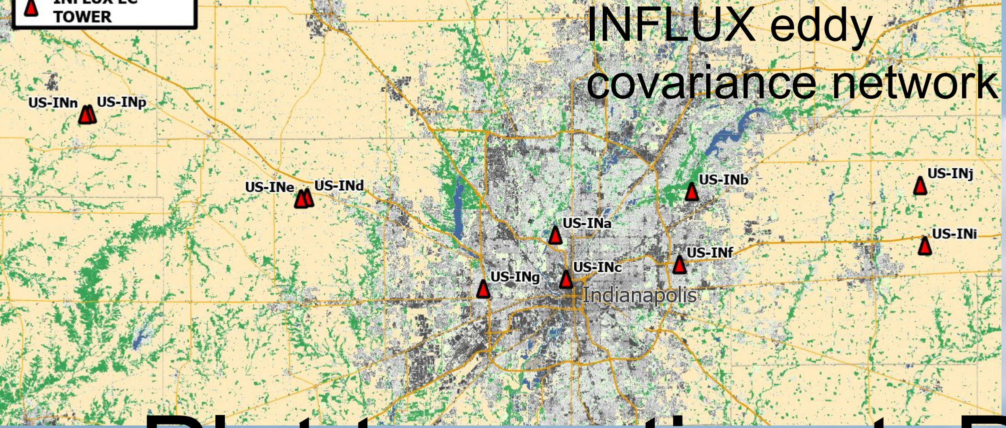
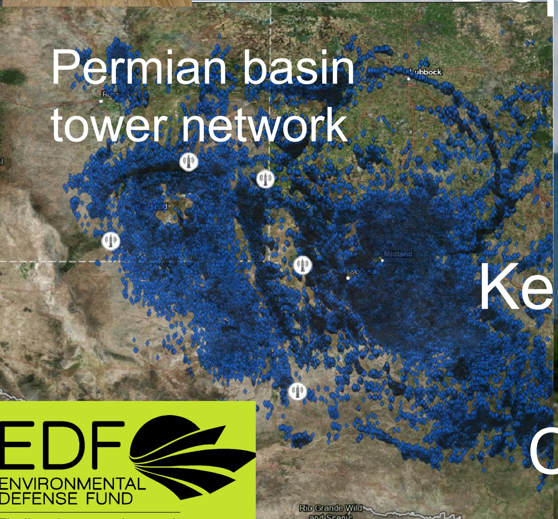


Plot to continent: Reflections from studying the terrestrial carbon cycle at multiple scales

Kenneth Davis
Department of Meteorology and Atmospheric Science
Earth and Environmental Systems Institute,
The Pennsylvania State University



Keck Institute for Space Studies short course on Quantifying Emissions through Greenhouse Gases and Transport

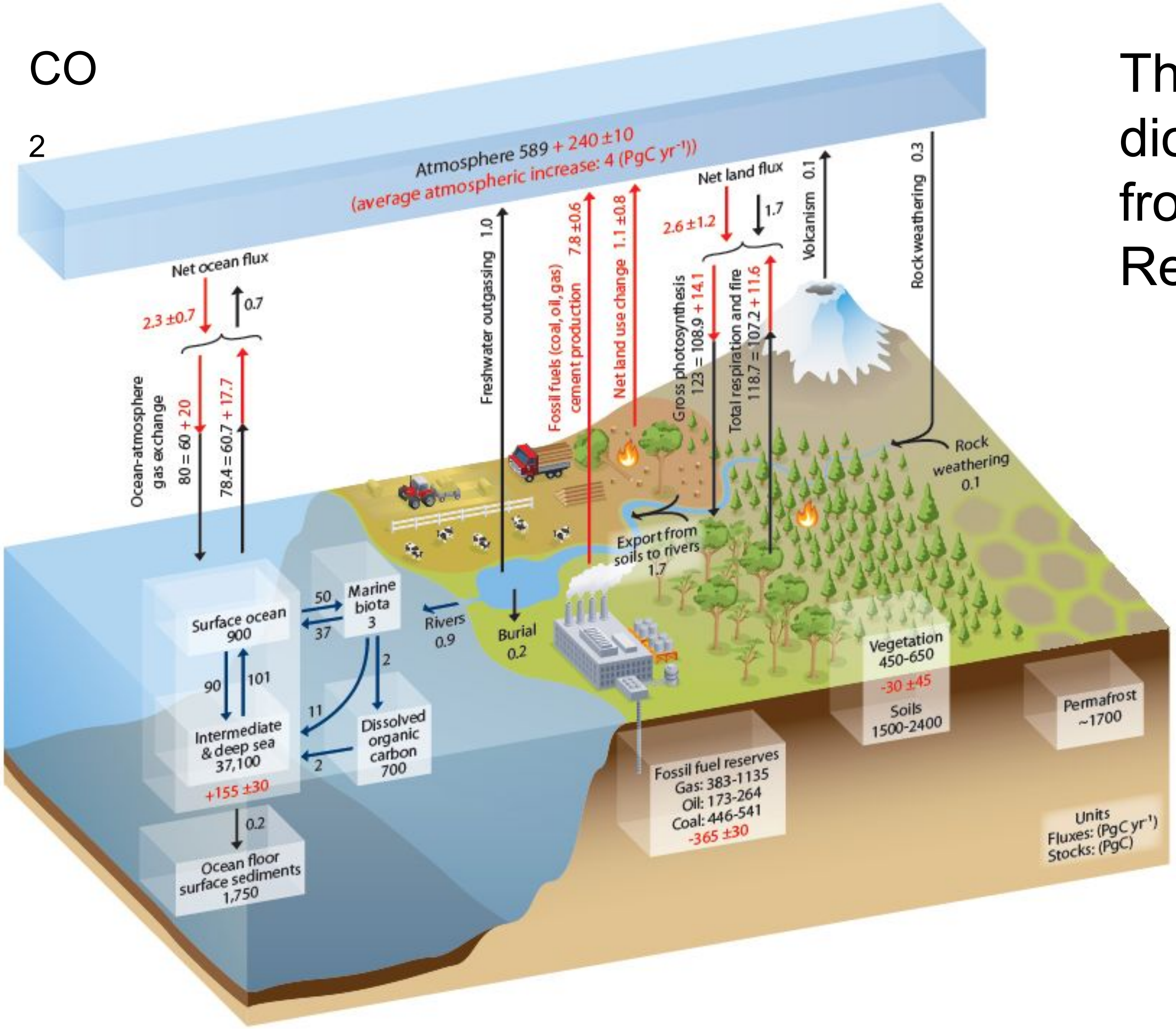
California Institute of Technology 7 October, 2024

Big picture

- We know global GHG budgets from the atmosphere, not from adding up emissions inventories.

CO

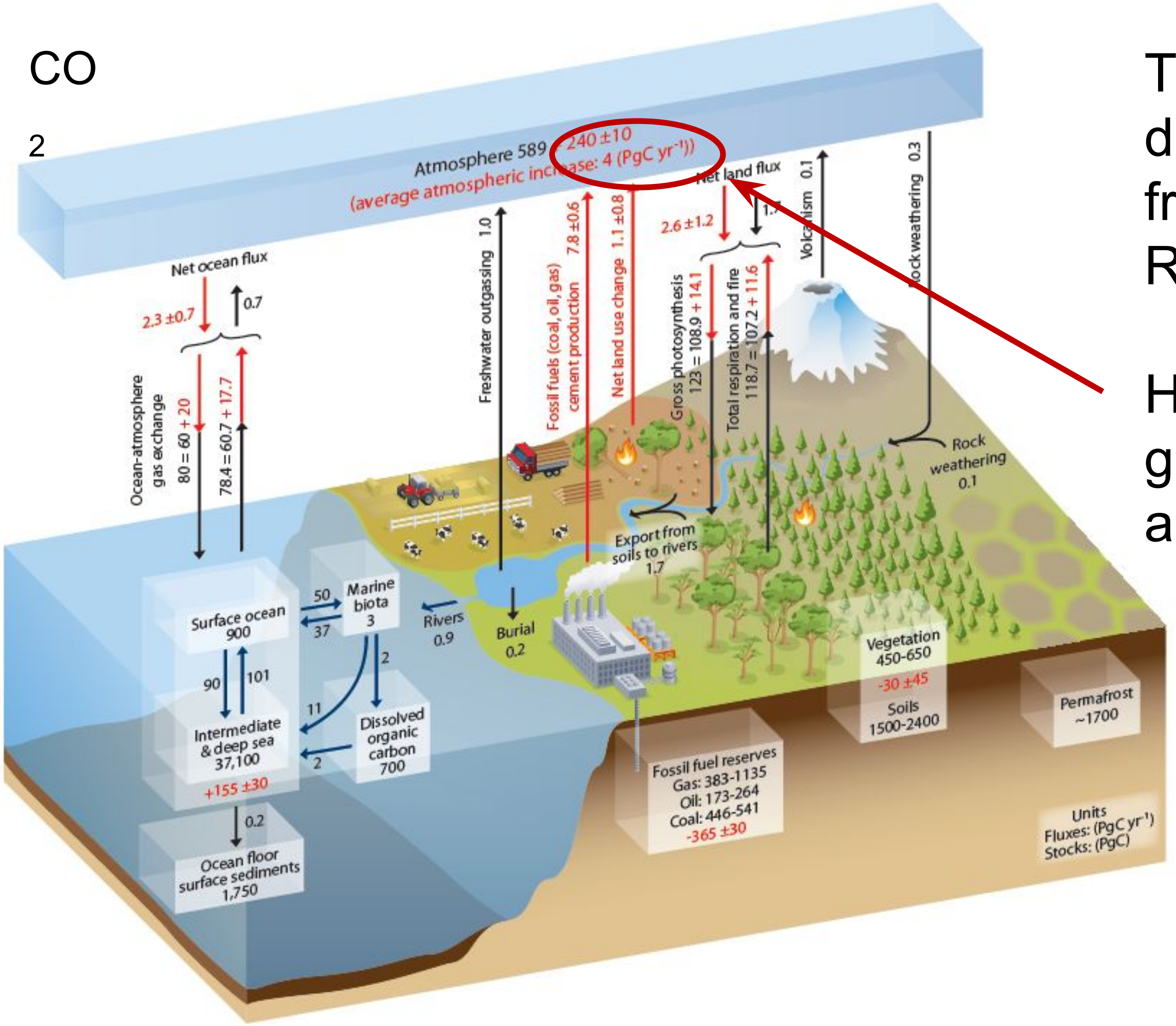
2



The global carbon dioxide (CO_2) budget from the 5[th] Assessment Report of the IPCC .

IPCC, WG1, AR5, Fig 6.1

CO_2



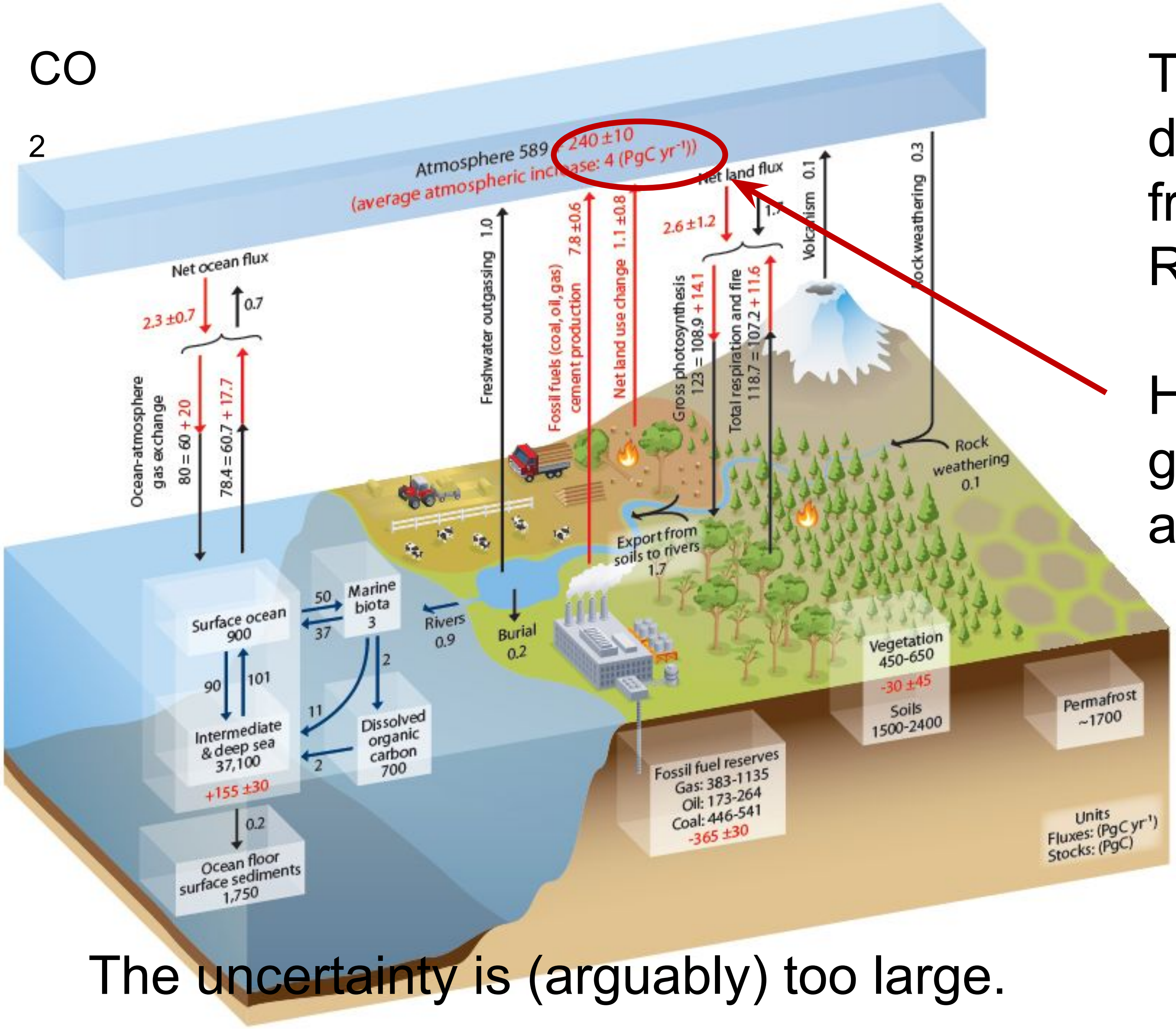
The global carbon dioxide (CO_2) budget from the 5th Assessment Report of the IPCC .

How do we know the global sum of sources and sinks of CO_2?

IPCC, WG1, AR5, Fig 6.1

CO

2



The uncertainty is (arguably) too large.

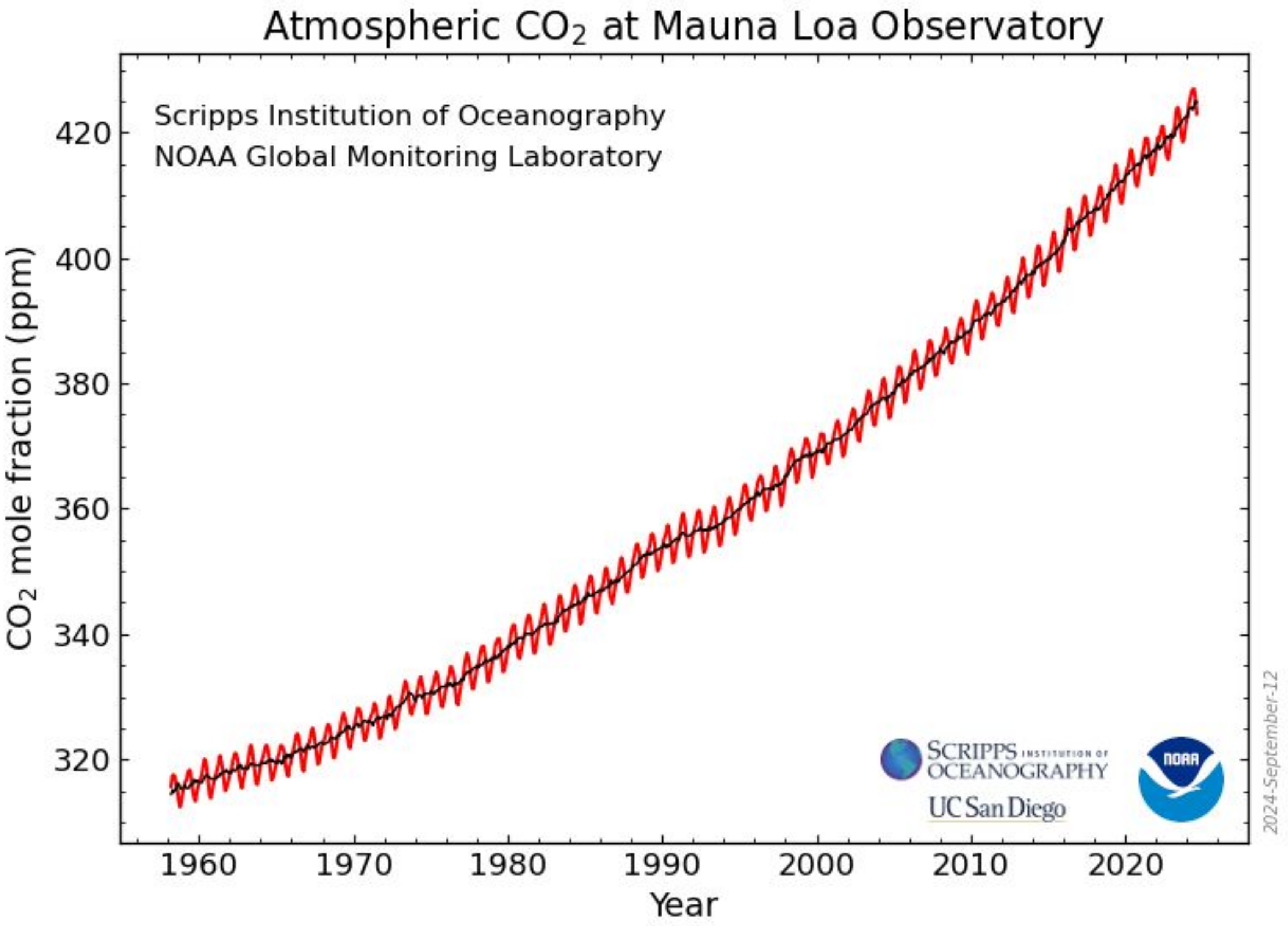
The global carbon dioxide (CO_2) budget from the 5[th] Assessment Report of the IPCC .

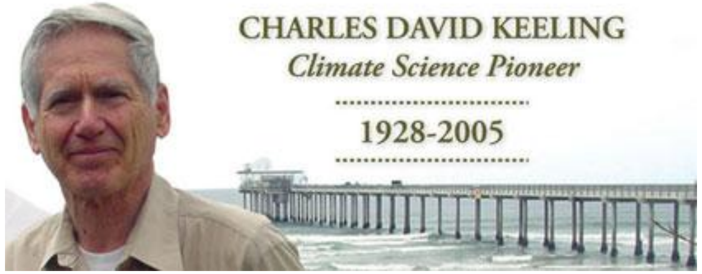
How do we know the global sum of sources and sinks of CO_2?

Not by adding up all the individual sources and sinks!

IPCC, WG1, AR5, Fig 6.1


NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
NOAA
U.S. DEPARTMENT OF COMMERCE
MAUNA LOA
OBSERVATORY
Earth System Research Laboratories
Global Monitoring Division
Est. June 28, 1956 • Elevation 3,396m (11,141 ft.)



