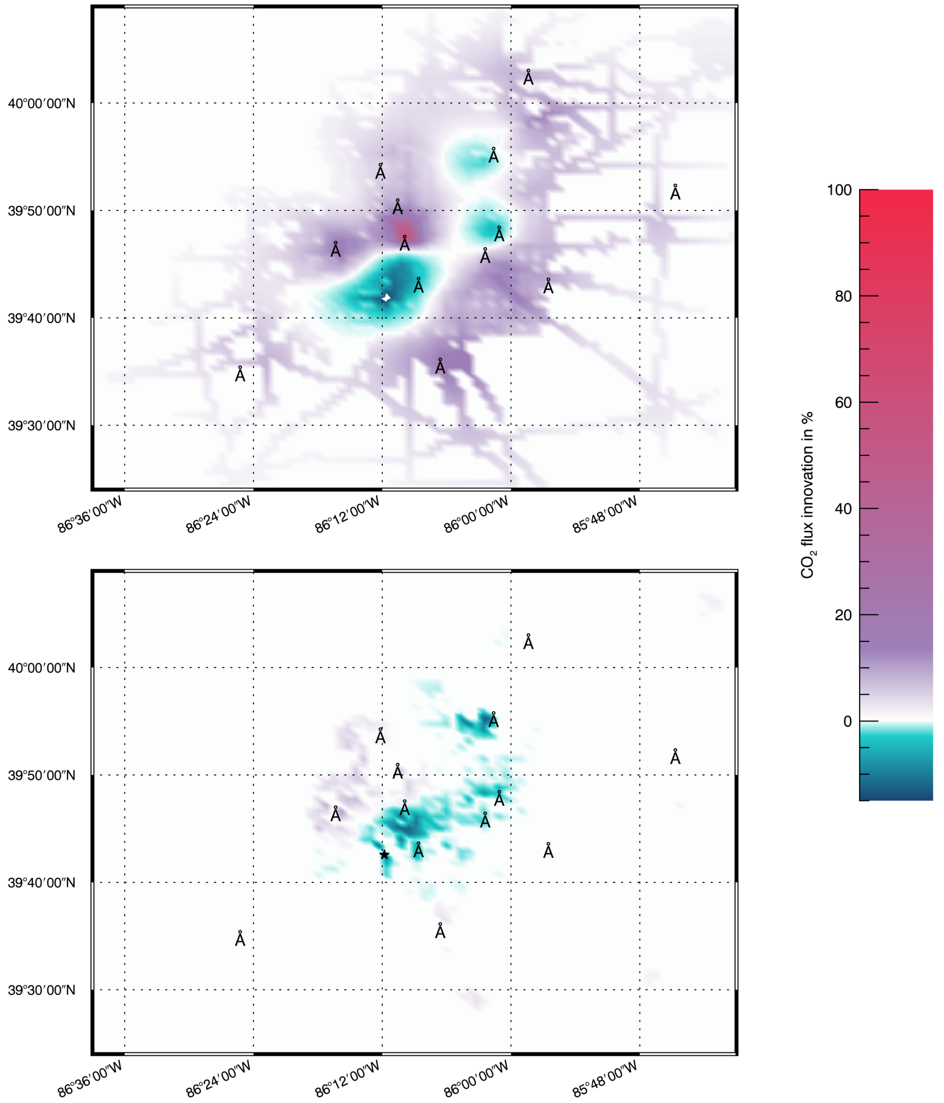


Prior and inverse CO_2 emissions (2012-2013) for 16 inverse system configurations (1km resolution)

Inferring trace gas emissions from urban areas: Indianapolis

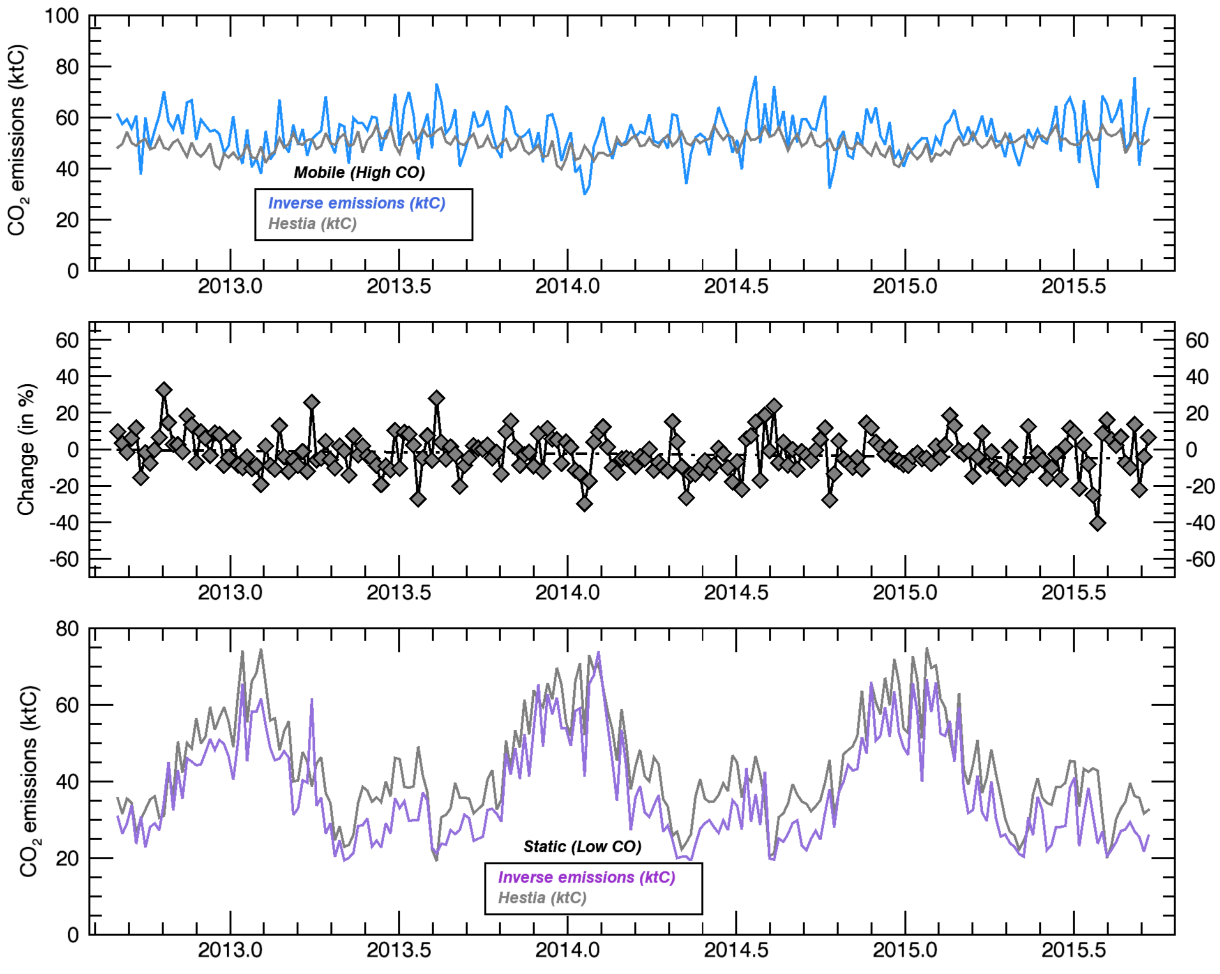


Sectoral CO_2 emissions (2012-2015) and overall emission trend before and after inversion (1km resolution)