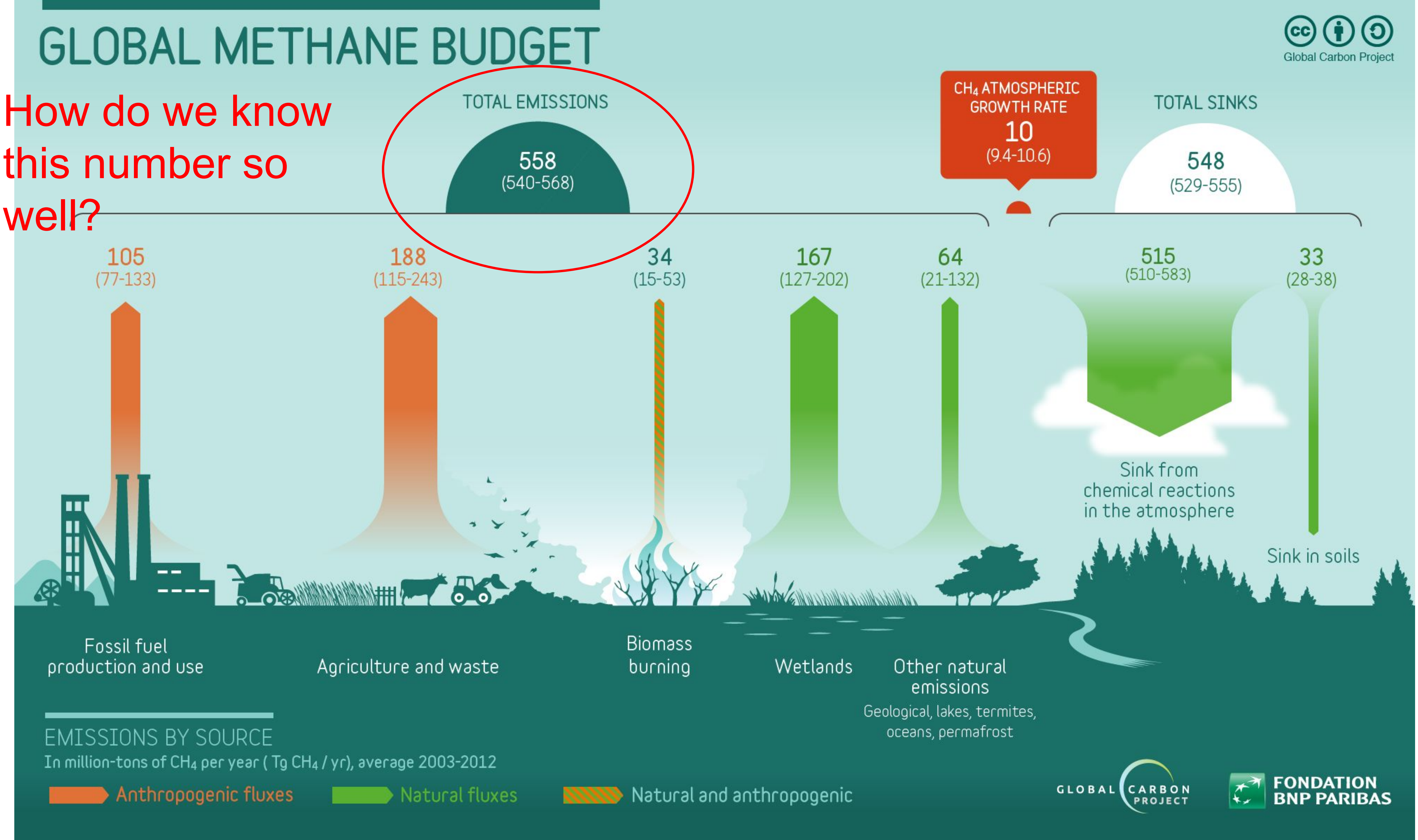


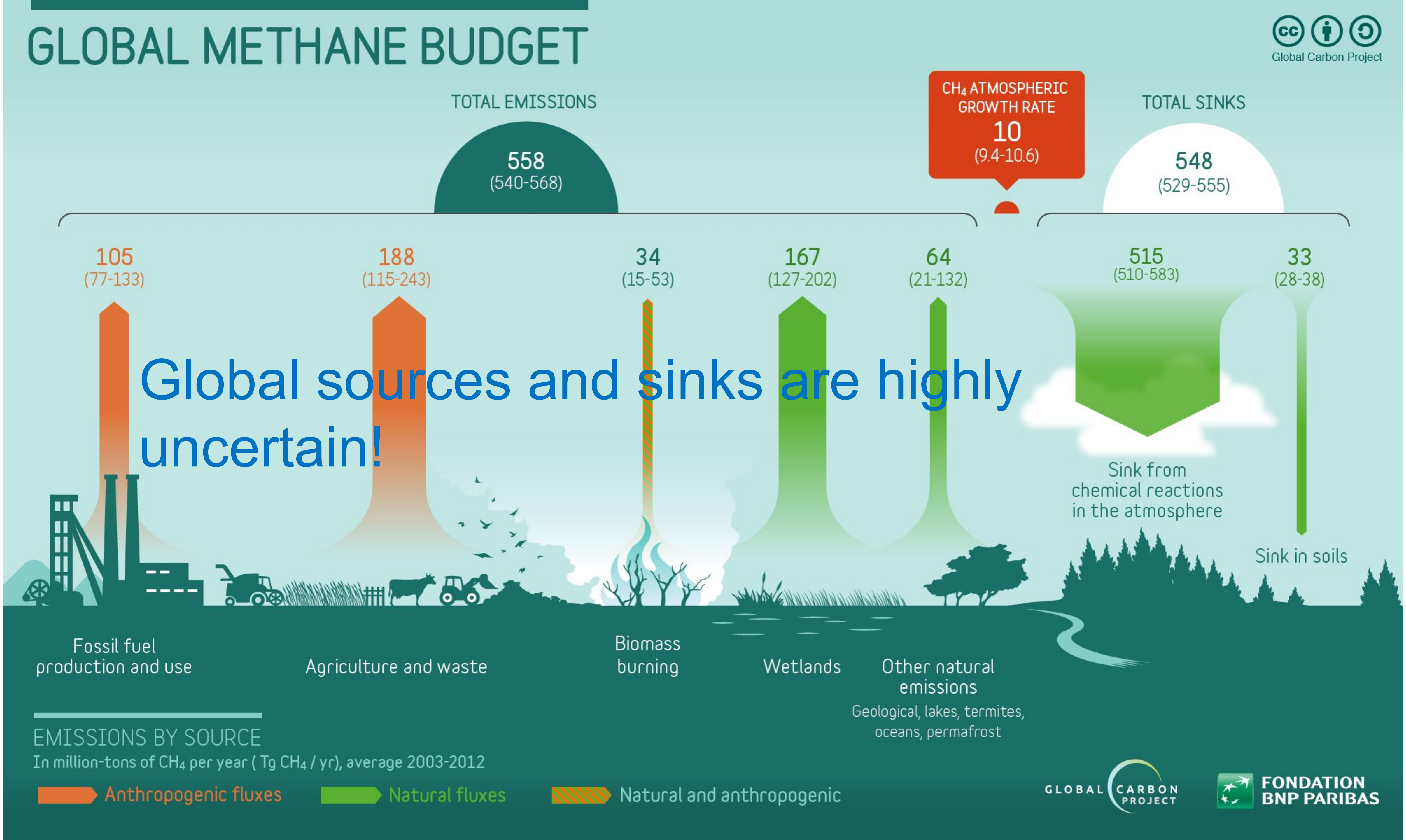
The slope of this line tells us the net rate of CO_2 accumulation in the earth's atmosphere.

NOAA GML, 2024

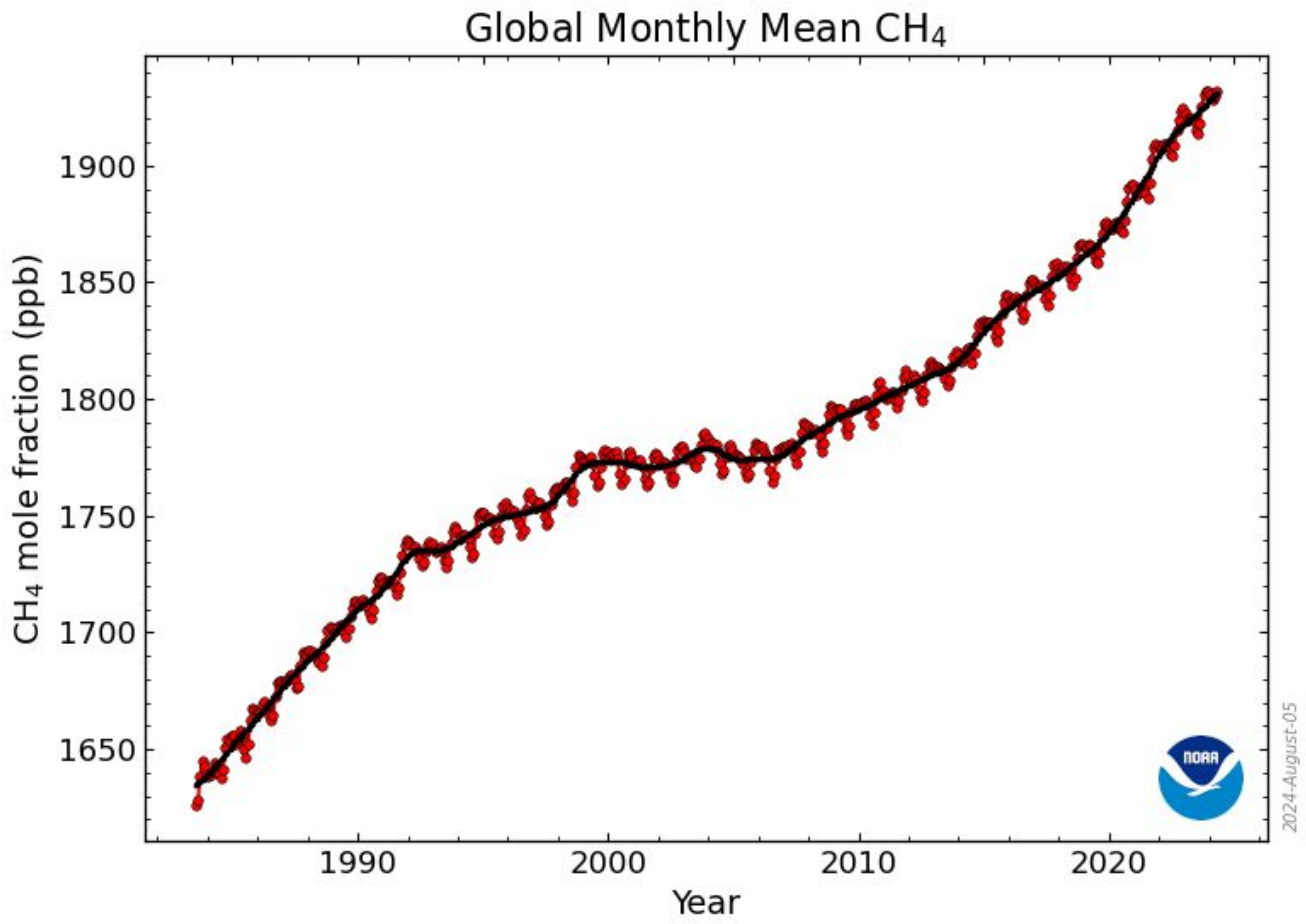
Data site:
https://gml.noaa.gov/ccgg/

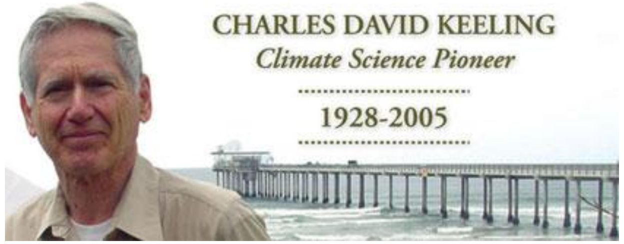
How do we know this number so well?

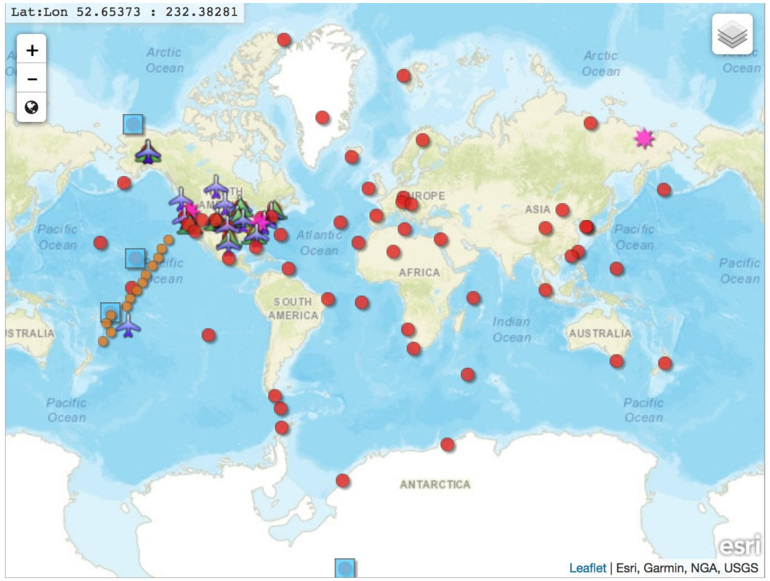




Global sources and sinks are highly uncertain!







NOAA GML, 2024

Data site: https://gml.noaa.gov/ccgg/

"Top-Down." The atmosphere tells us the global sum of the sources of methane.

- Measure global atmospheric CH_4 – concentration and rate of change – very accurately.
- Estimate atmospheric OH – the primary sink for CH_4 – by measuring trace gases with known sources.
- Solve for the global source of CH_4 needed to balance the global atmospheric budget.

$$Source_{CH4} = k[OH][CH_4]$$

- *You cannot compute the global sum of methane sources with any accuracy by adding up the "bottom-up" estimates of the individual sources.*

e.g. Dlugocencky et al., 2003

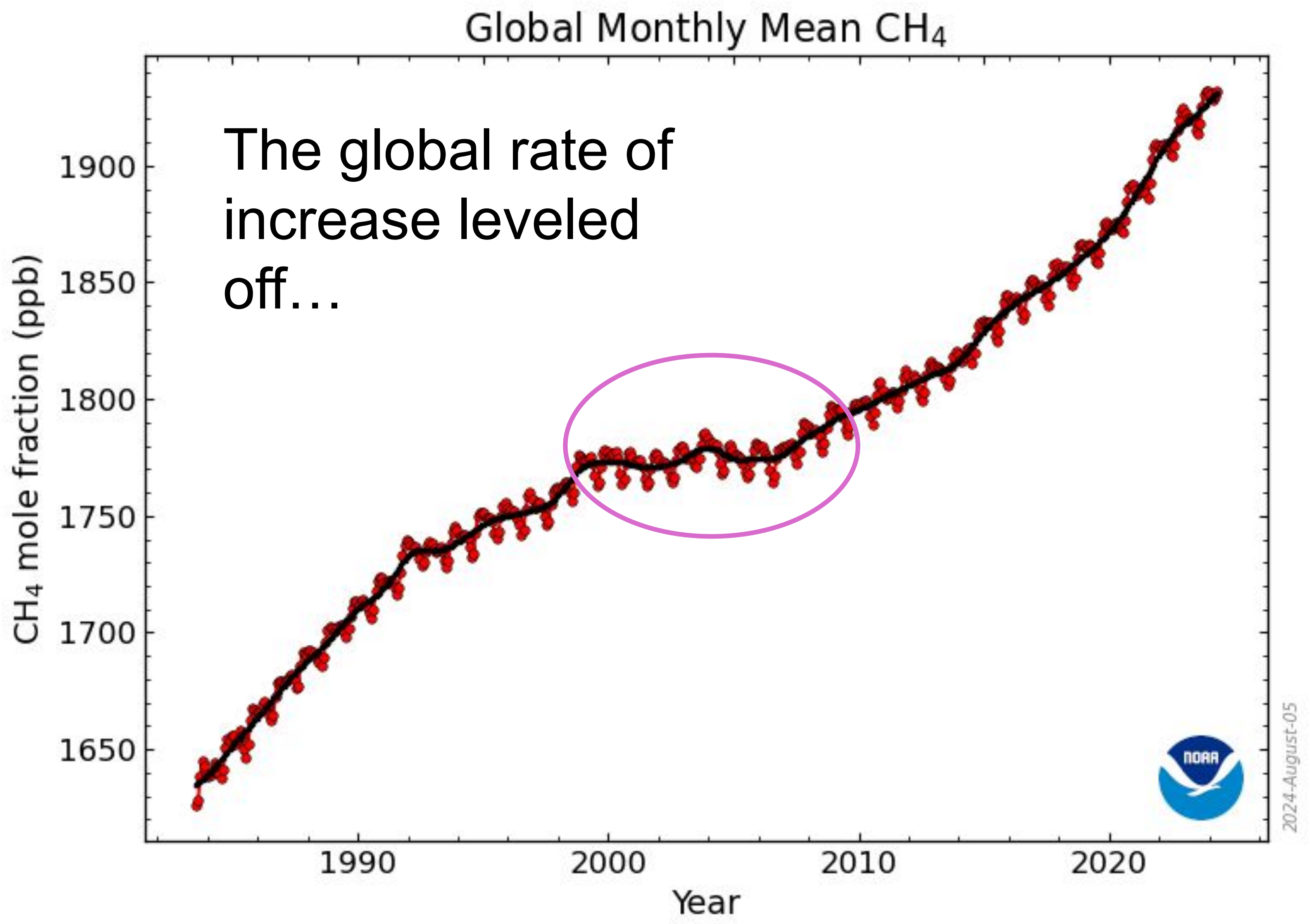
Big picture

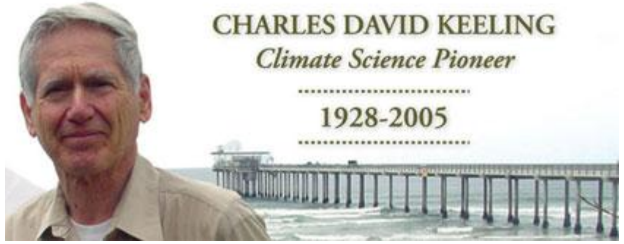
- We know global GHG budgets from the atmosphere, not from adding up emissions inventories.
  - The atmosphere ‘sees all.’
  - We call this a “top down” method of estimating GHG fluxes.

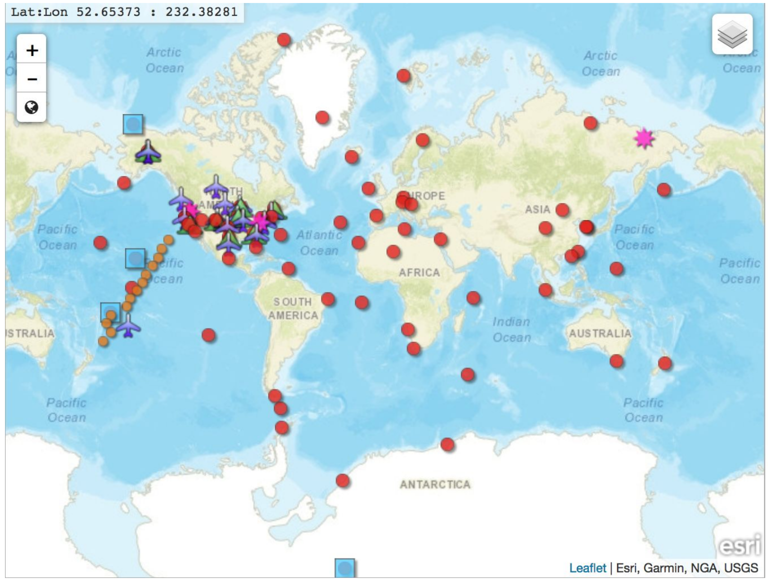
Big picture

- We know global GHG budgets from the atmosphere, not from adding up emissions inventories.
  - The atmosphere ‘sees all.’
  - We call this a “top down” method of estimating GHG fluxes.
- But we don’t easily discern the processes that govern GHG budgets from atmospheric data.
  - We need inventories and “process models” - “bottom-up” methods of estimating GHG fluxes.

The global rate of increase leveled off…





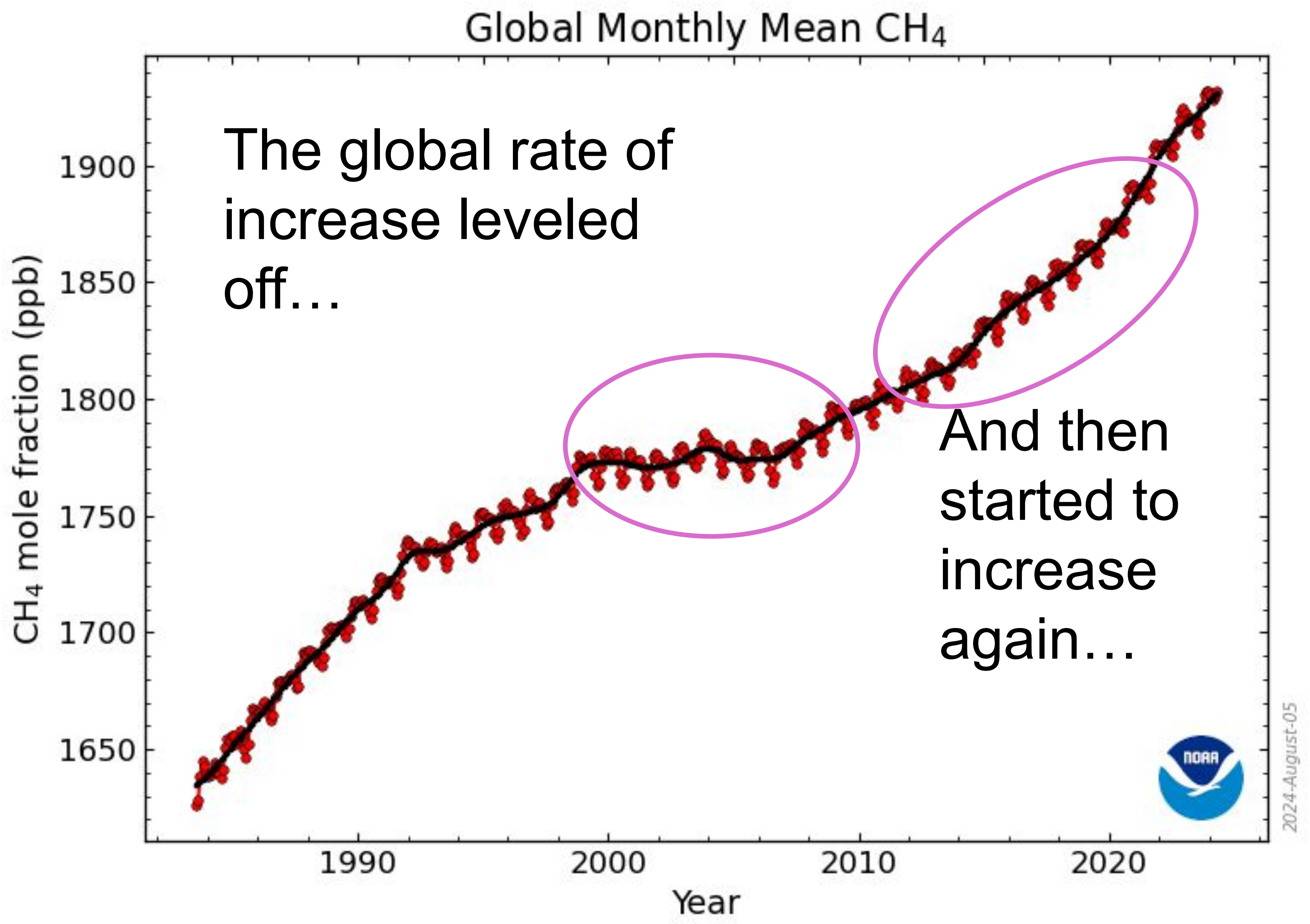


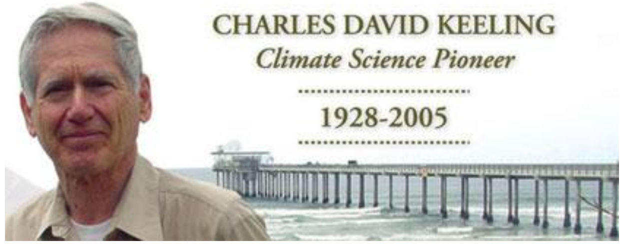
NOAA GML, 2024

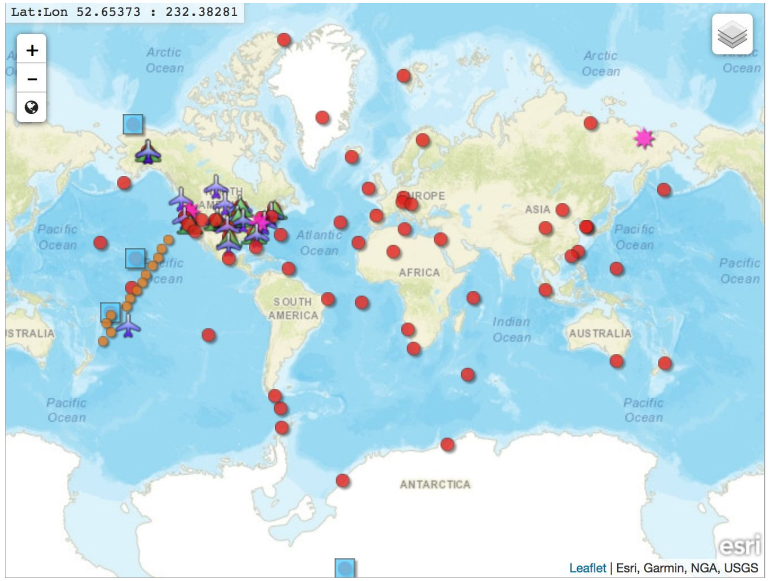
Data site: https://gml.noaa.gov/ccgg/

The global rate of increase leveled off…

And then started to increase again…

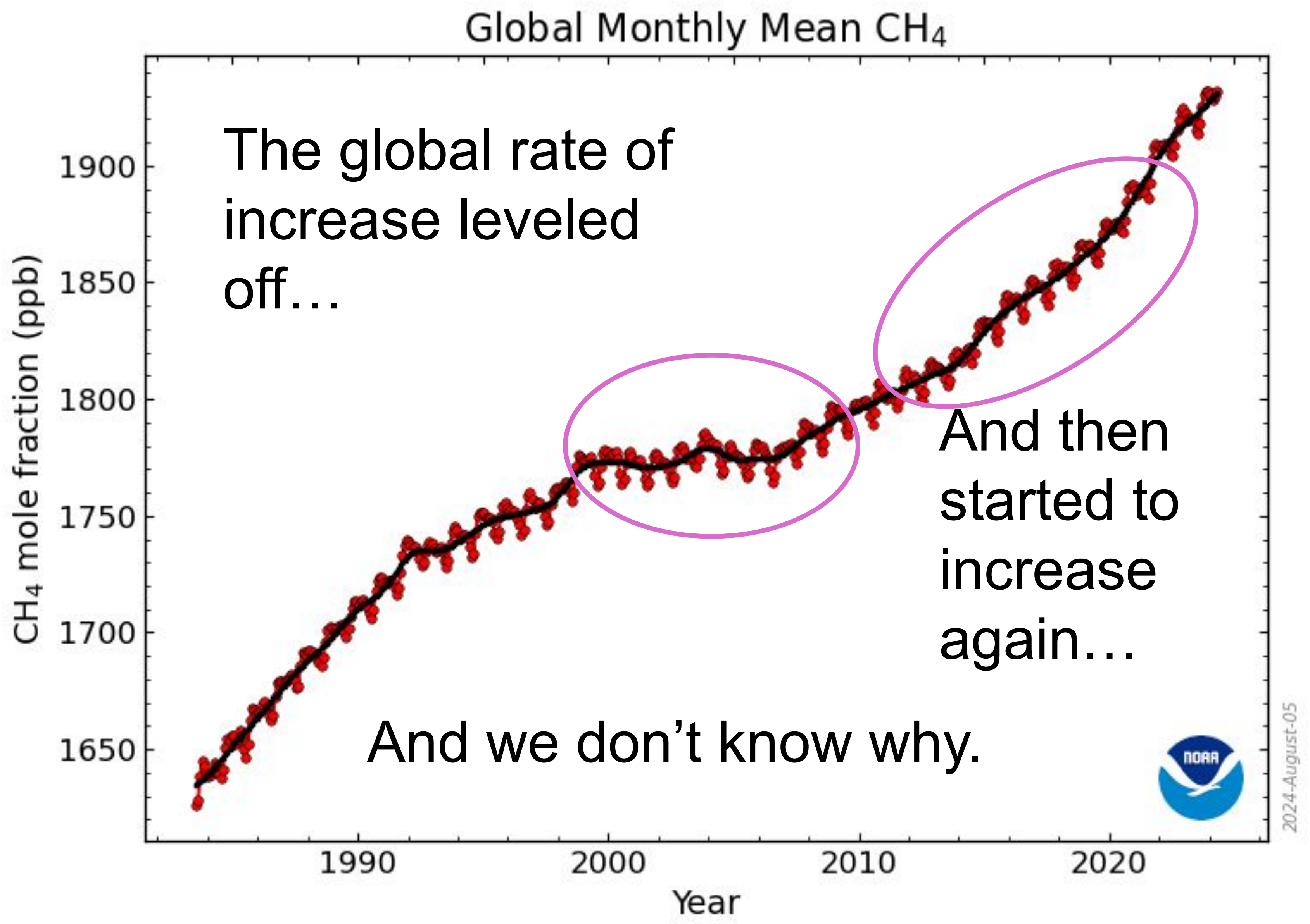






NOAA GML, 2024

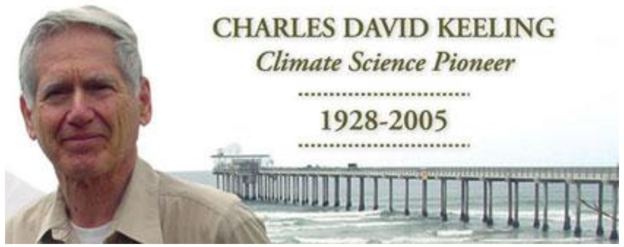
Data site: https://gml.noaa.gov/ccgg/

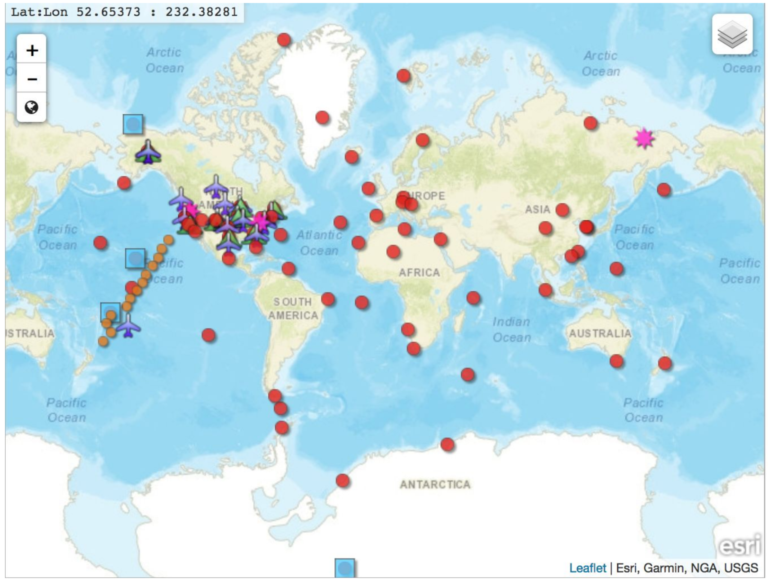


The global rate of increase leveled off…

And then started to increase again…

And we don't know why.





NOAA GML, 2024

Data site: https://gml.noaa.gov/ccgg/

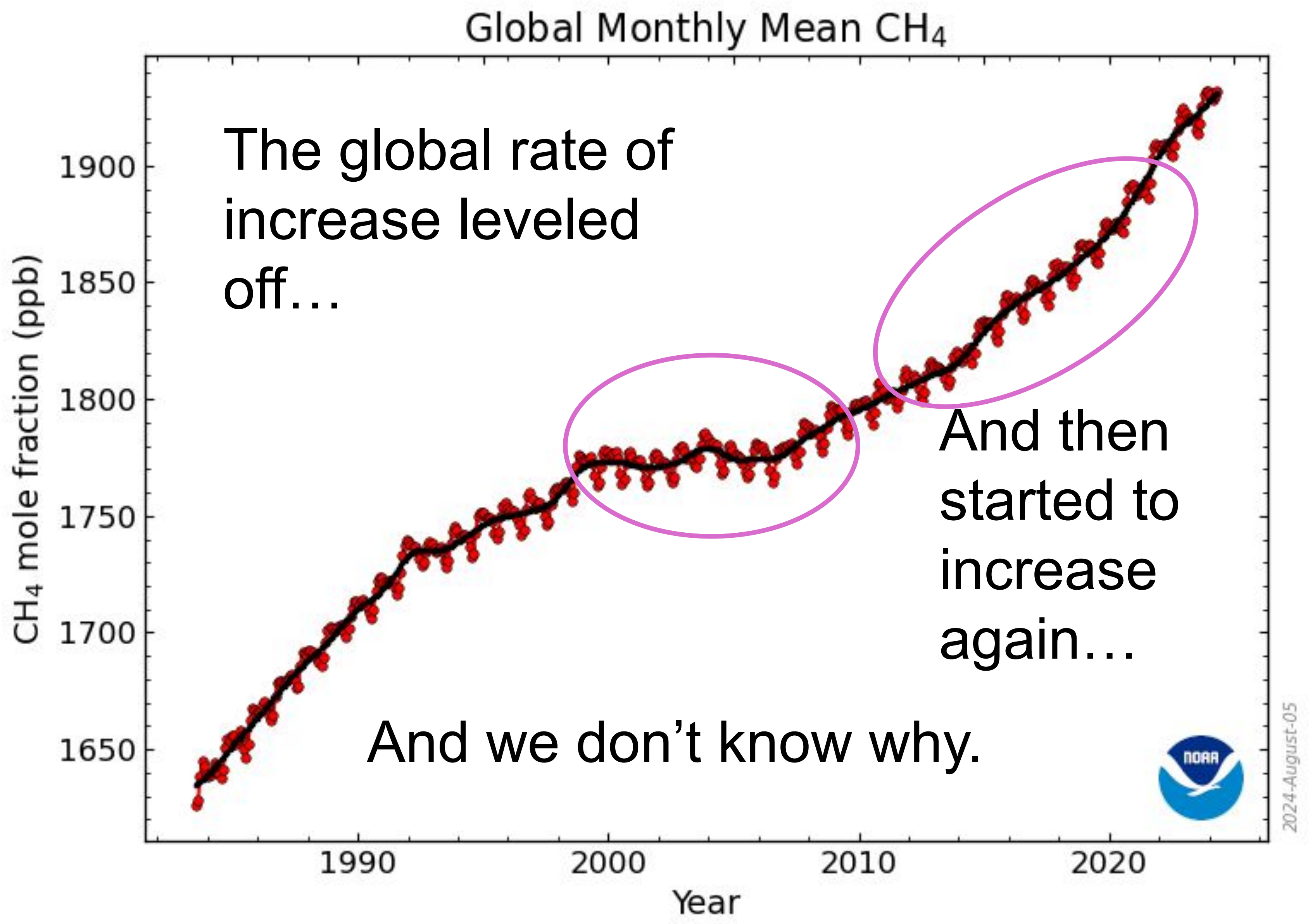
Big picture

- We know global GHG budgets from the atmosphere, not from adding up emissions inventories.
  - The atmosphere ‘sees all.’
  - We call this a “top down” method of estimating GHG fluxes.
- But we don’t easily discern the processes that govern GHG budgets from atmospheric data.
  - We need inventories and “process models” - “bottom-up” methods of estimating GHG fluxes.
  - For example…
    - Estimates of CO_2 emissions from fossil fuel consumption data
    - Simulations of how ecosystem growth and respiration responds to environmental conditions.
    - Accounting of methane emissions from oil and gas production.
    - Simulations of enteric fermentation from cattle.

Big picture

- We know global GHG budgets from the atmosphere, not from adding up emissions inventories.
    - The atmosphere ‘sees all.’
    - We call this a “top down” method of estimating GHG fluxes.
- But we don’t easily discern the processes that govern GHG budgets from atmospheric data.
    - We need inventories and “process models” - “bottom-up” methods of estimating GHG fluxes.
- Without these *complementary* methods, we won’t understand (or be able to manage effectively) the global carbon cycle.

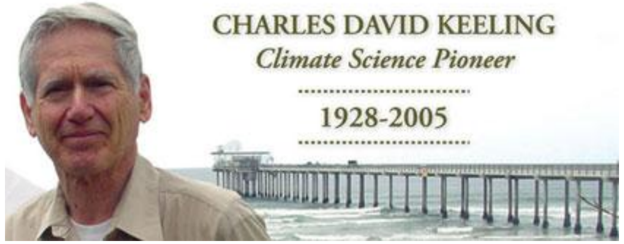
But “process” to “globe” is too big a jump.

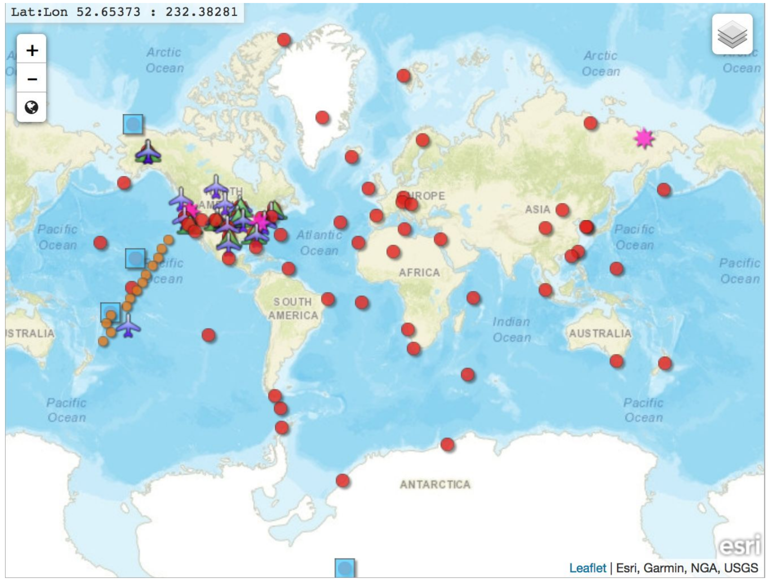


The global rate of increase leveled off…

And then started to increase again…

And we don't know why.