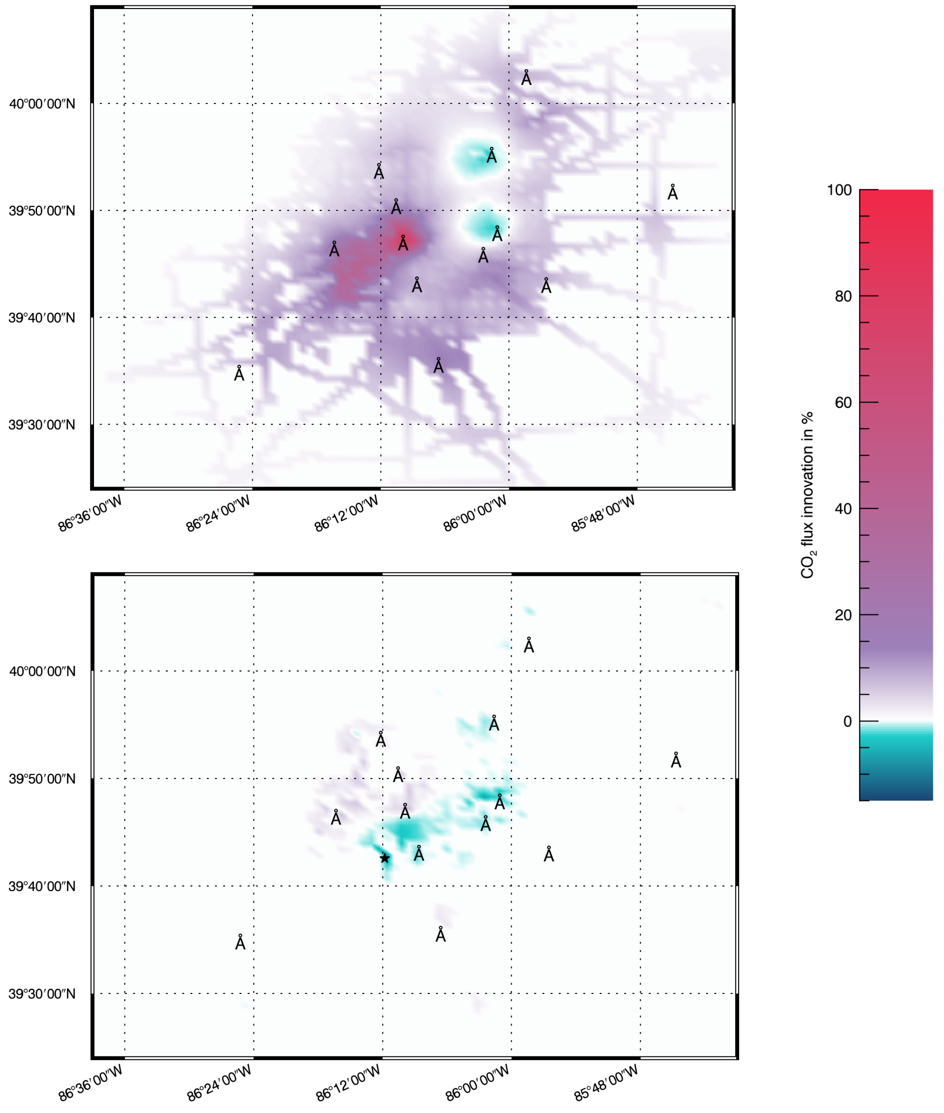


Change after inversion in sectoral CO_2 emissions (2012-2015)

Inferring trace gas emissions from urban areas: Indianapolis

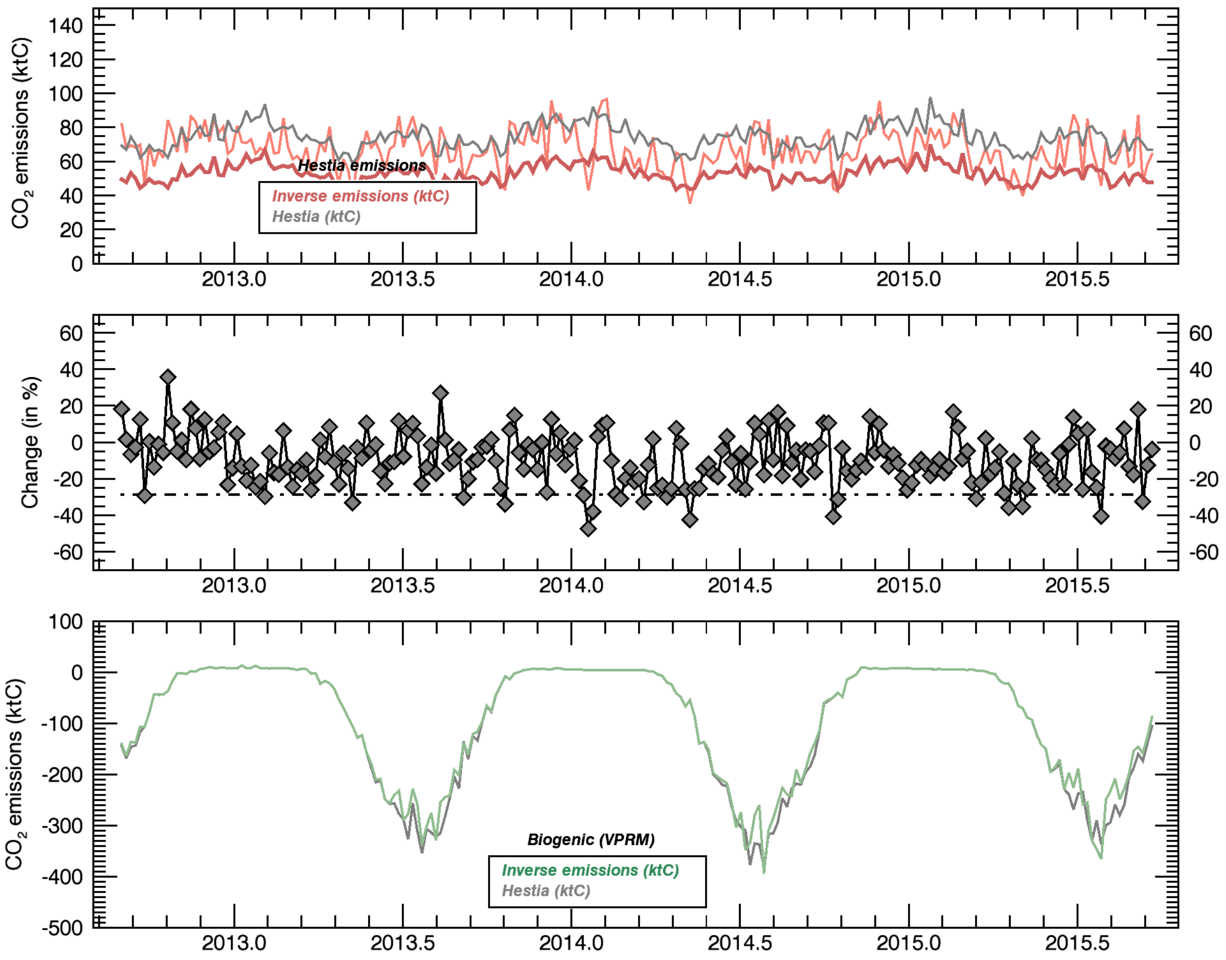


Sectoral CO_2 emissions (2012-2015) and overall emission trend before and after inversion (1km resolution)