NOAA GML, 2024

Data site: https://gml.noaa.gov/ccgg/

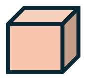
Big picture

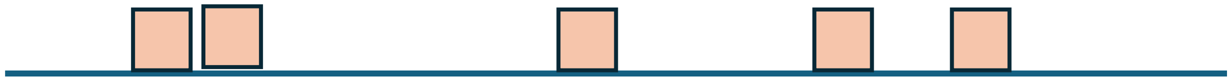
- The community has converged / is converging (I think) on a multi-scale approach.

Basic plan for multi-scale land-atmosphere interaction studies

- Adopt a “bottom-up,” processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.

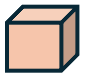
Imagine a field of “emitting widgets,”

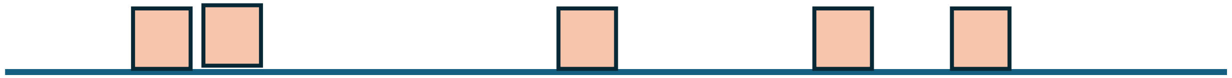




Simple model example:
Pneumatic valves that leak methane. Count widgets, apply an emissions factor for methane leaked /widget / time.

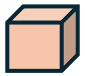
Imagine a field of “emitting widgets,”

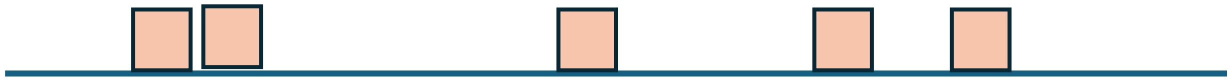




Complex model example:
An ecosystem. Soil and vegetation properties must be specified or predicted. Climate drivers are needed to estimate fluxes. Complex system of diagnostic or prognostic equations.

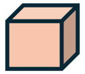
Imagine a field of “emitting widgets,”

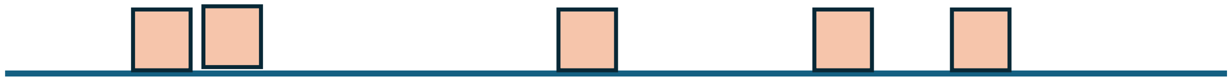




Mixed model example:
A city. Widgets include human activities (e.g. traffic) and ecosystem elements. Wide variety of input data and models are required.

Imagine a field of “emitting widgets,”



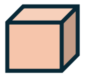


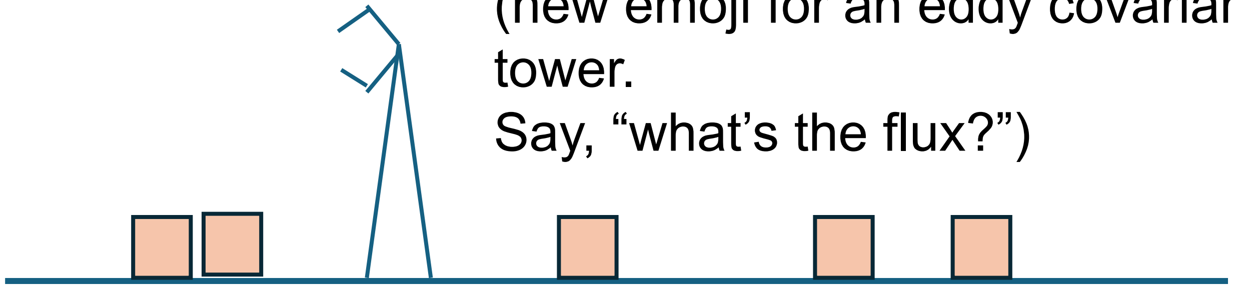
Observations are needed to drive the process model that predicts fluxes.

Basic plan for multi-scale land-atmosphere interaction studies

- Adopt a “bottom-up,” processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.
- Make “local” flux measurements
  - Chambers for things you can put in a box.
  - Plume measurements for point sources.
  - Eddy covariance for areally distributed sources (or sinks).
  - Why? Test and improve the process model.

Imagine a field of “emitting widgets,”

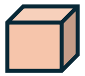


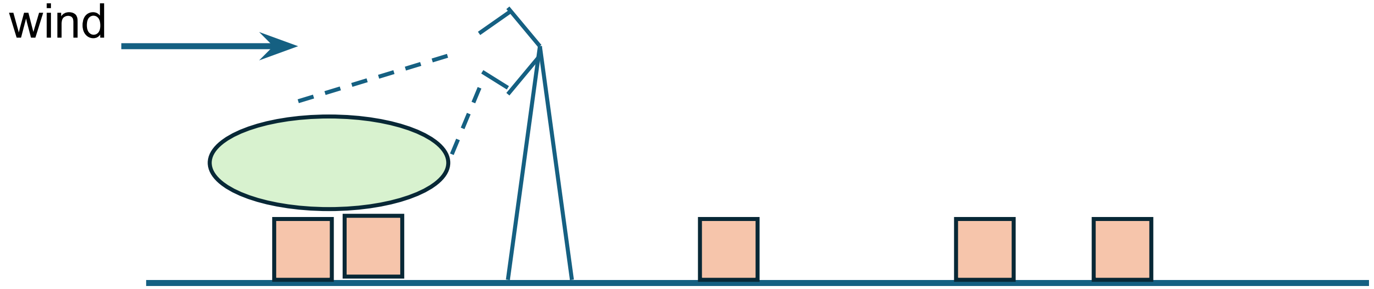


(new emoji for an eddy covariance flux tower.
Say, “what’s the flux?”)

Observations are needed to drive the process model that predicts fluxes.

Imagine a field of "emitting widgets,"

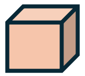


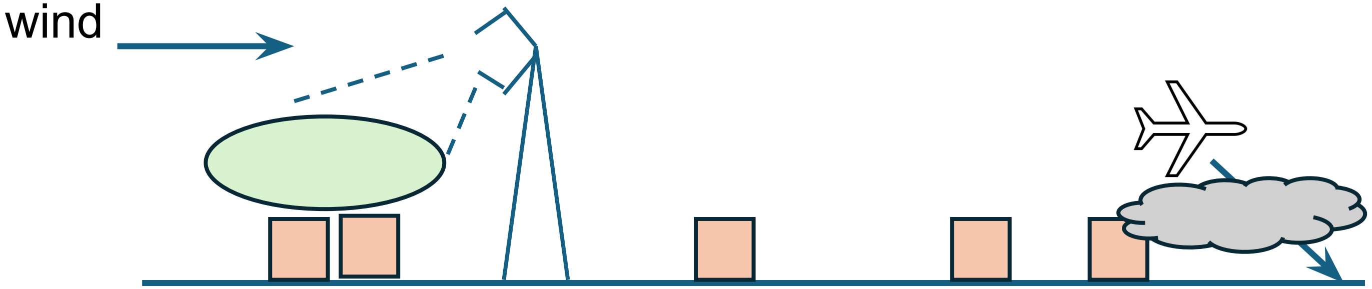


Local flux measurements:
Measure fluxes from an upwind area.

Observations are needed to drive the process model that predicts fluxes.

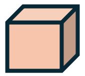
Imagine a field of “emitting widgets,”



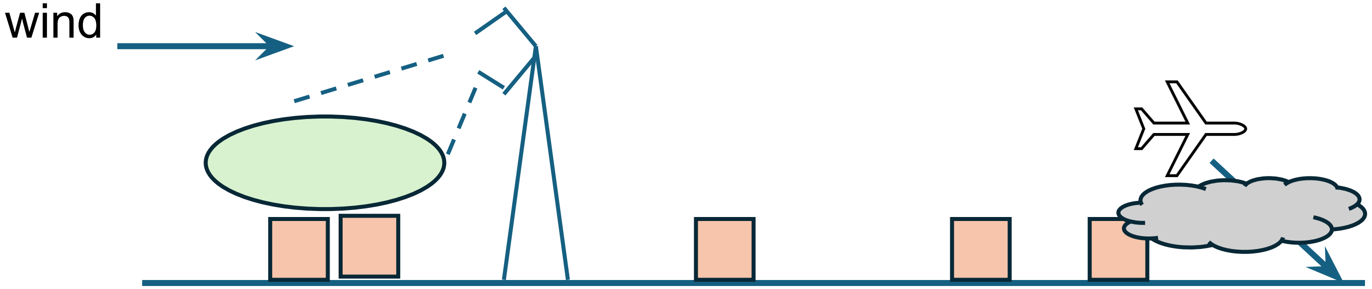


Observations are needed to drive the process model that predicts fluxes.

Imagine a field of “emitting widgets,”

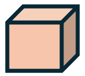


Local flux measurements:
Measure fluxes from an upwind area.
Or from an upwind point source.

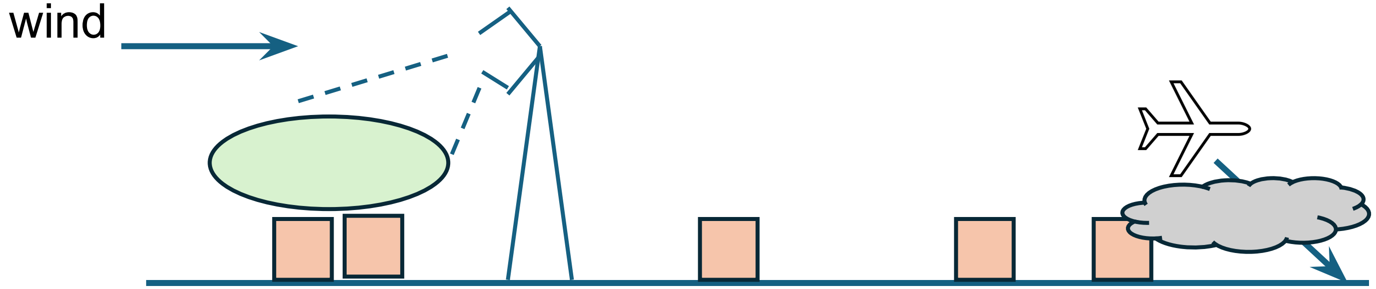


Observations are needed to drive the process model that predicts fluxes.

Imagine a field of “emitting widgets,”



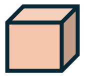
Atmospheric turbulence limits areas sensed to ~ a few kilometers ^2.
For chambers, area sensed is the size of the box.



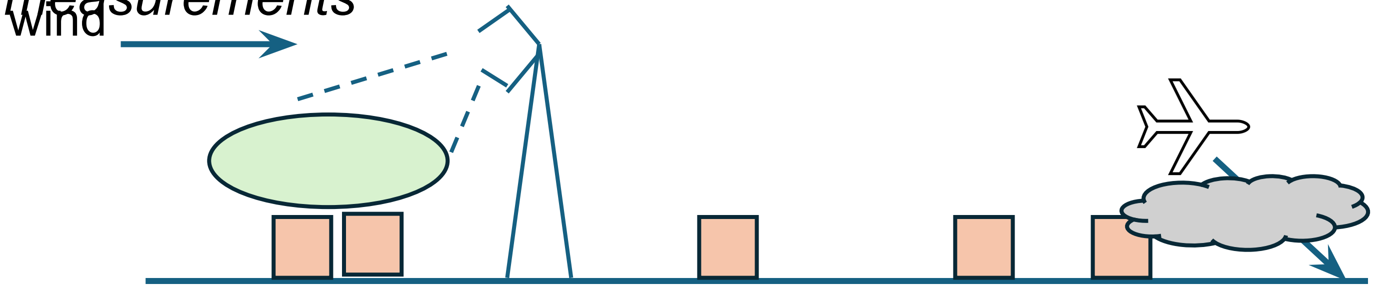
Local flux measurements:
Measure fluxes from an upwind area.
Or from an upwind point source.

Observations are needed to drive the process model that predicts fluxes.

Imagine a field of “emitting widgets,”



Test and improve the process model using “local” flux measurements

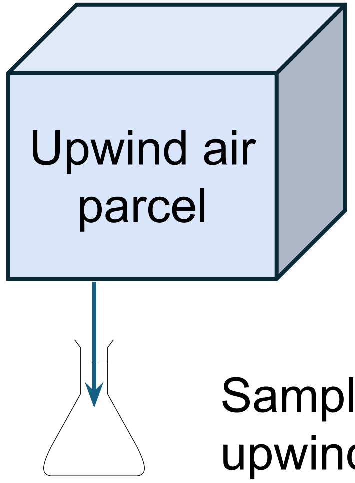


Observations are needed to drive the process model that predicts fluxes.

Basic plan has emerged for multi-scale land-atmosphere interaction measurements

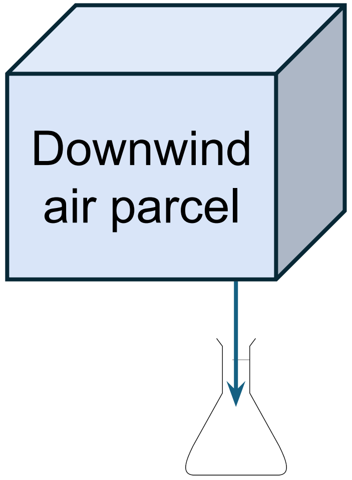
- Adopt a “bottom-up,” processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.
- Make “local” flux measurements
  - Chambers for things you can put in a box.
  - Plume measurements for point sources.
  - Eddy covariance for areally distributed sources (or sinks).
  - Why? Test and improve the process model.
- Measure atmospheric state on a regional scale. “Top-down” approach.
  - Why? Evaluate the process-based model’s fluxes across regional scales.

Multi-scale, multi-state observations of earth-atmosphere interactions



Net flux is proportional to (the enhancement in concentration) x (wind speed) x (mixing depth).

Enhancement = downwind – upwind concentration.

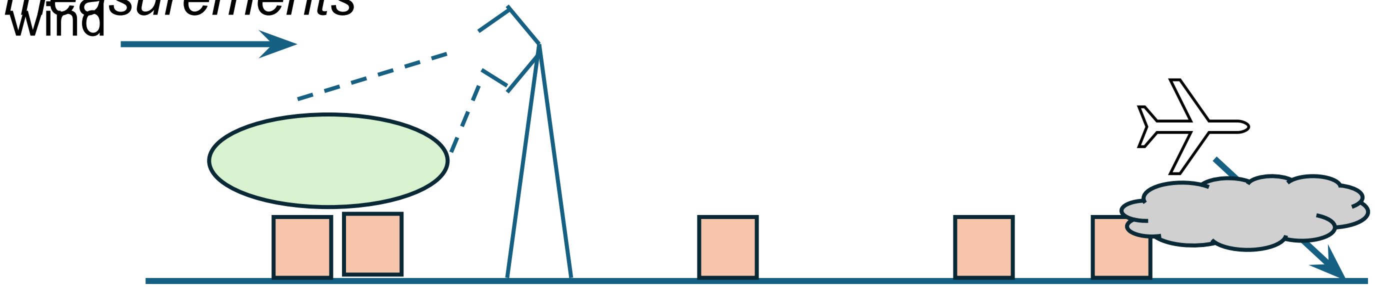


Sample air upwind

wind

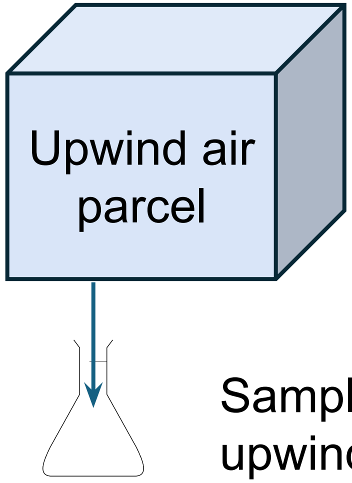
Sample air downwind

Test and improve the process model using "local" flux measurements

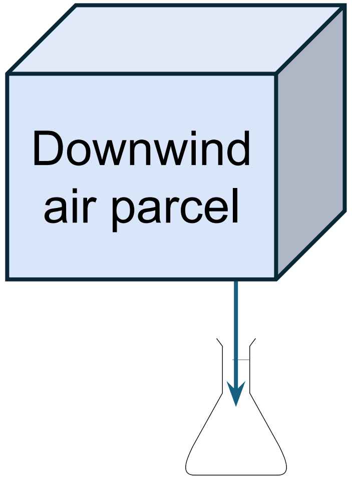


Observations are needed to drive the process model that predicts fluxes.

Multi-scale, multi-state observations of earth-atmosphere interactions



Measure regional flux to test the process model when aggregated over space.



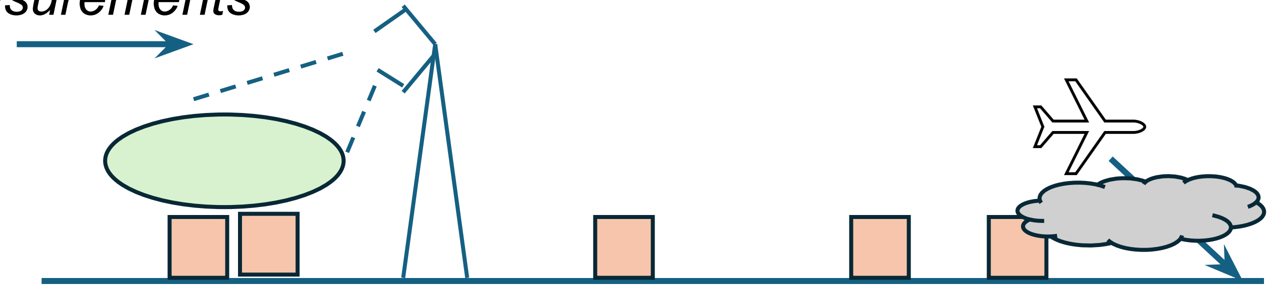
Sample air upwind

wind

Sample air downwind

Test and improve the process model using "local" flux measurements

Wind



Observations are needed to drive the process model that predicts fluxes.

Example: US GHG MMIS

Basic plan for multi-scale land-atmosphere interaction measurements

- Adopt a “bottom-up,” processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.
- Make “local” flux measurements
  - Chambers for things you can put in a box.
  - Plume measurements for point sources.
  - Eddy covariance for areally distributed sources (or sinks).
  - Why? Test and improve the process model.
- Measure atmospheric state on a regional scale. “Top-down” approach.
  - Why? Evaluate the process-based model’s fluxes across regional scales.
- Iterate. Improve. Monitor.

Basic plan for multi-scale land-atmosphere interaction measurements

- Adopt a "bottom-up," processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.
- Make "local" flux measurements
  - Chambers for things you can put in a box.
  - Plume measurements for point sources.
  - Eddy covariance for more areally distributed sources (or sinks).
  - Why? Test and improve the process model.
- Measure atmospheric state on a regional scale. "Top-down" approach.
  - Why? Evaluate the process-based model's fluxes across regional scales.
- Iterate. Improve. Monitor. Mitigate with confidence.

Basic plan for multi-scale land-atmosphere interaction measurements

- Adopt a “bottom-up,” processed-based model or inventory
  - Uses process measurements, traits and parameters and activity data.
- Make “local” flux measurements
  - Chambers for things you can put in a box.
  - Plume measurements for point sources.
  - Eddy covariance for more areally distributed sources (or sinks).
  - Why? Test and improve the process model.
- Measure atmospheric state on a regional scale. “Top-down” approach.
  - Why? Evaluate the process-based model’s fluxes across regional scales.
- Iterate. Improve. Monitor. Mitigate with confidence.
- Measurements at each step can be in situ or remote, mobile or stationary, ground-based, airborne or space-based.

This layer of air is the atmospheric boundary layer.

It is our “box of air.”

This layer of air is the atmospheric boundary layer.

It is our “box of air.”

It is turbulent!
(during the day)

This layer of air is the atmospheric boundary layer.

It is our “box of air.”

It is turbulent!
(at least during the day)

Emissions from the surface get mixed into it, and then are carried away by the wind. Turbulence keeps it “well mixed.”

A view from above.

The clouds show the top of the layer.

Clouds form at the top of the convective updrafts that keep the ABL “well-mixed.”

A case without many clouds.

A case with no clouds at all.

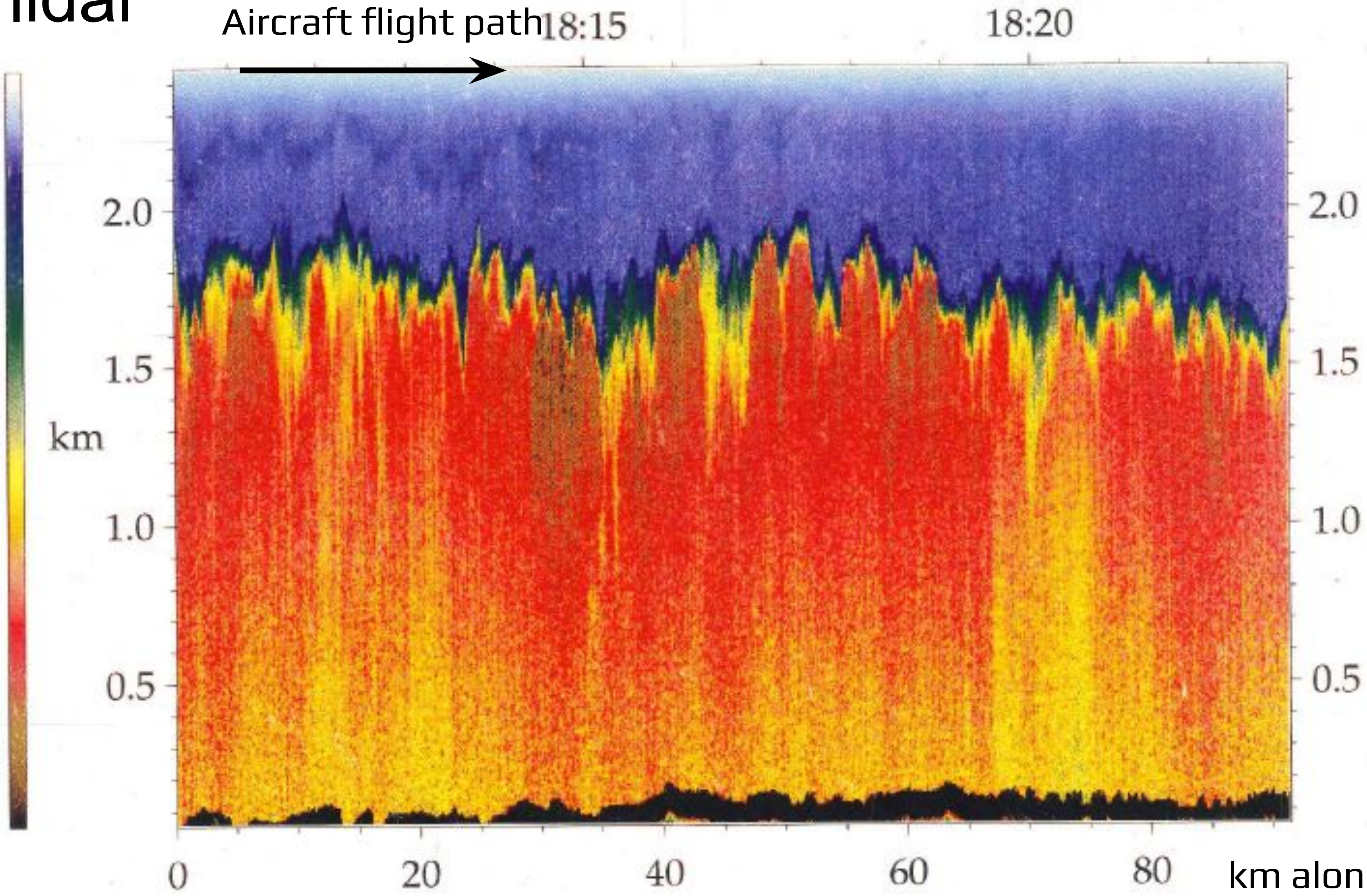
Is there an ABL?

A case with no clouds at all.

Is there an ABL?

Yes! How can we tell?

A clear-air atmospheric boundary layer seen via airborne lidar



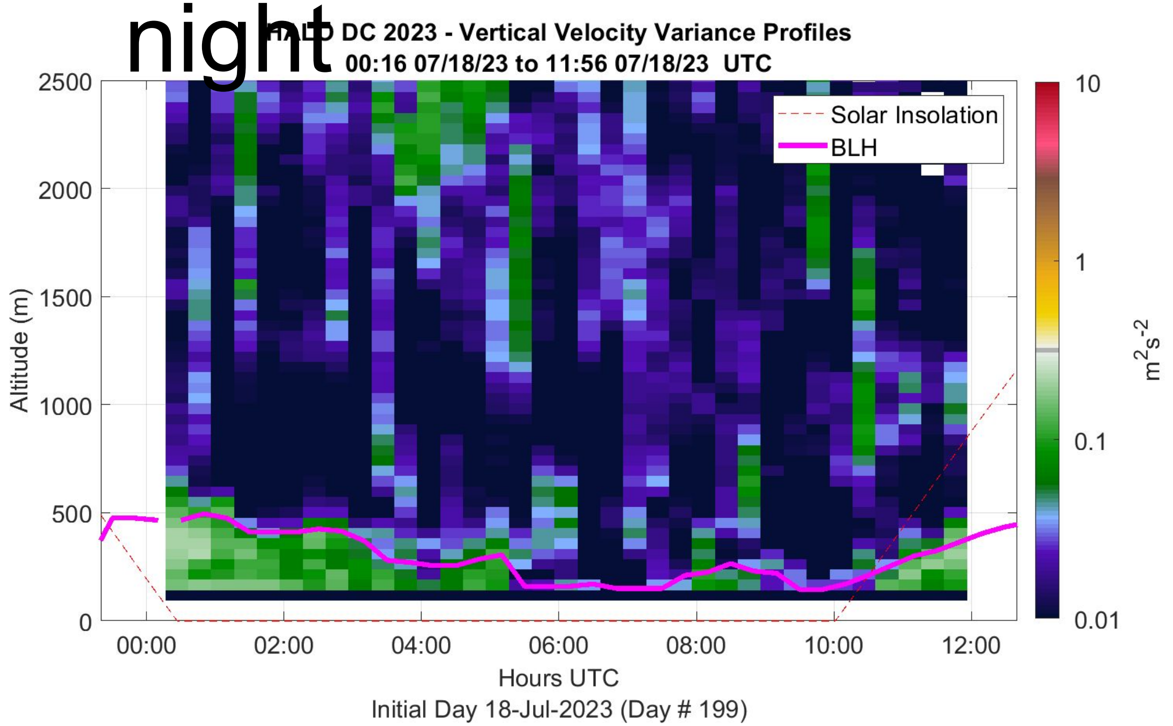
BOREAS airborne lidar backscatter. Time in UT at top. Warm colors = more backscatter. Note horizontal scale is highly compressed.

km MSL (above mean sea level)

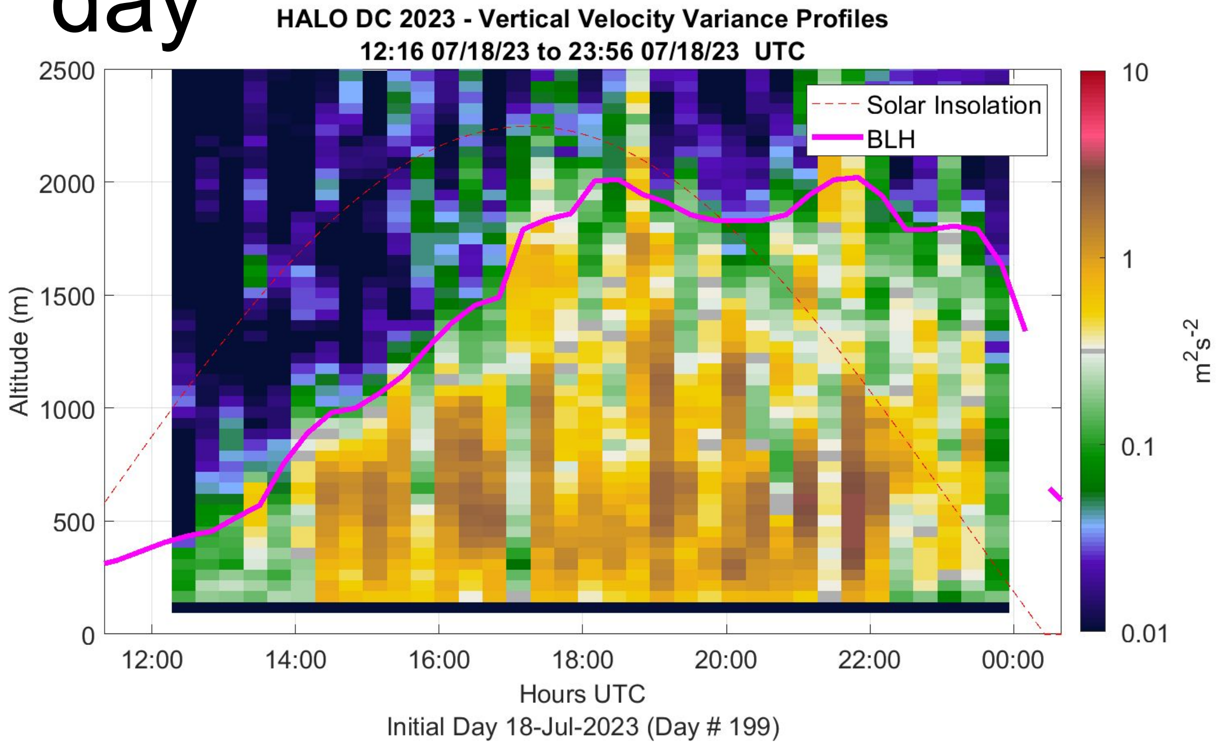
Kiemle et al., 1997

km along flight track

Little turbulence at night



Lots of turbulence in the day

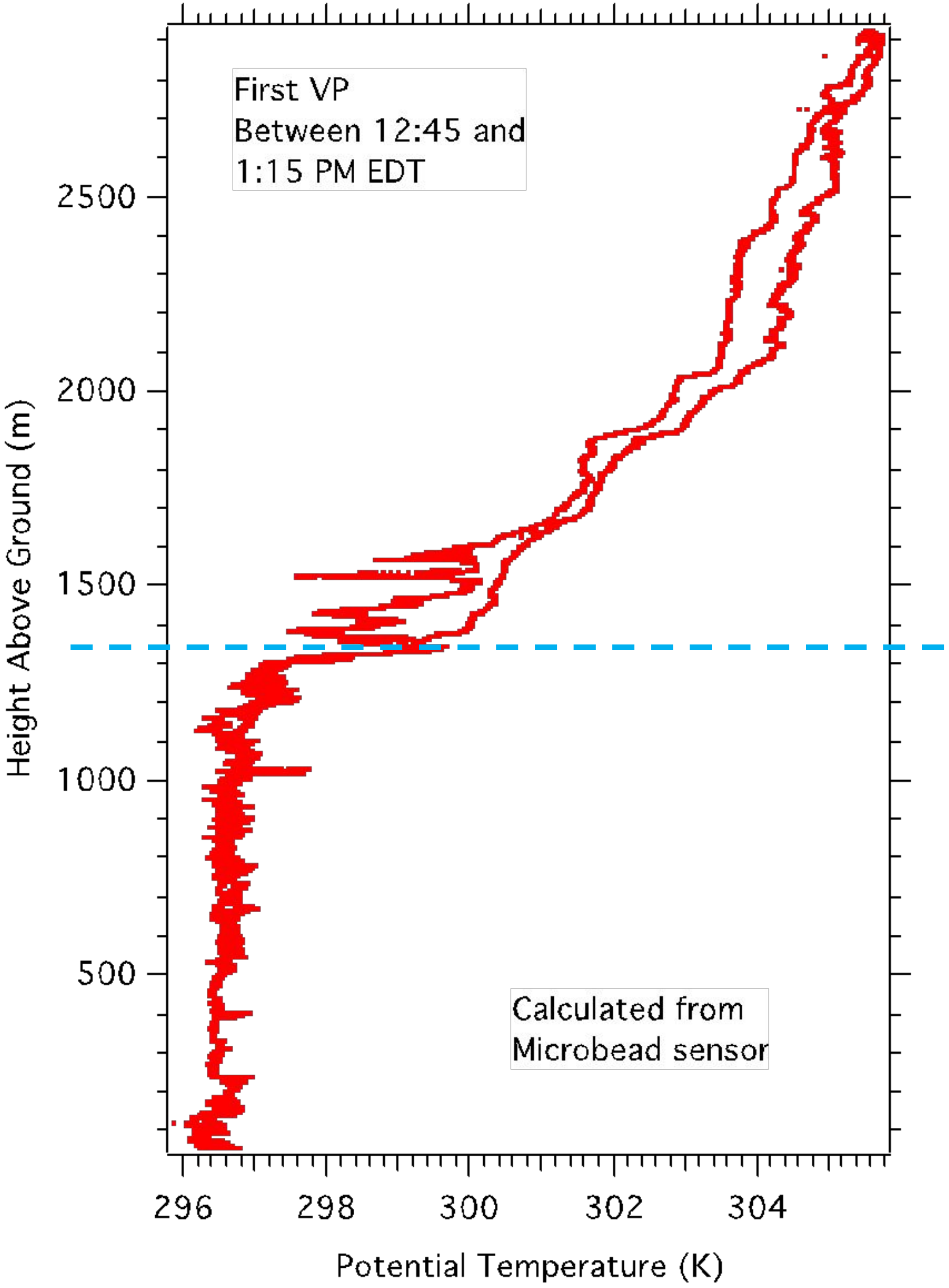


Velocity variance vs. altitude and time

7pm 2am 7am

2pm 7pm

https://csl.noaa.gov/groups/csl3/measurements/2021dcflux/



“Free atmosphere” (not so well mixed)

Capping inversion

Atmospheric boundary layer “well-mixed!”

A clear-air ABL “seen” via (potential) temperature measurements

Purdue aircraft profiles over Indianapolis, IN

June 1, 2011

A menace for my lovely atmospheric boundary layer

These things punch holes in the lid of my atmospheric boundary layer (ABL).

Return to the main event

Basic plan for multi-scale land-atmosphere interaction measurements

- Adopt a “bottom-up,” processed-based model or inventory
    - Uses process measurements, traits and parameters and activity data.
- Make “local” flux measurements
    - Chambers for things you can put in a box.
    - Plume measurements for point sources.
    - Eddy covariance for more areally distributed sources (or sinks).
    - Why? Test and improve the process model.
- Measure atmospheric state on a regional scale. “Top-down” approach.
    - Why? Evaluate the process-based model’s fluxes across regional scales.
- Iterate. Improve. Monitor. Mitigate with confidence.
- Measurements at each step can be in situ or remote, mobile or stationary, ground-based, airborne or space-based.

What do we need to understand GHG sources and sinks?

- Accurate and precise, regional, top-down flux estimates
  - Regional-scale atmospheric mole fraction data
  - Regional-scale atmospheric transport data
- Process models / bottom-up flux models
  - Data are needed to inform these models
- Process-level top-down flux measurements to test the processes
  - Flux towers, plume measurements

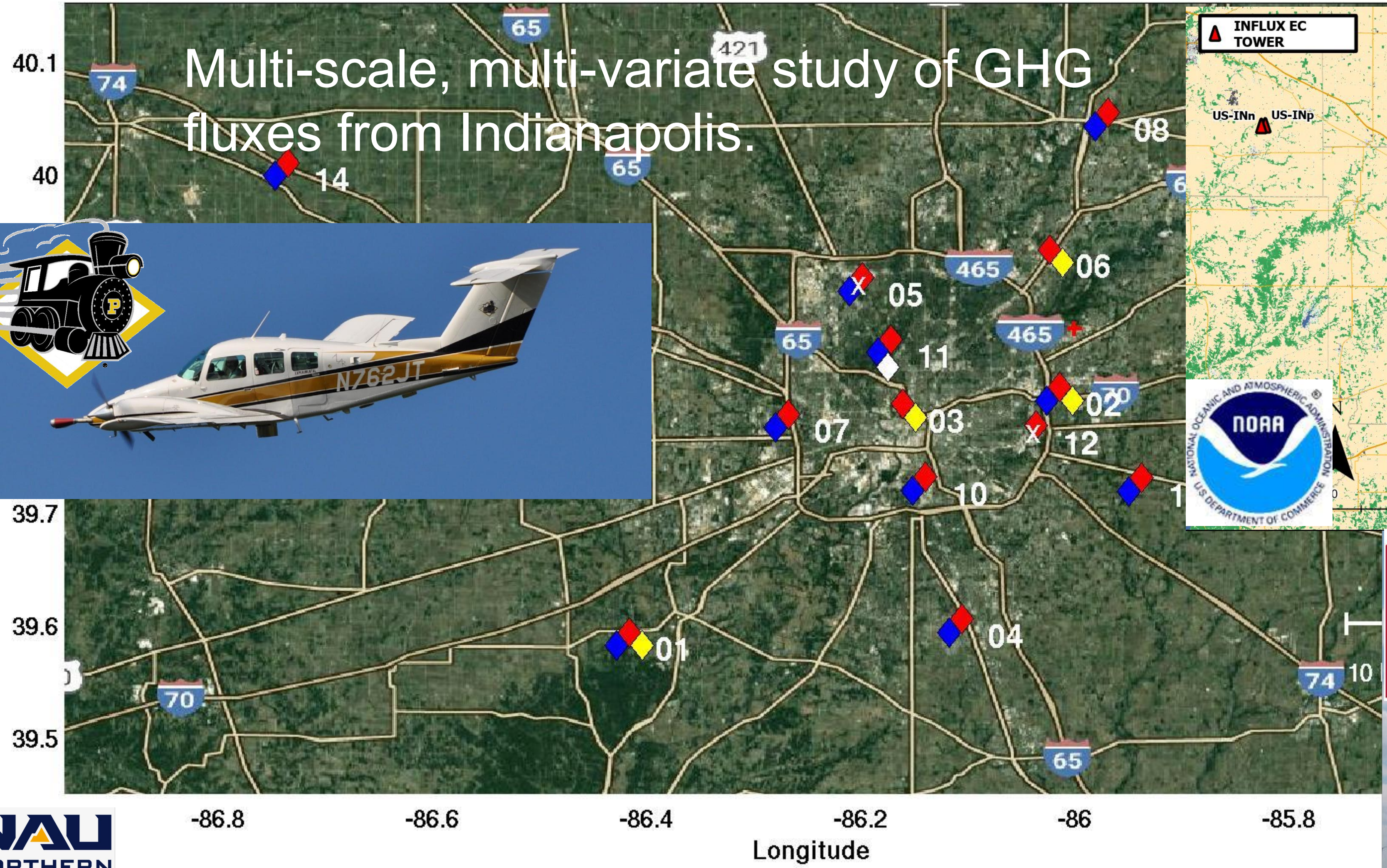
What's needed?