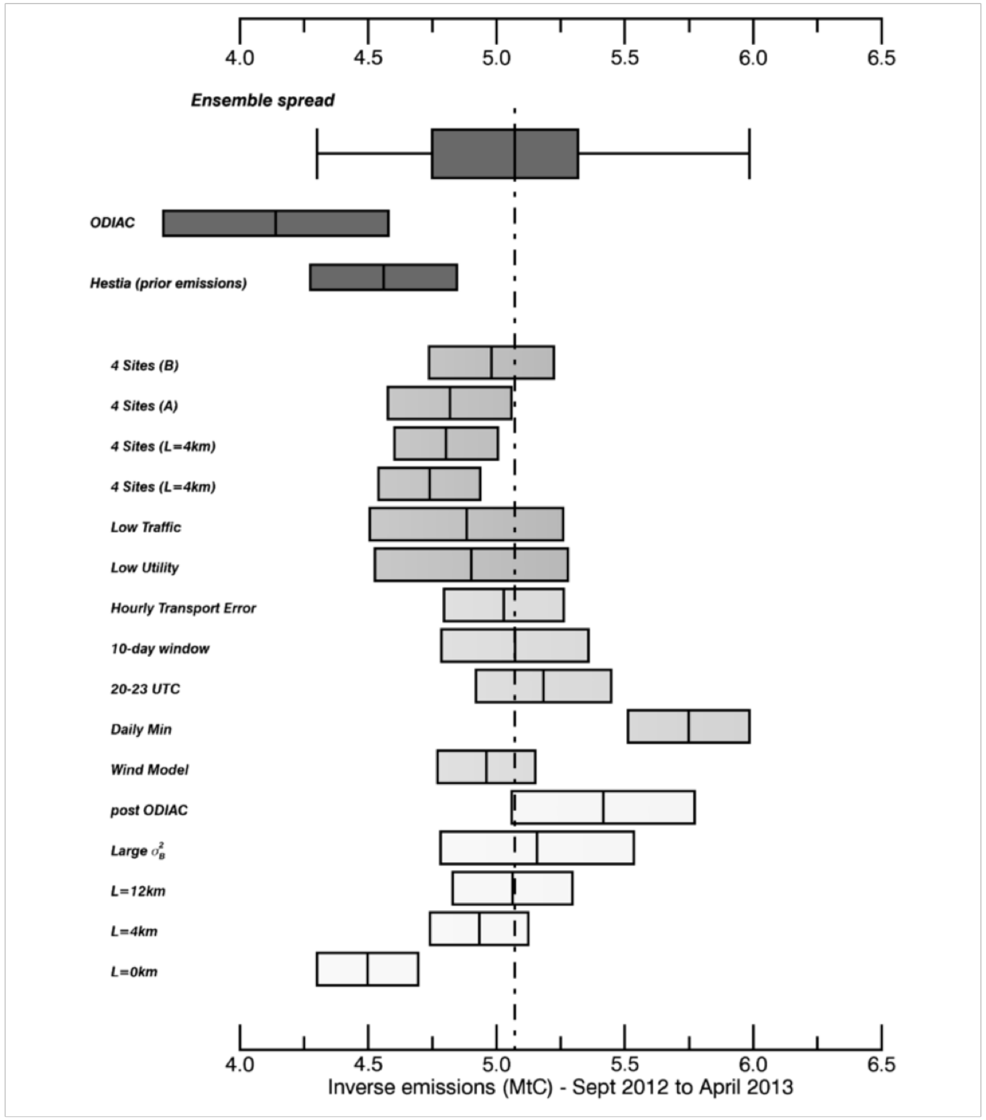


Change after inversion in sectoral CO_2 emissions (2012-2015)

Inferring trace gas emissions from urban areas: Indianapolis



Total CO_2 emissions and biogenic fluxes (2012-2015) and overall emission trend before and after inversion (1km resolution)



Prior and inverse CO_2 emissions (2012-2013) for 16 inverse system configurations (1km resolution)

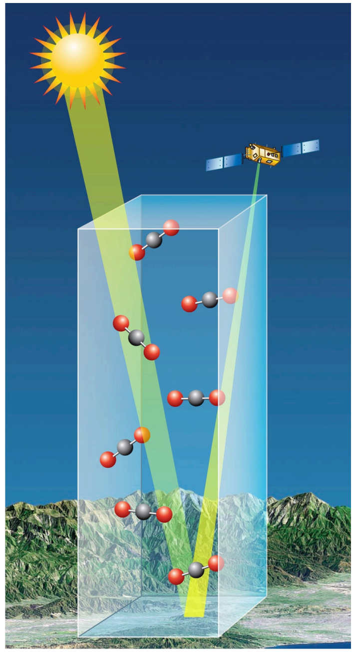
Urban emissions from space: first results from OCO-2

Xinxin Ye, Sha Feng
Department of Meteorology, Pennsylvania State University

Eric Kort, Emily Yang
University of Michigan, Ann Harbor

John Lin, Dien Wu
University of Utah, Salt Lake City

The Orbiting Carbon Observatory (OCO-2) mission

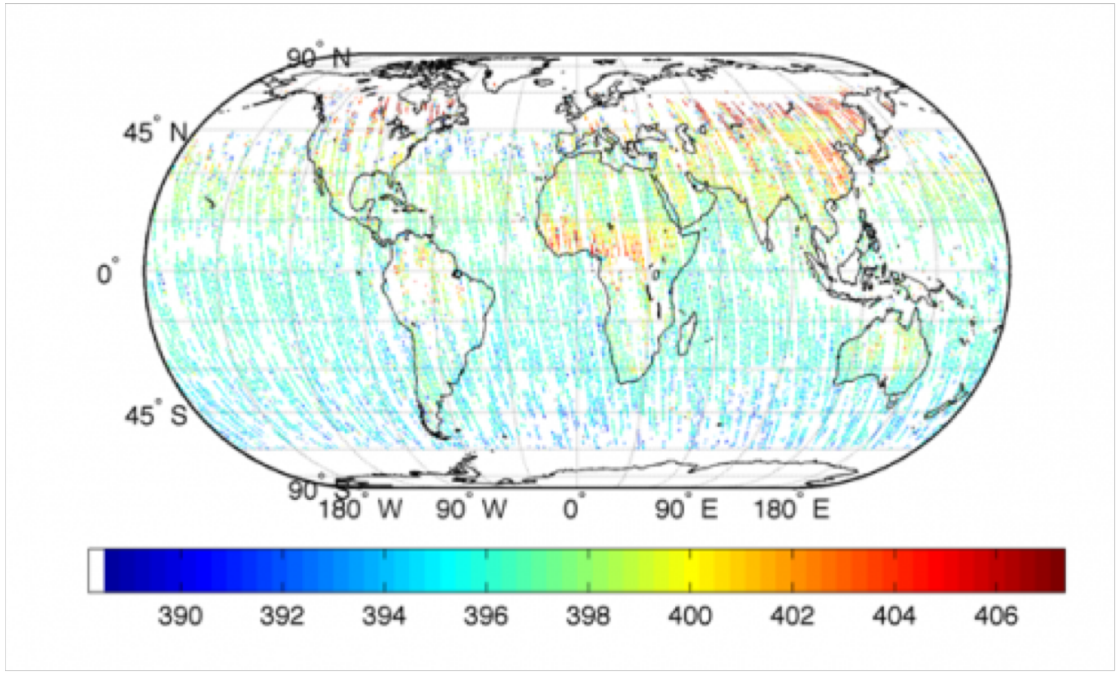


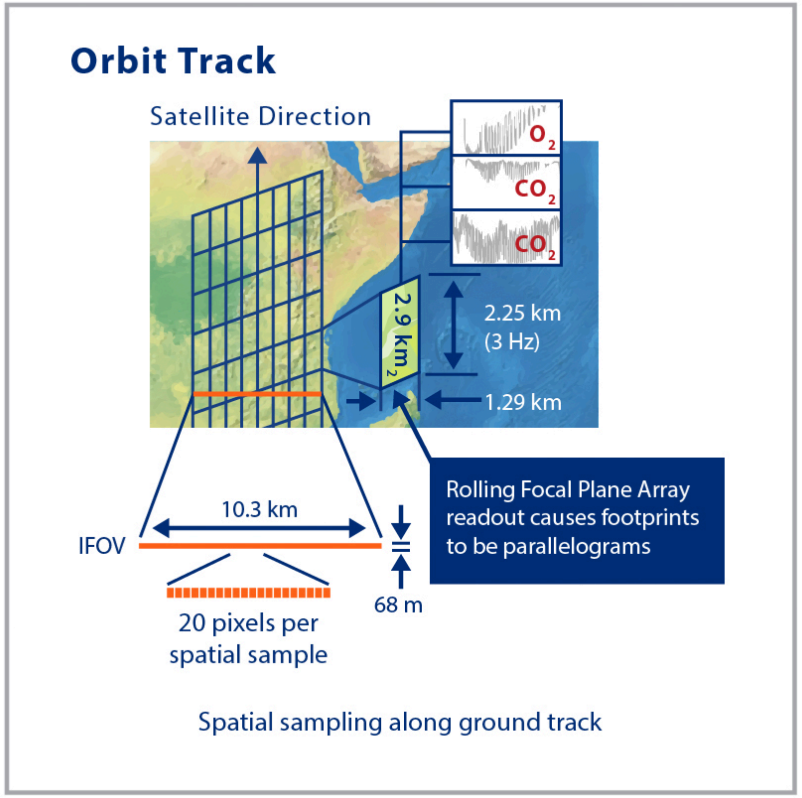
Passive instrument measuring total XCO_2 mole fraction

Revisit time of 16 days

Three modes: Nadir, Glint, Target

Operational since Oct 2014





OCO-2 ground tracks with 8 surface footprints of 1.3km by 2.3km

In collaboration with Jet Propulsion Laboratory
Annmarie Elderling, David Crisp

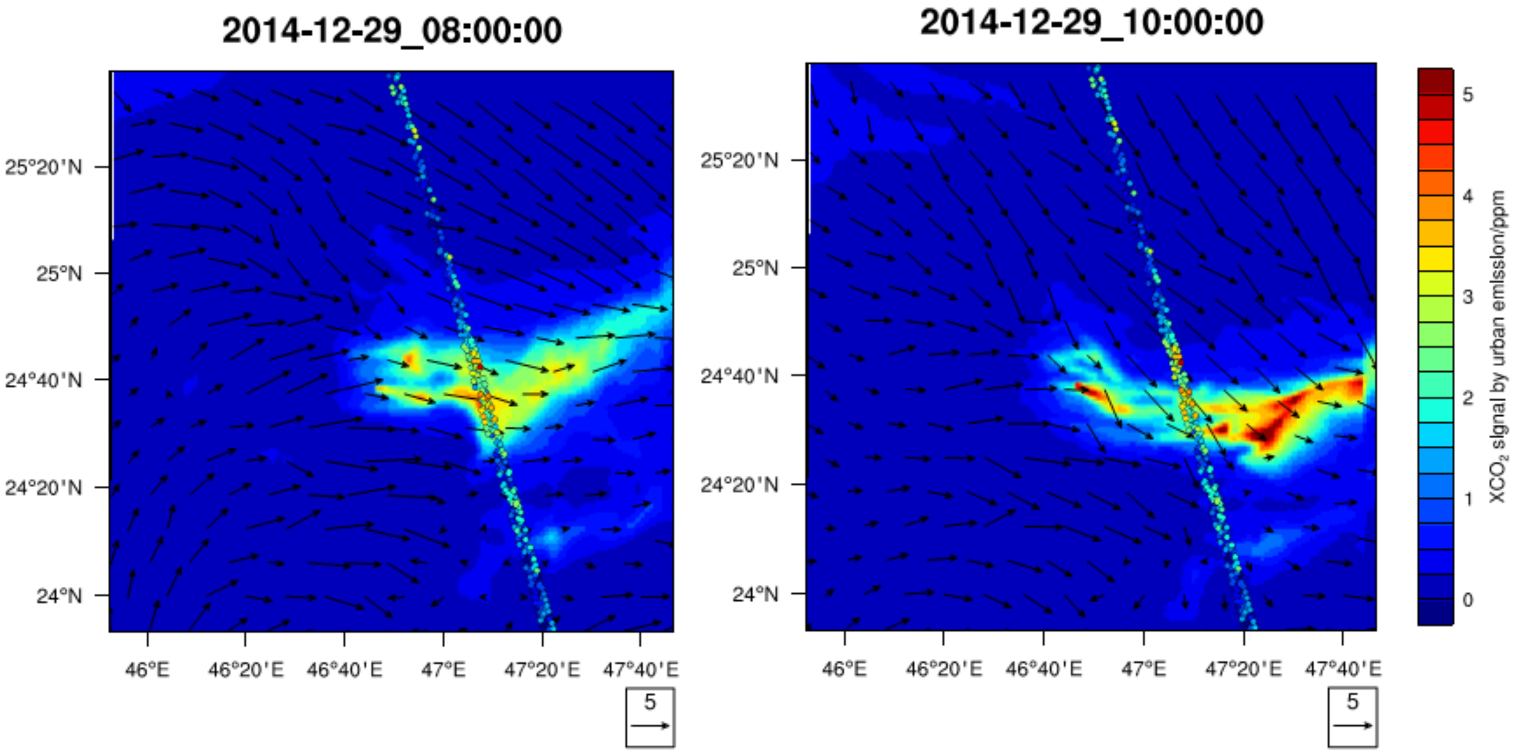
Render to Caesar the things that are Caesar's

Dr. Xinxin Ye

Now Post-doctoral researcher, at University of California Los Angeles

Current project: FIREX (NOAA) Project, studying
CO emissions from forest fires in the US
(P.I.: Pr. Pablo Saide)

Urban plume detection from OCO-2 retrievals and WRF-Chem simulations



XCO_2 retrievals from OCO-2 track near Riyadh compared to WRF-ODIAC simulations at 1km resolution with wind vectors at 100m agl (in ppm and m/s)

WRF-Chem simulations at 1km resolution coupled to ODIAC (Oda et al., 2010)

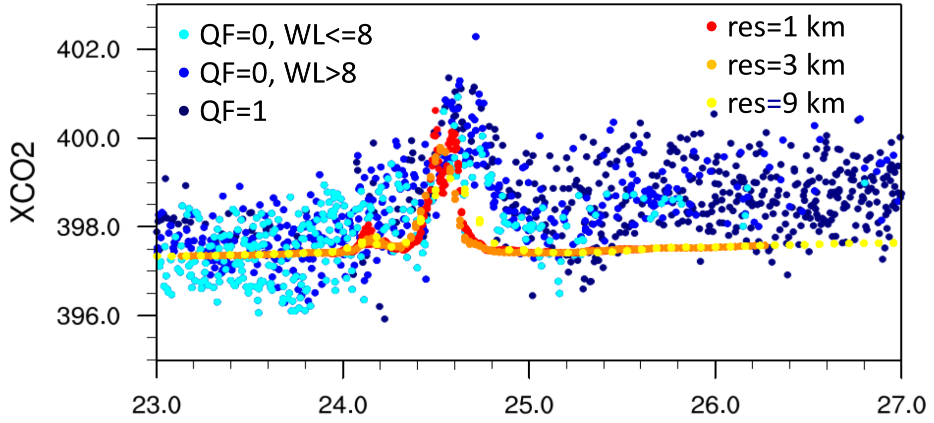
Nested configurations (9-/3-/1-km domains)

Mesoscale non-hydrostatic equations with turbulent closure scheme (order 2.5) for the Planetary Boundary Layer

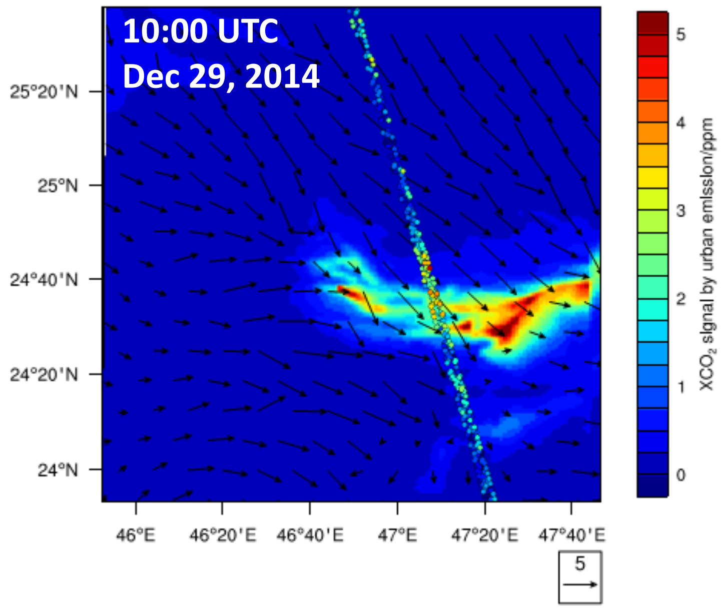
Tomhiro Oda, NASA Goddard; Xinxin Ye, UCLA

Imprints of urban CO_2 emissions detected by Orbiting Carbon Observatory-2 (OCO-2)