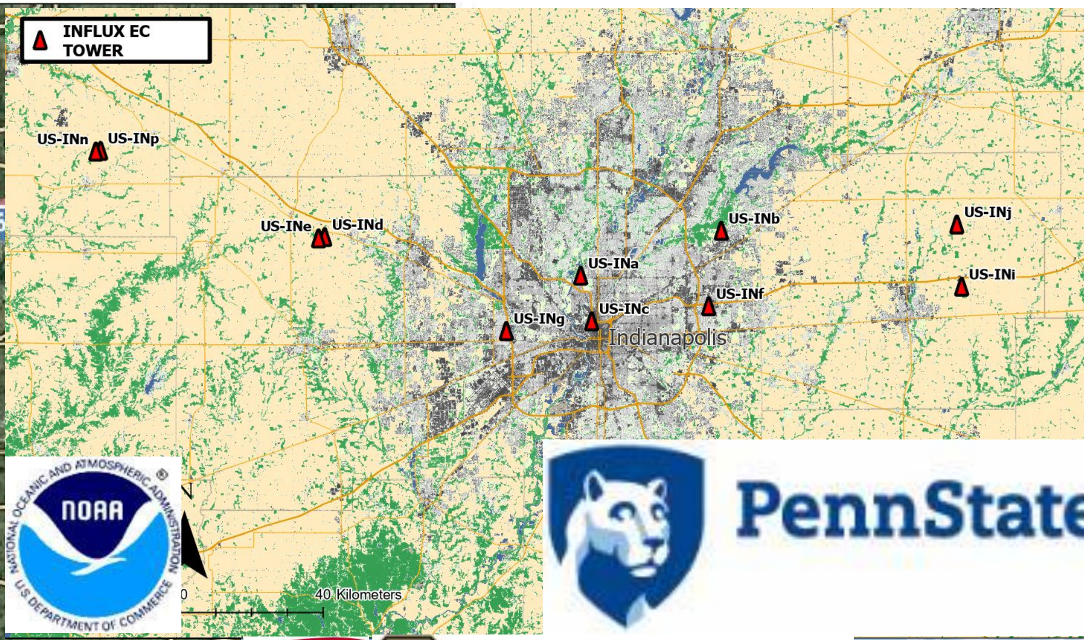
- Accurate and precise, regional, top-down flux estimates
  - Regional-scale atmospheric mole fraction data
  - Regional-scale atmospheric transport data
- Process models / bottom-up flux models
  - Data are needed to inform these models
- Process-level top-down flux measurements to test the processes
  - Flux towers, plume measurements

Two test-bed examples

INFLUX (Indianapolis Flux Experiment)

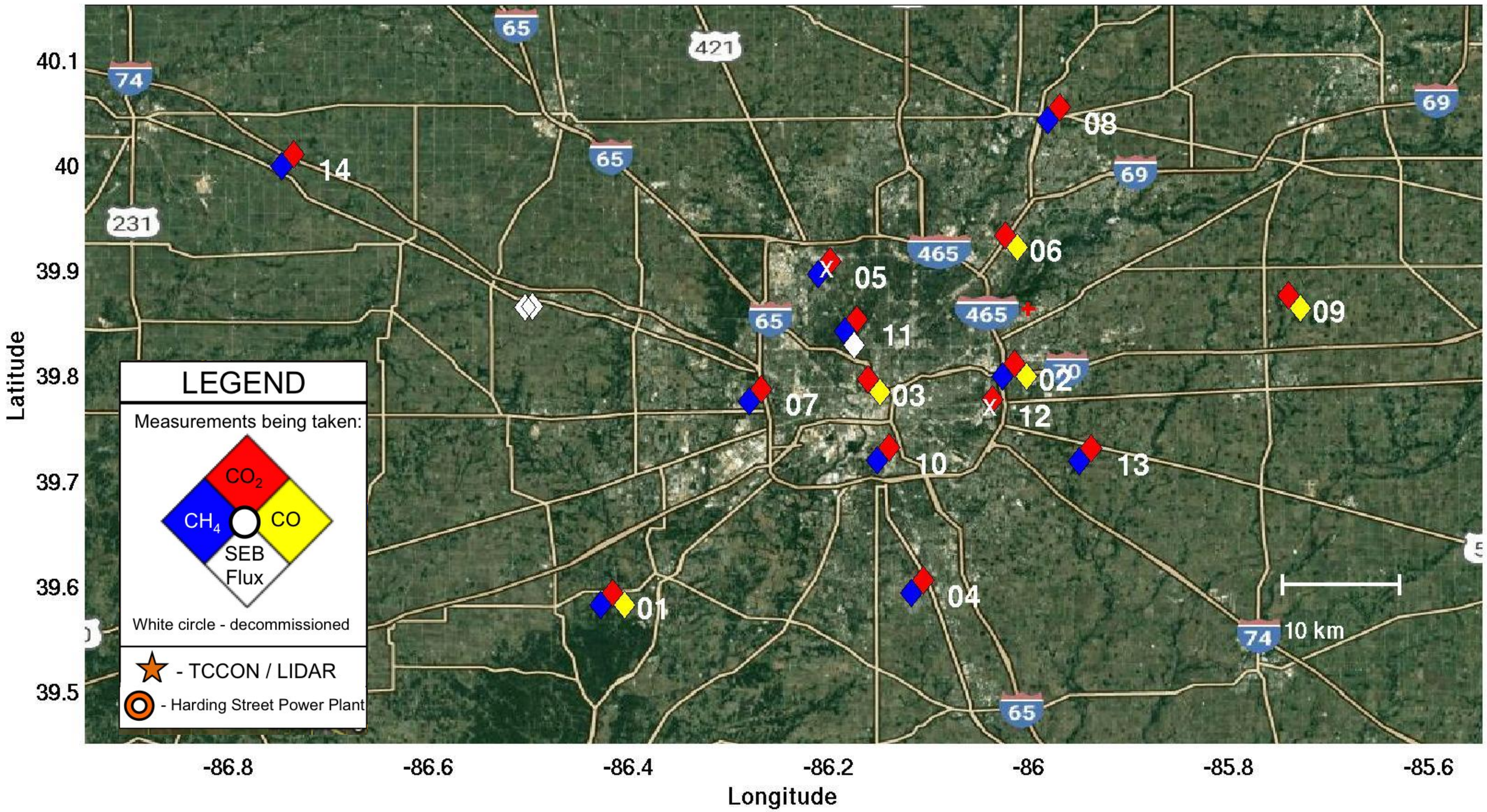
Multi-scale, multi-variate study of GHG fluxes from Indianapolis.





Davis et al., 2017; Miles et al., 2017; Heimburger et al., 2017

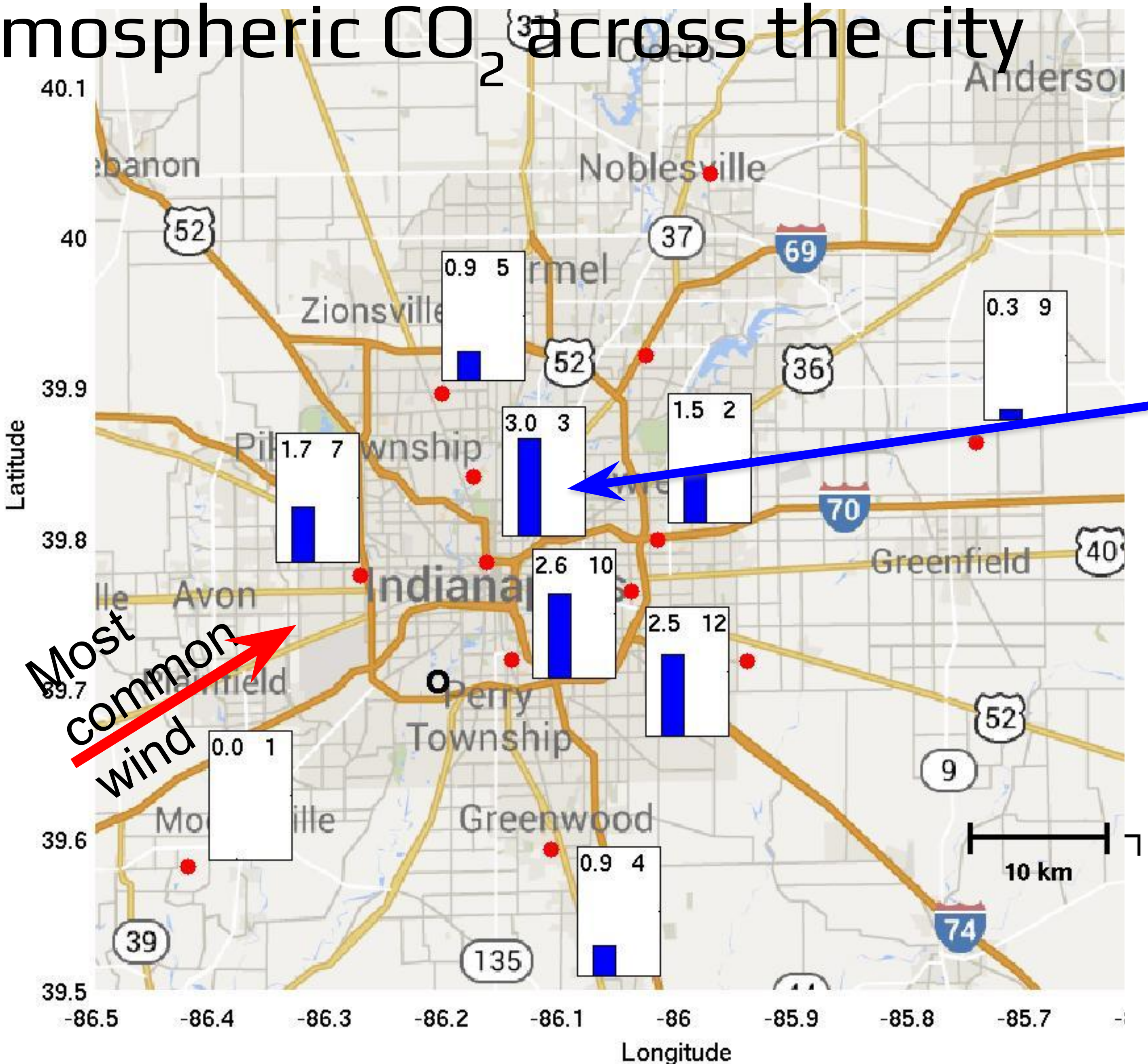
Indianapolis tower-based GHG measurement network



- Communications towers ~100 m AGL
- Picarro CRDS sensors measuring CO2, CH4, and CO
- NOAA automated flask samplers
- Eddy flux at 3-4 towers

Davis et al, 2017, http://doi.org/10.1525/elementa.188 ;
Miles et al., 2017, http://doi.org/10.1525/elementa.127 ;
Richardson et al, 2017, http://doi.org/10.1525/elementa.140

Urban emissions cause modest increases in atmospheric CO_2 across the city



- Observed CO_2: afternoon values, averaged Jan-April 2013
- Site 03: measures larger [CO_2] by 3 ppm

- City of 1.5 million.
- Mean CO_2 enhancement in the daytime ABL of about 2-3 ppm.
- Measurement challenge!

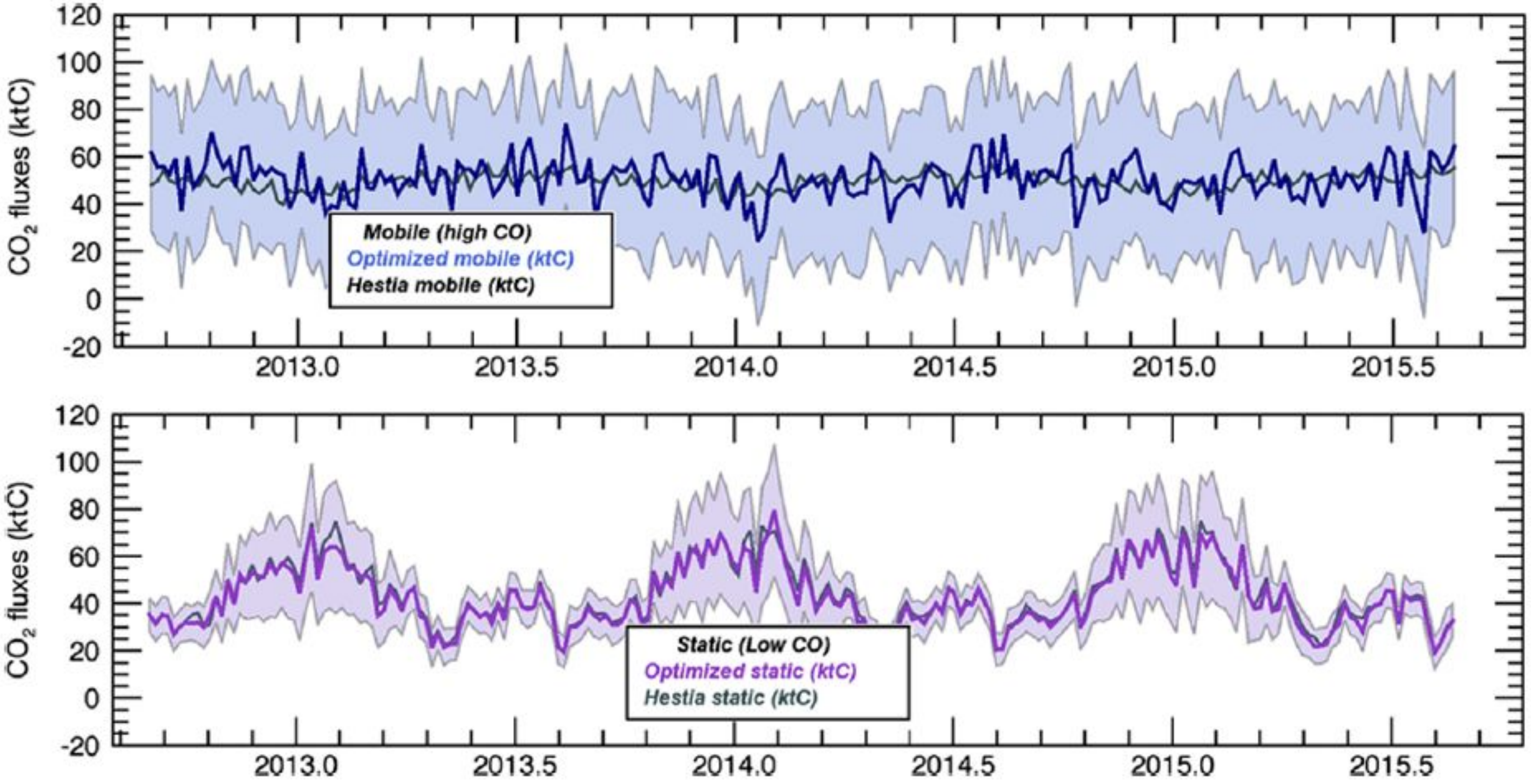
Miles et al, Elementa, 2017

Use an atmospheric model with a first guess of emissions to simulate the enhancement.

Compare the simulated enhancement to the measured enhancement.

Make adjustments to the emissions!

Indianapolis carbon dioxide emissions closely track a research-grade emissions inventory



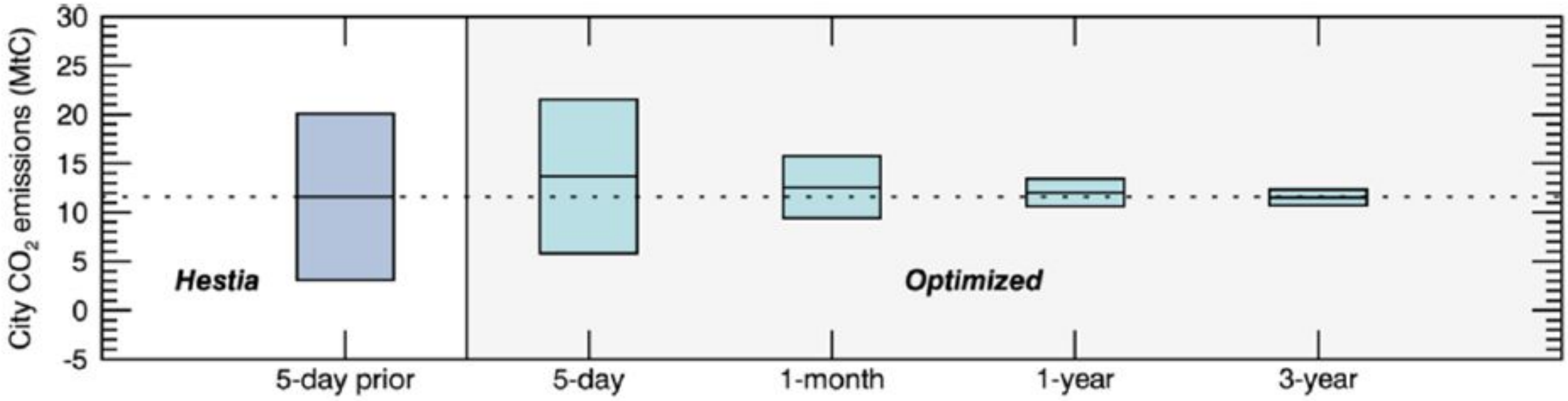
Traffic emissions are steady over time.

Stationary sources vary seasonally.

Both track the Hestia prior very closely.

Lauvaux et al., 2020, https://doi.org/10.1021/acs.est.0c00343

Indianapolis carbon dioxide atmospheric and inventory emissions agree to within 3% on an annual basis



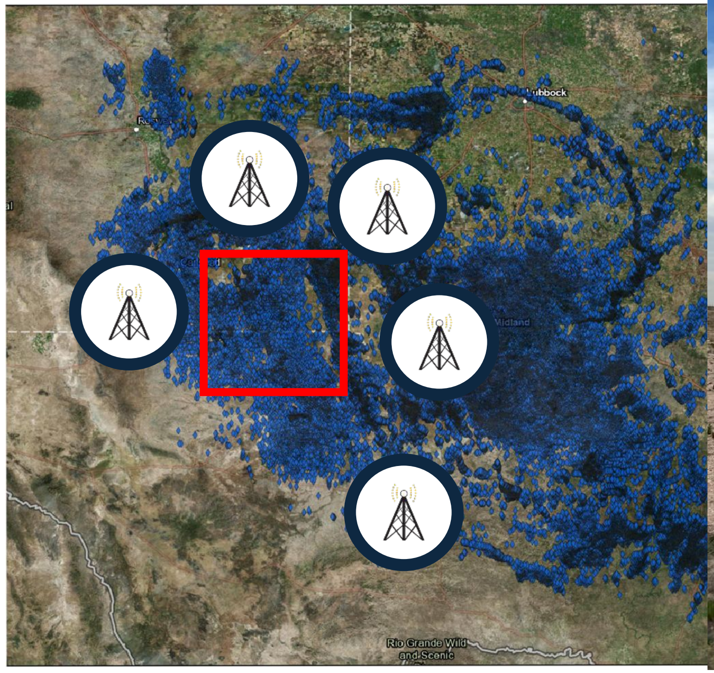
Dotted line is the Hestia inventory estimate.
Line and bars represent the mean and uncertainty of inverse flux estimates.

This level of accuracy is sufficient to track progress toward emissions mitigation.