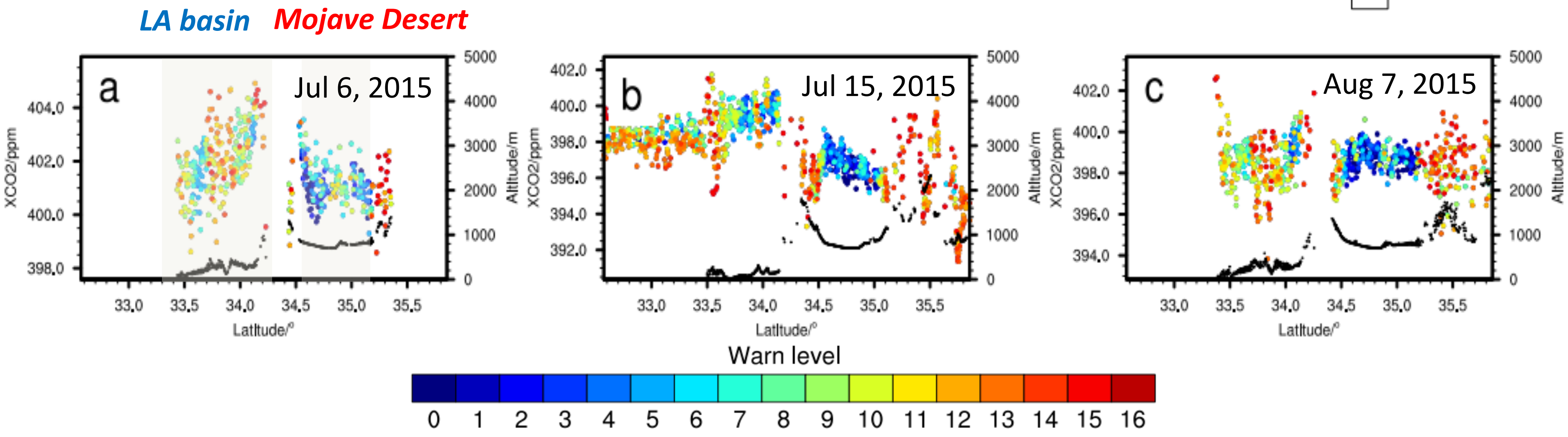
Plume city: Riyadh



Simulated XCO2 by WRF-Chem



Basin city: Los Angeles



Two examples of city plume detection frm space:
OCO-2 tracks near Riyadh and Los Angeles

OCO-2 characteristics
Repeat cycle of 2 weeks
Footprints: 1.5x2.5 km

Simulation using WRF-Chem at 1km resolution

Emissions from nightlight data combined with national reported emissions (ODIAC)

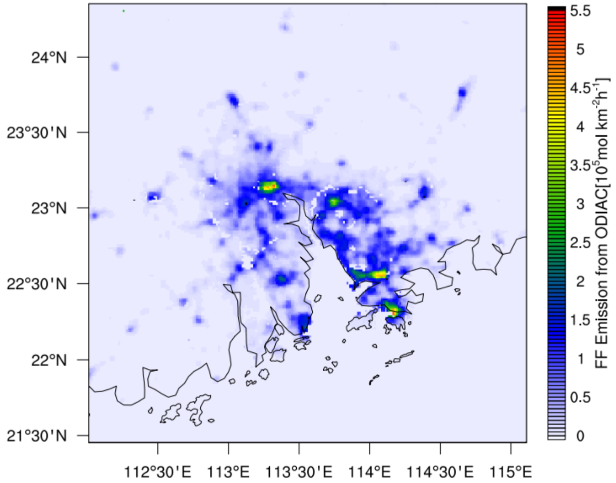
XCO2: total column dry air mole fraction of CO_2

Work of Xinxin Ye, now at UCLA

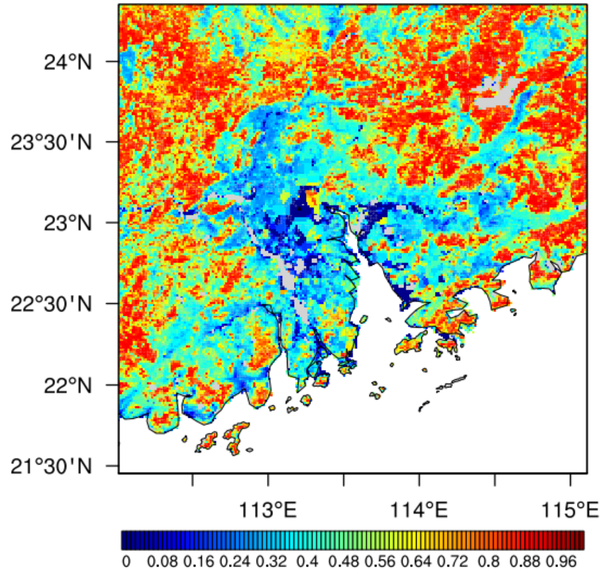
Biogenic fluxes and fossil fuel emissions

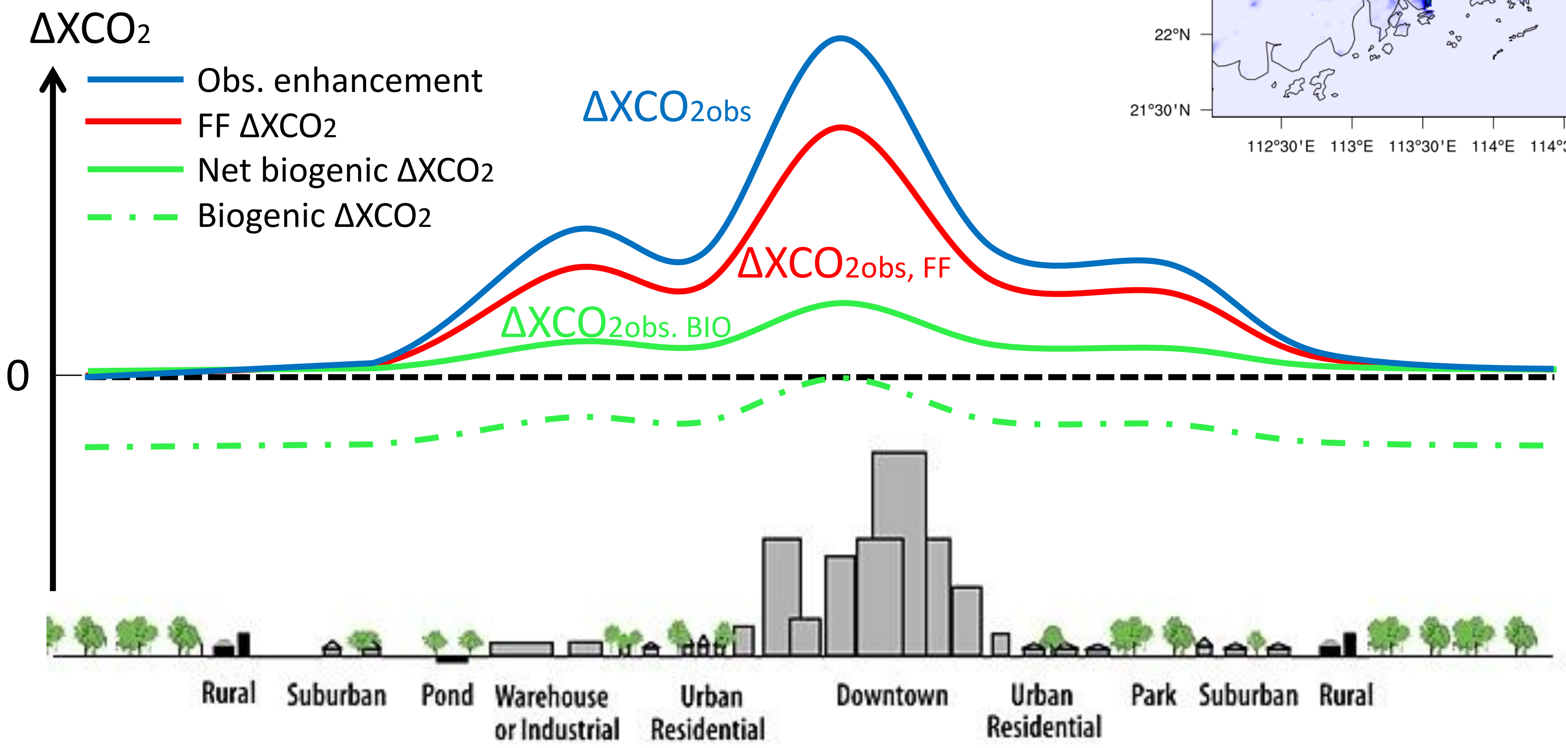
Biogenic flux maps based on:
- ensemble of 15 biogeochemical models
- upscaled using GVF from MODIS
- urban and rural vegetation assumed similar
-

FF CO_2 Emission (ODIAC)



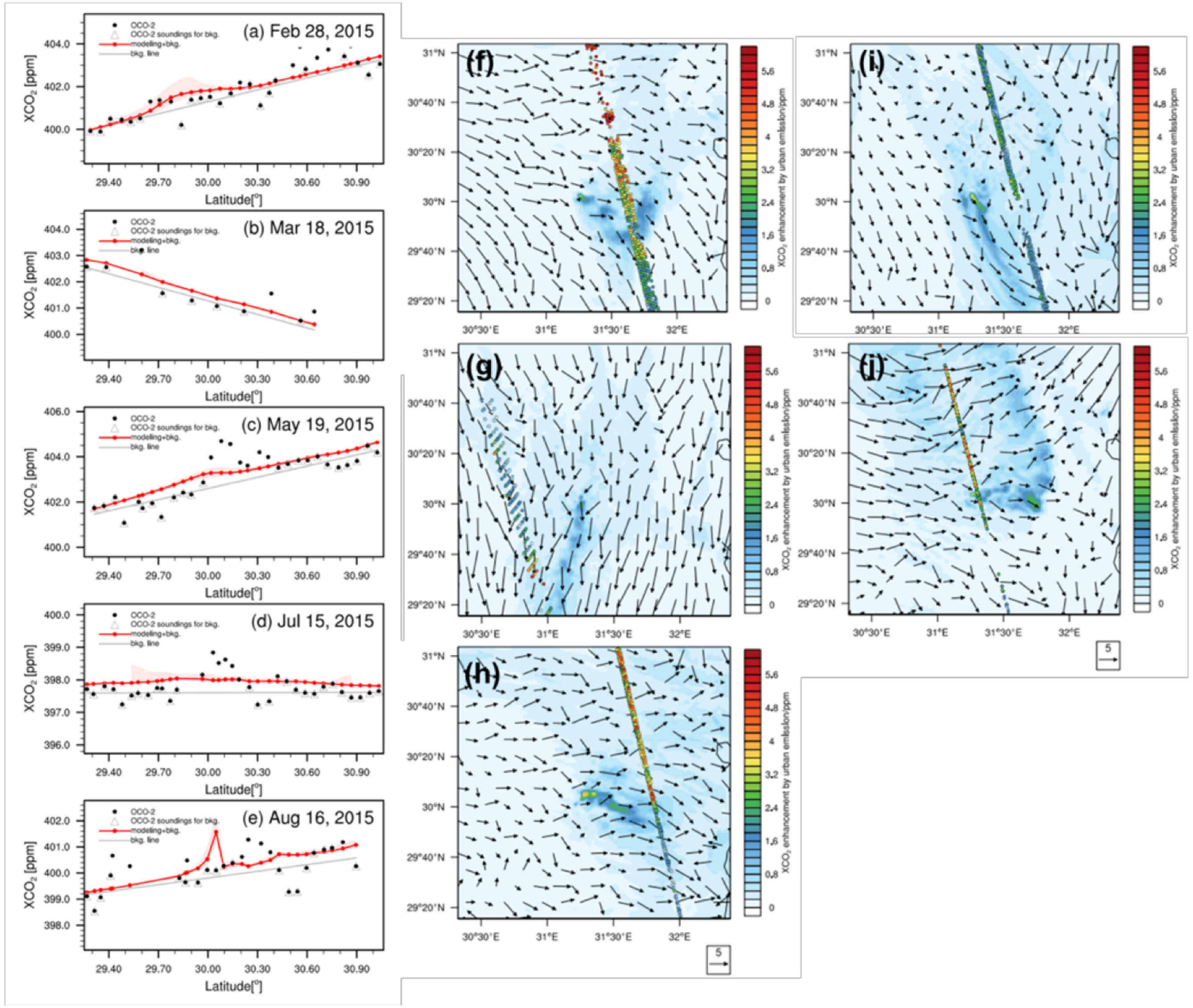
MODIS Green vegetation fraction





Work of Xinxin Ye, now at UCLA

Optimal Fossil Fuel CO_2 emissions: examples of Riyadh and Cairo



XCO_2 retrievals from OCO-2 track near Riyadh and Cairo compared to WRF-ODIAC simulations at 1km resolution with wind vectors at 100m agl (in ppm and m/s)

Technical challenges

- Linear interpolation of background XCO2
- Non-Gaussian structures for most cases
- Complex wind fields despite relatively flat terrain

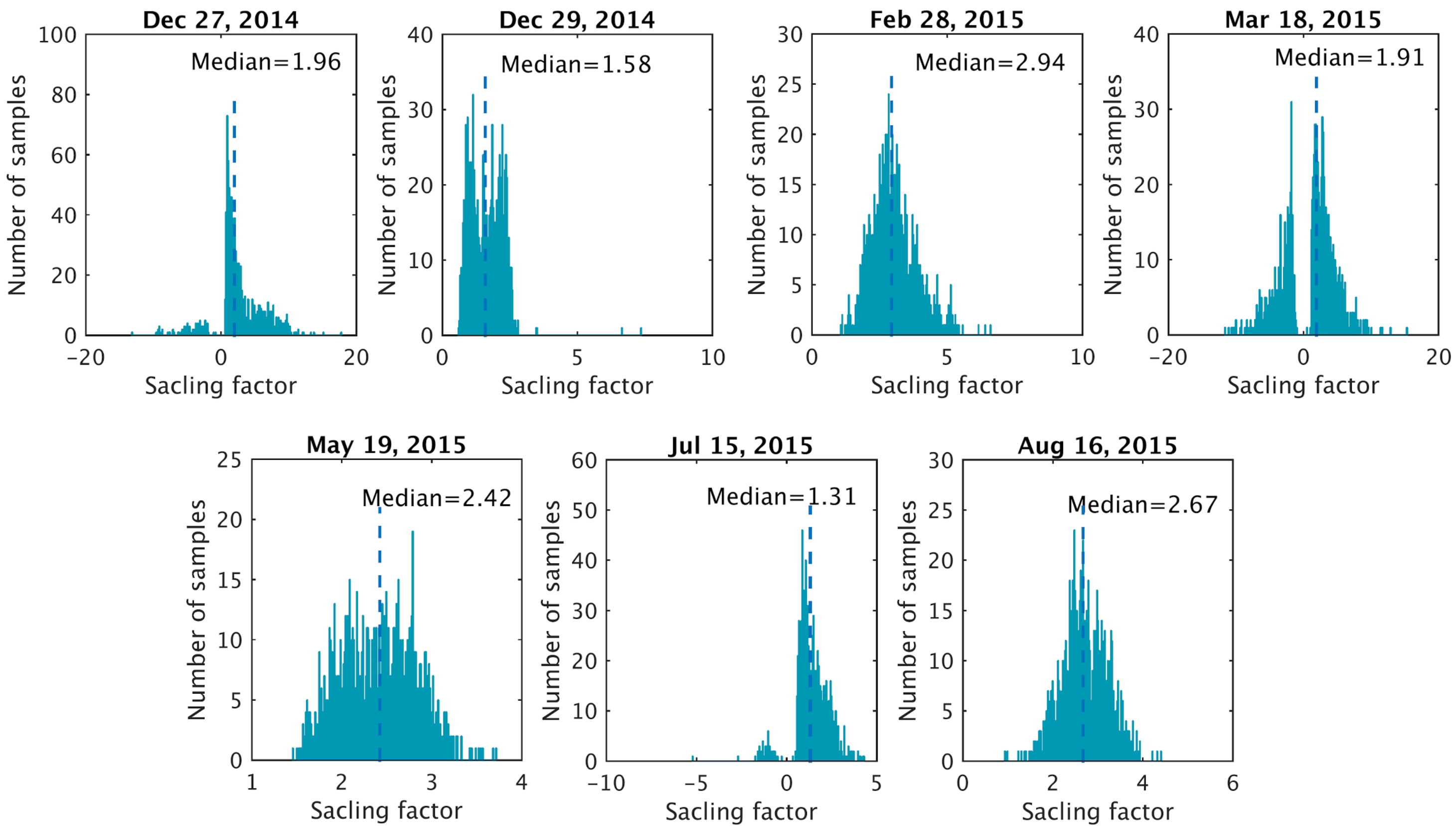
Magnitude of plumes remains low for both cities