Lauvaux et al., 2020, https://doi.org/10.1021/acs.est.0c00343

Permian basin tower-based measurement network

Five sites distributed around the Delaware portion of the Permian basin, TX/NM.



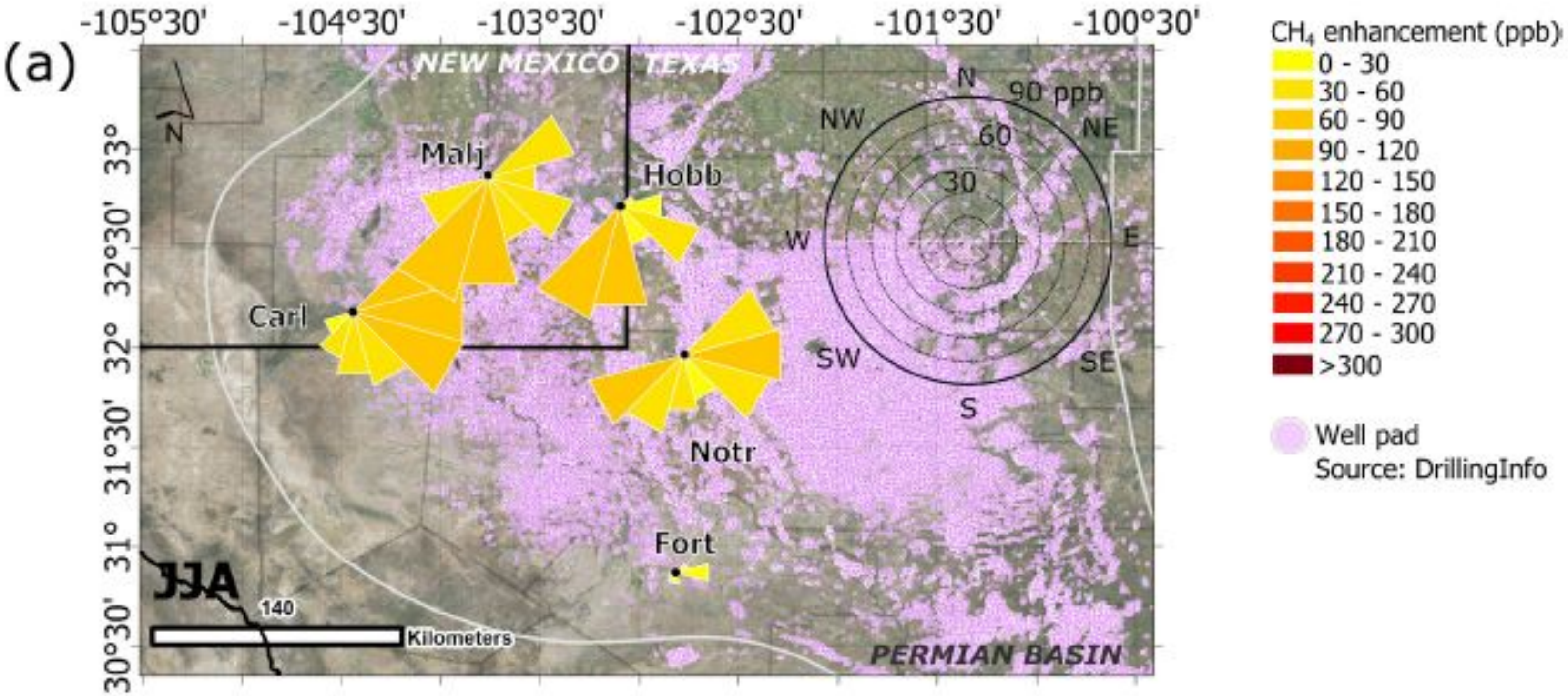
Inlets for cavity ring-down spectrometers at ~100 m above ground.

EDF ENVIRONMENTAL DEFENSE FUND Finding the ways that work

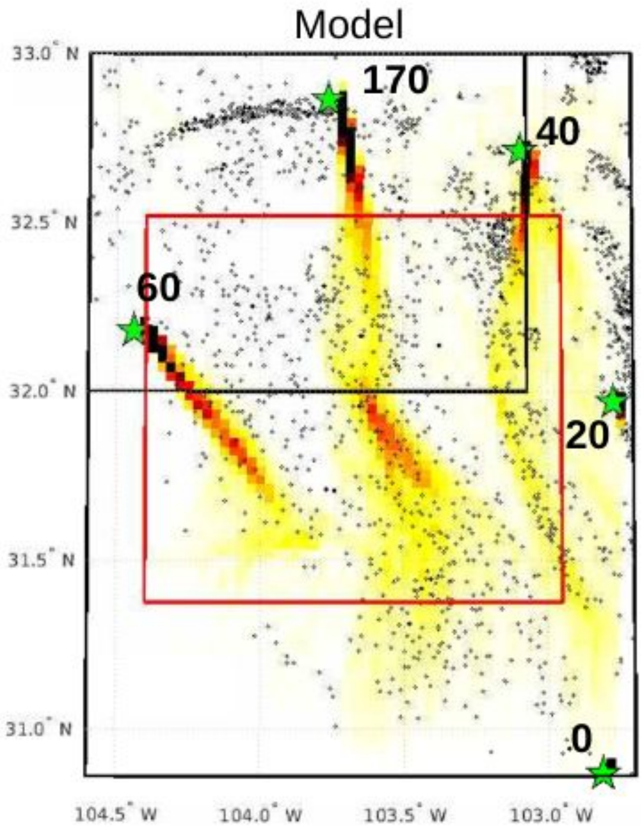
Monteiro et al., 2022, https://doi.org/10.5194/essd-14-2401-2022

PennState

Area flux mapping: Tower, in situ



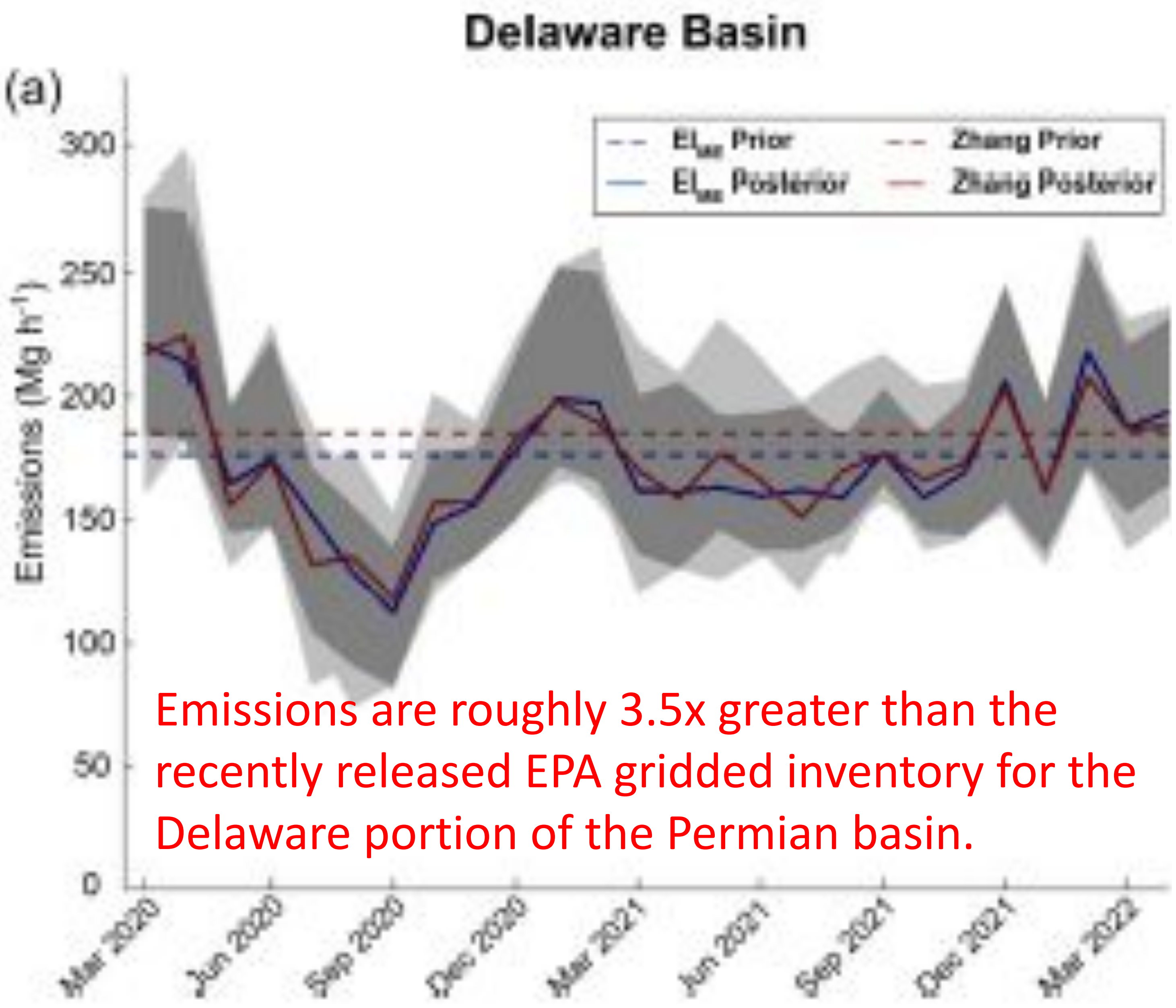
Observed CH_4 enhancements vs. wind direction



Atmospheric modeling to attribute each tower observation to what's upwind.

Monteiro et al., 2022

EDF ENVIRONMENTAL DEFENSE FUND
Finding the ways that work



Emissions are roughly 3.5x greater than the recently released EPA gridded inventory for the Delaware portion of the Permian basin.

Continuous, monthly whole-basin methane emissions estimated with 20% uncertainty.

Emissions exceed EPA inventories by at least a factor of three.

Barkley et al, 2023, https://doi.org/10.5194/acp-23-6127-2023

EDF ENVIRONMENTAL DEFENSE FUND Finding the ways that work

DEPARTMENT OF ENERGY UNITED STATES OF AMERICA

What’s needed?

- Accurate and precise, regional, top-down flux estimates
  - Regional-scale atmospheric mole fraction data
  - Regional-scale atmospheric transport data
- Process models / bottom-up flux models
  - Data needed to inform these models
- Process-level top-down flux measurements
  - Flux towers, plume measurements

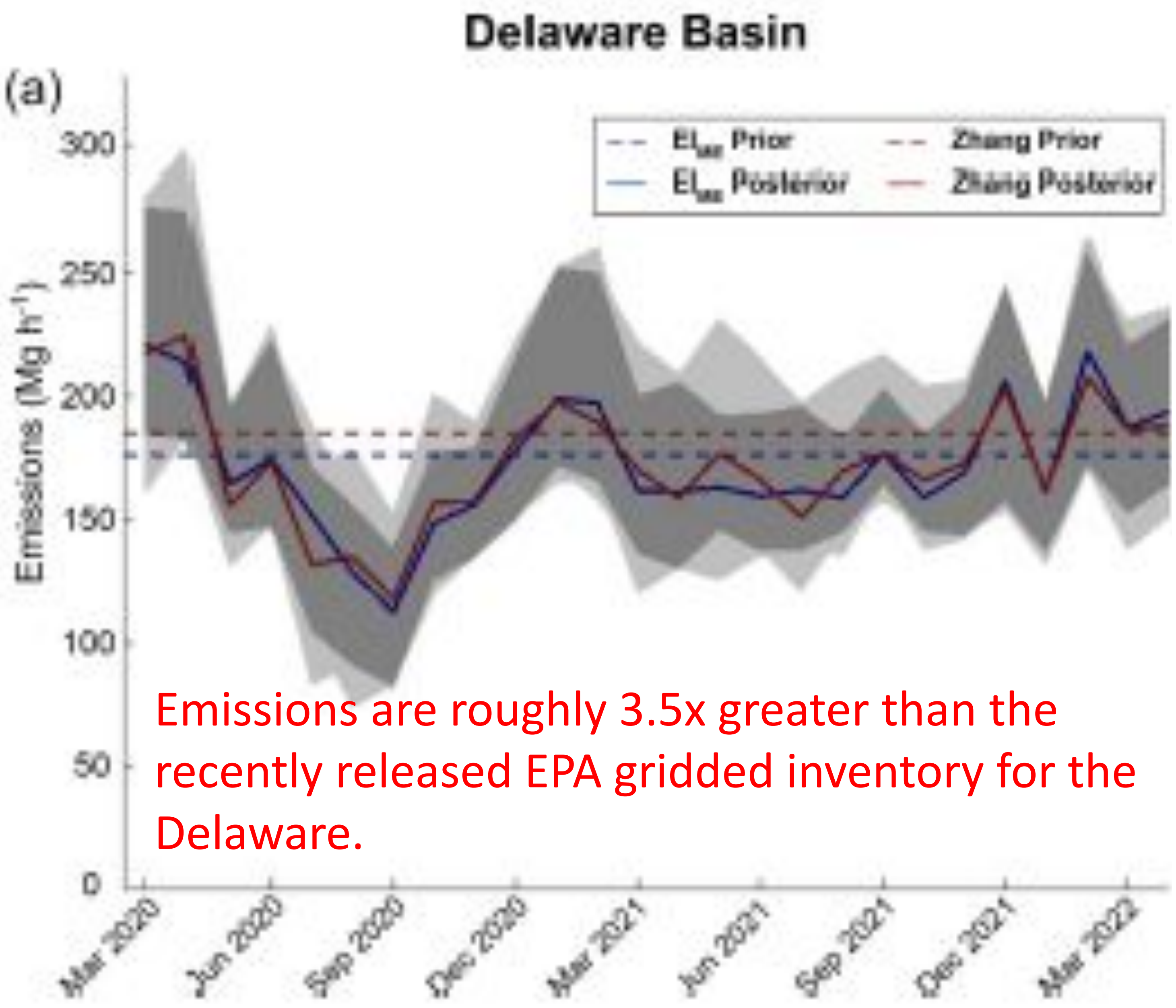
Two test-bed examples

Regional atmospheric GHG data get the job done!

But we can’t build testbeds everywhere.

Clearly high-resolution, regional-scale, ABL-resolving GHG observations from space would be powerful.

One of these examples illustrates another need…



Emissions are roughly 3.5x greater than the recently released EPA gridded inventory for the Delaware.

Continuous, monthly whole-basin methane emissions estimates with 20% uncertainty.

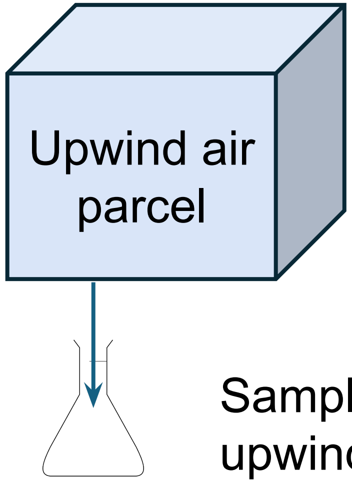
Emissions that exceed EPA inventories by at least a factor of three.

Why?

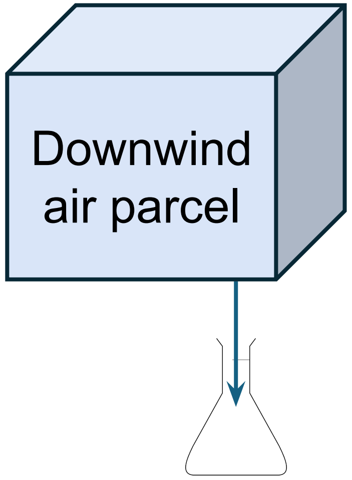
Barkley et al, 2023, https://doi.org/10.5194/acp-23-6127-2023

ENVIRONMENTAL DEFENSE FUND
Finding the ways that work

Multi-scale, multi-state observations of earth-atmosphere interactions



Measure regional flux to test the process model when aggregated over space.

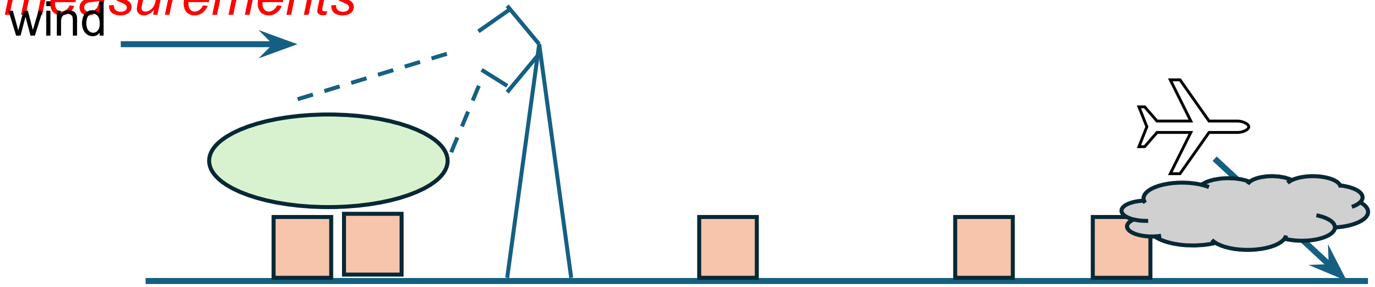


Sample air upwind

wind

Sample air downwind

Test and improve the process model using "local" flux measurements



Observations are needed to drive the process model that predicts fluxes.

What’s needed?

- Accurate and precise, regional, top-down flux estimates
  - Regional-scale atmospheric mole fraction data
  - Regional-scale atmospheric transport data
- Process models / bottom-up flux models
  - Data needed to inform these models
- Process-level top-down flux measurements
  - Flux towers, plume measurements

Atmospheric measurements: Site-level. Ground-based.