Optimization method:

- Perfect distribution: adjusting a single scaling factor for each day

- Reduced transport errors: adjustment of the integral of the XCO2 enhancement

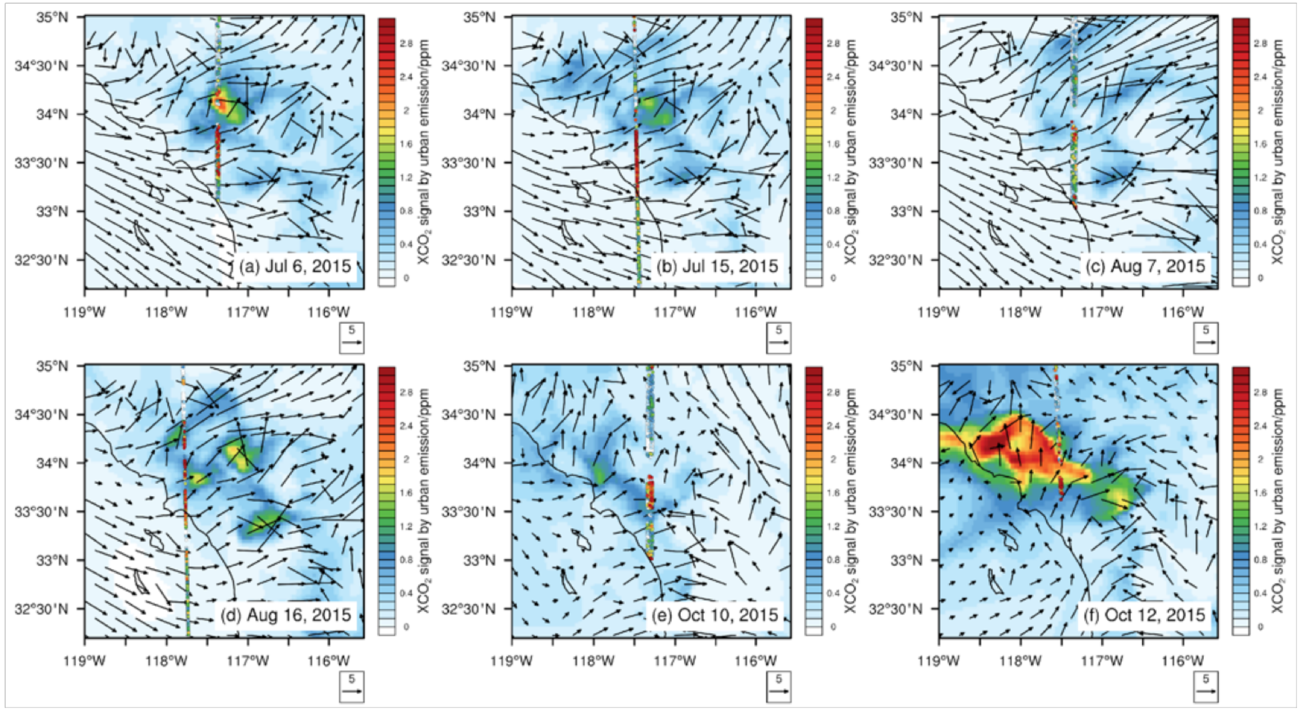
Optimal Fossil Fuel CO_2 emissions: examples of Riyadh and Cairo

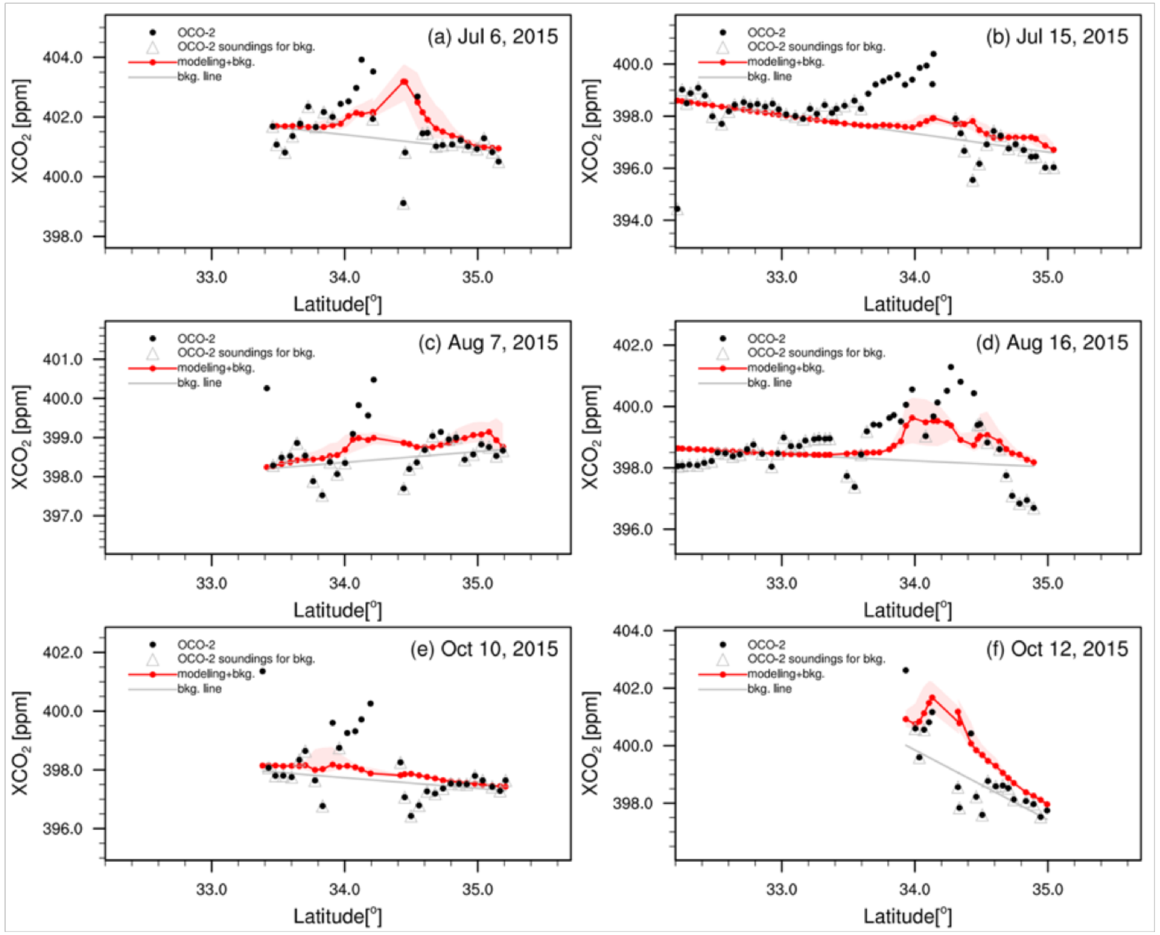


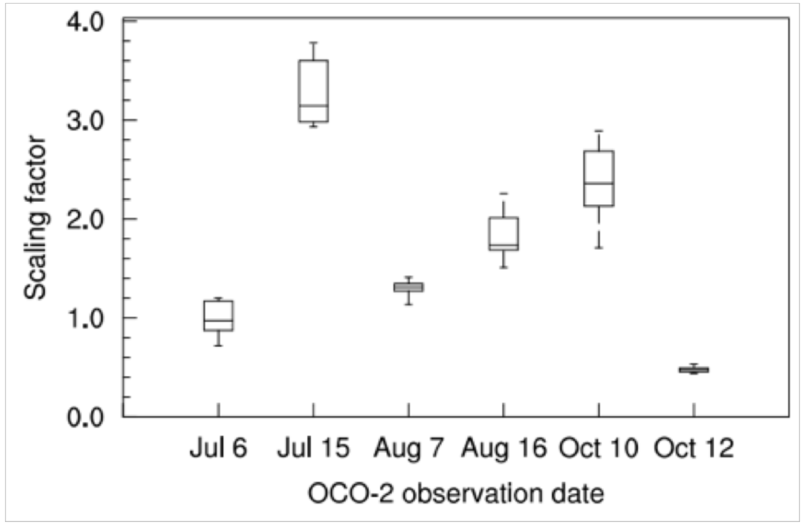
- Non-Gaussian distribution despite Normal Errors:
    Non-linear effect when plume - track angle low (less than 30 degrees)
- Errors are significant for each OCO-2 track

- Convergence of inverse emissions: higher estimates than ODIAC

Optimal Fossil Fuel CO_2 emissions: example of Los Angeles

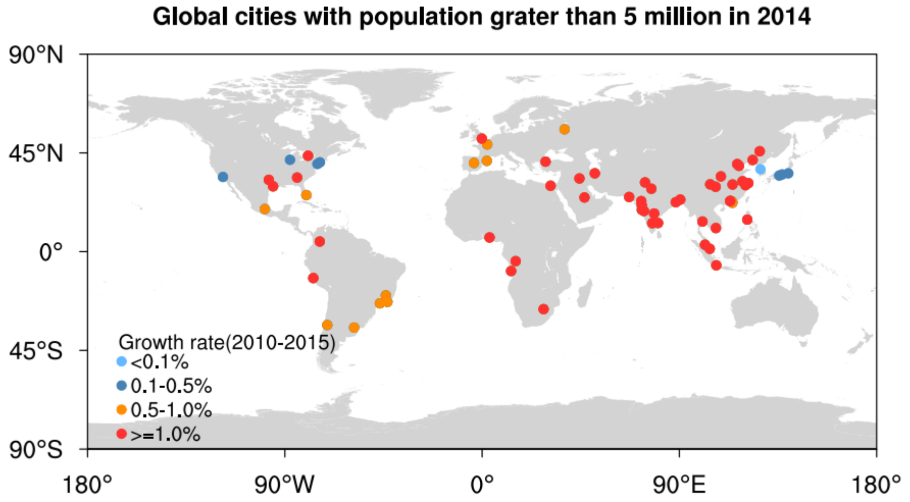




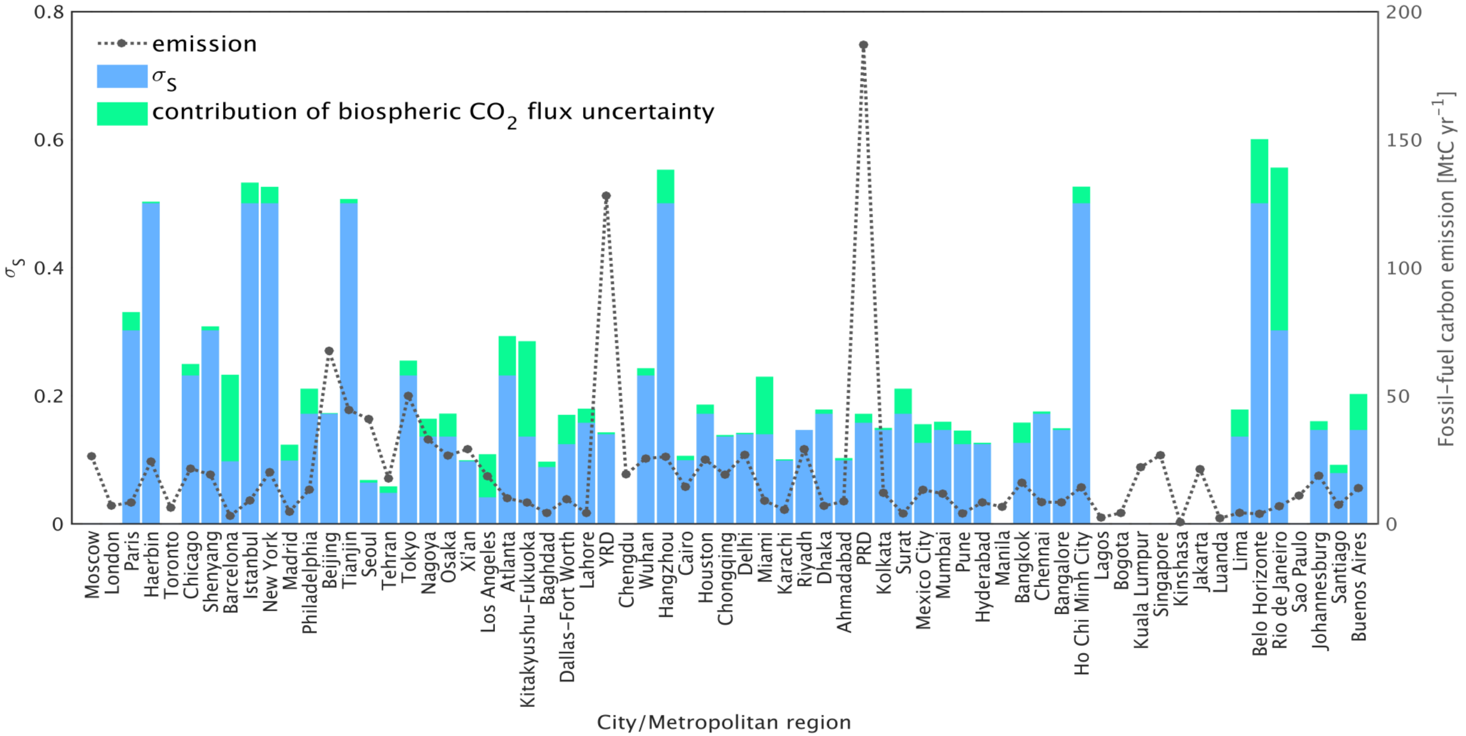


XCO_2 retrievals from OCO-2 track near Los Angeles compared to WRF-ODIAC simulations at 3km resolution with wind vectors at 100m agl (in ppm and m/s)

Aggregated emissions over the largest metropolitan areas



Urban centers (>5M in population) across the globe and associated growth rates



Uncertainties in emission quantification from vegetation fluxes, transport model errors, and amount of retrievals available over two years of OCO-2 operations (2014-2016)

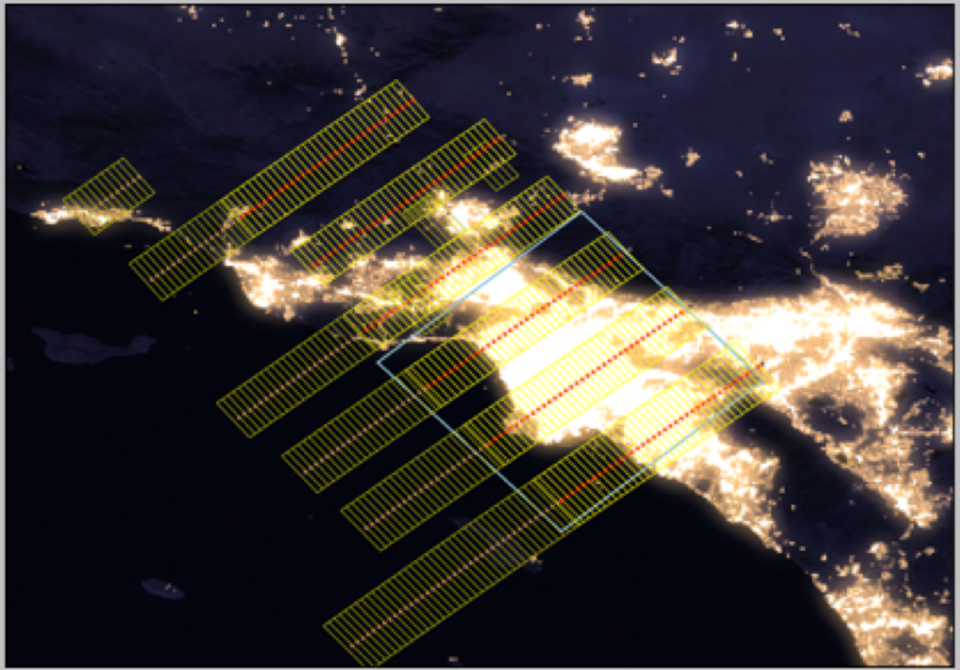
Ye et al., in prep.

Conclusions and perspectives

Convergence of a high-resolution inventory and an inversion possible (Indianapolis, IN)

Current satellite data are promising for emission evaluation over large metropolitan areas

Coming soon: April 25th, 2019 OCO-3 launch with hundreds of targets



Images: NASA, SpaceX, L2 imagery: Brady Kennison and Chris Gebhardt for NASASpaceFlight.com