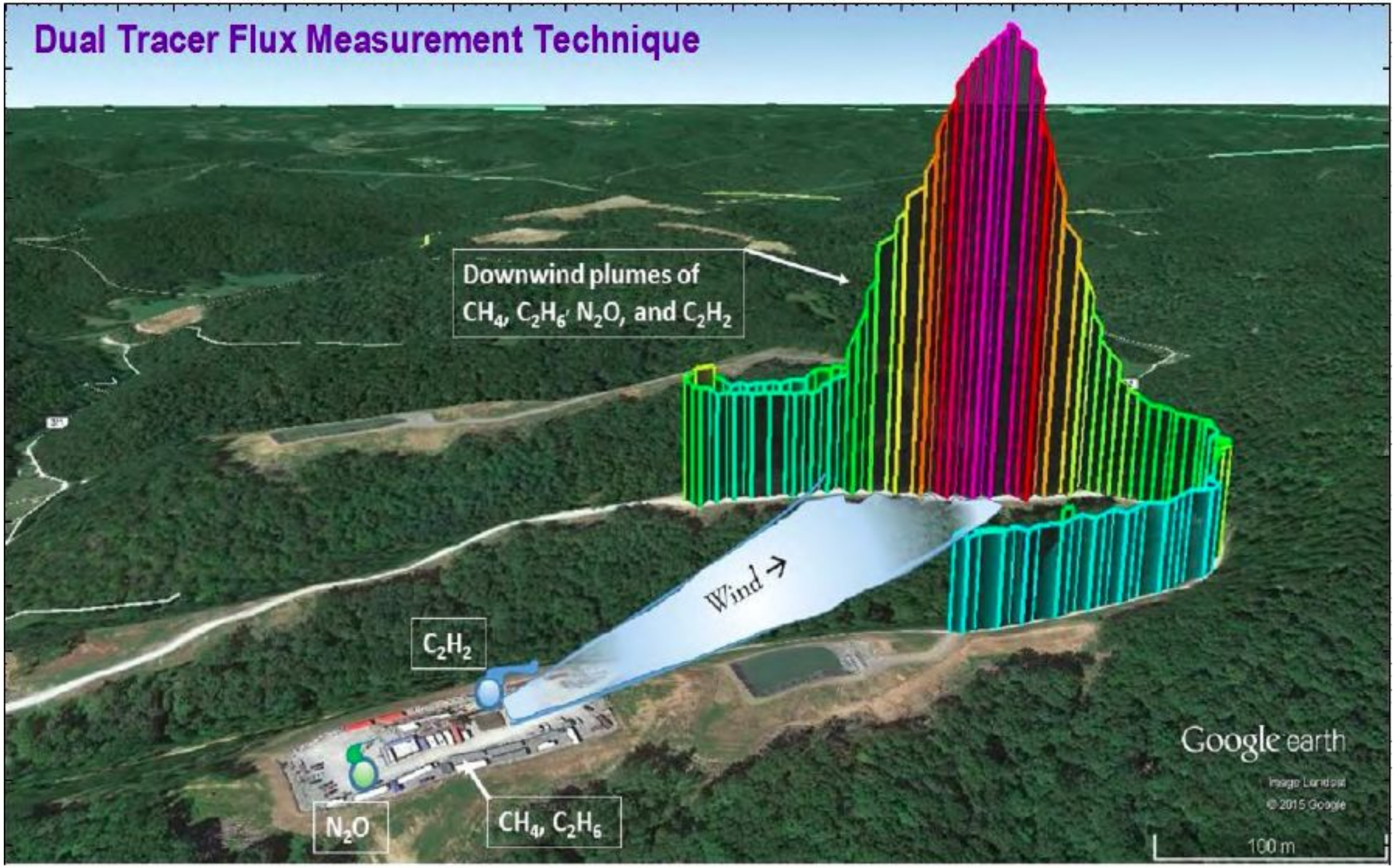
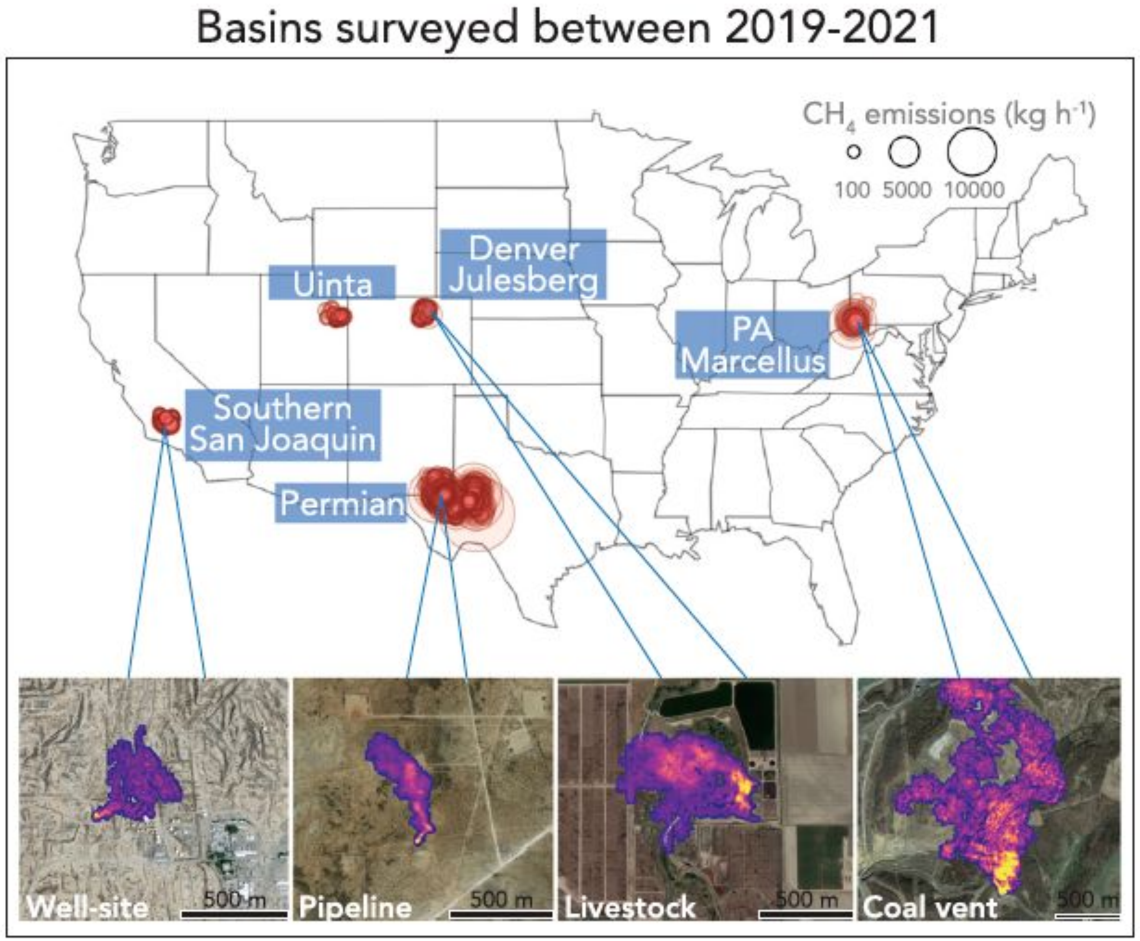
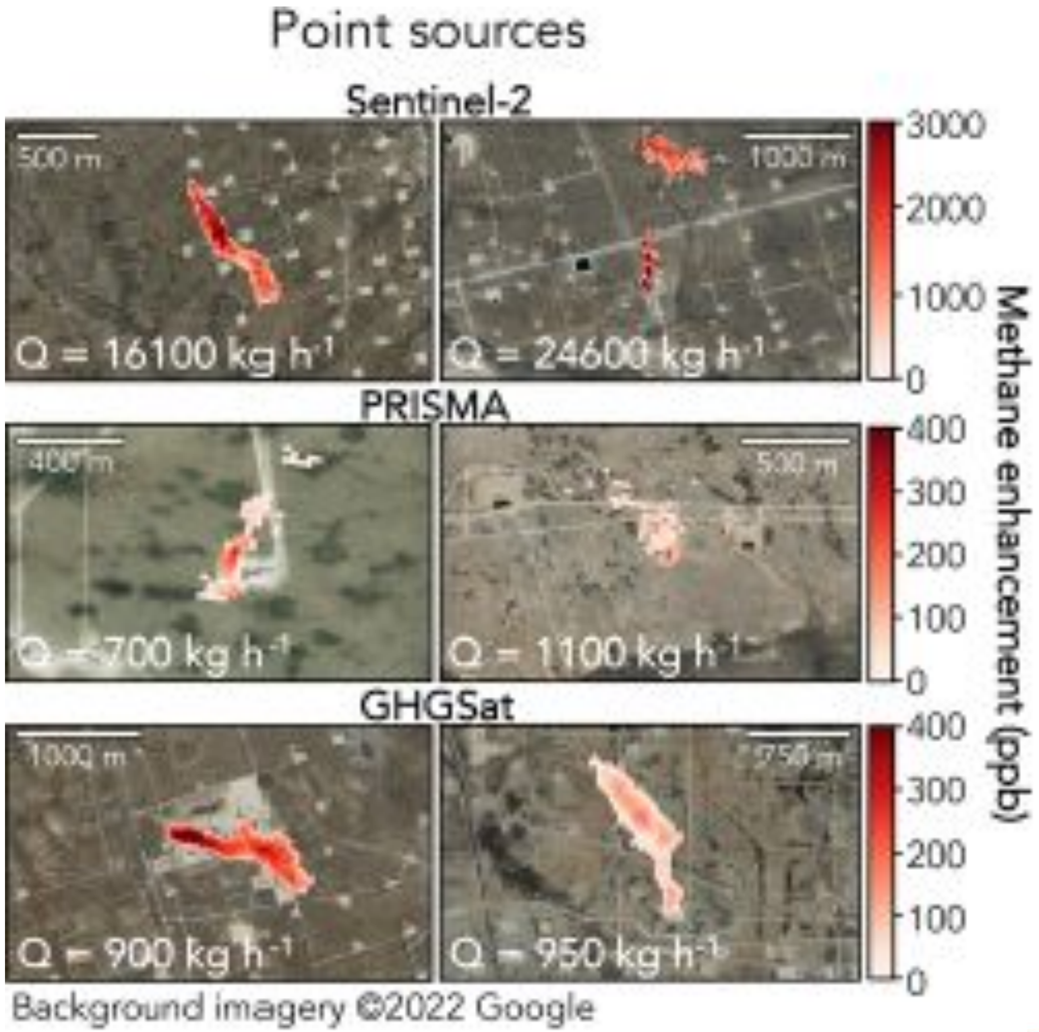


Illustration by Omara and Presto, Carnegie Mellon University

Omara et al., 2016; Caulton et al., 2019

Remote sensing can quantify emissions from individual point sources





Aircraft (CarbonMapper)

Satellite (various)

Cusworth et al.,

Jacob et al.,

pause

What's needed?

- Accurate and precise, regional, top-down flux estimates
  - Regional-scale atmospheric mole fraction data
  - Regional-scale atmospheric transport data
- Process models / bottom-up flux models
  - Data needed to inform these models
- Process-level top-down flux measurements
  - Flux towers, plume measurements

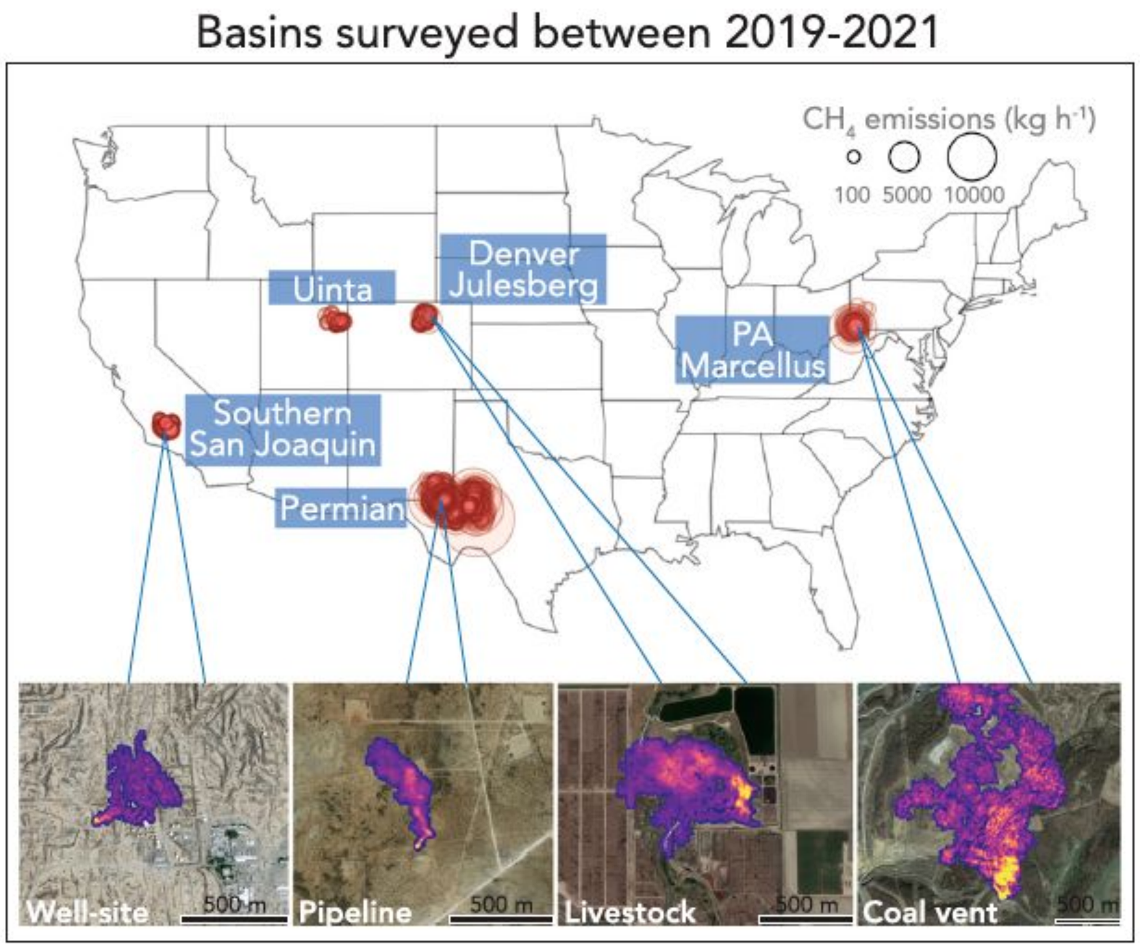
Multi-scale flux measurements require multi-scale atmospheric data

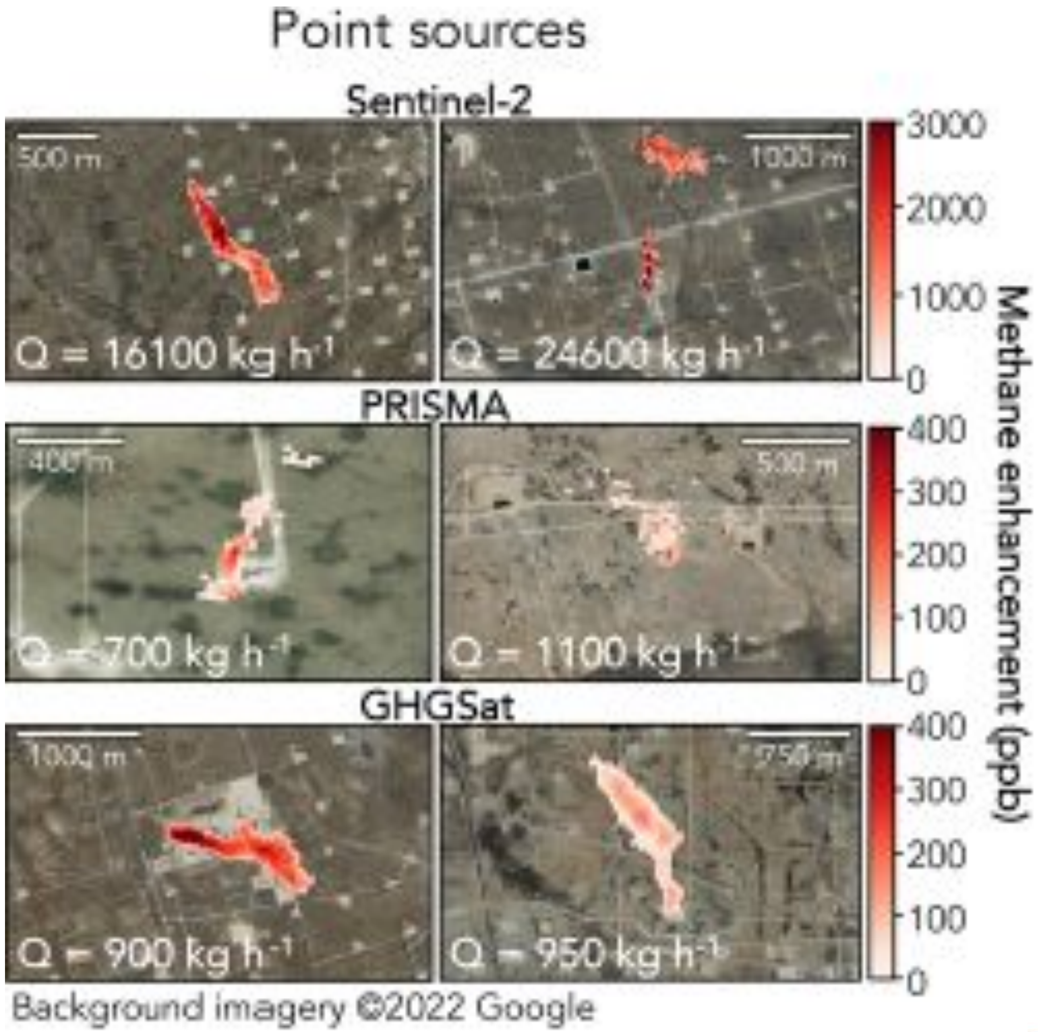
- Turbulent scales
- Small regions
- Large regions

Multi-scale flux measurements require multi-scale atmospheric data

- Turbulent scales
- Small regions
- Large regions

Remote sensing can pick out individual point sources





Aircraft (CarbonMapper)

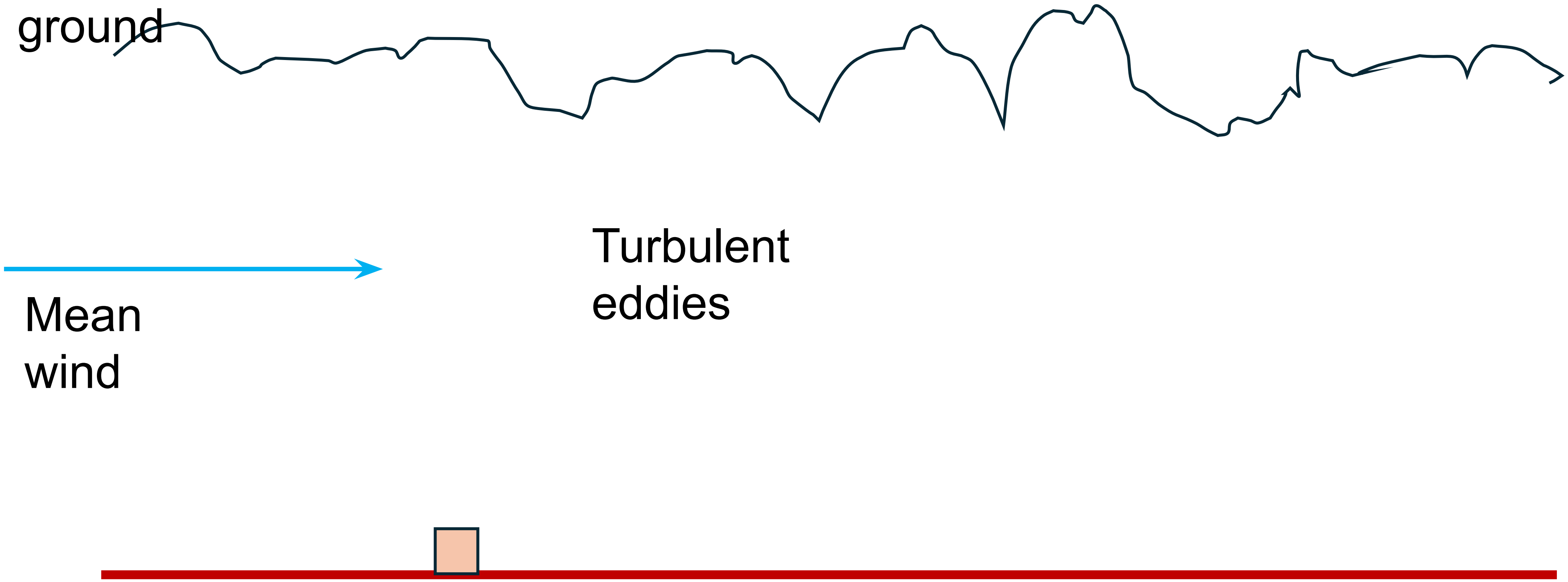
Satellite (various)

Cusworth et al.,

Jacob et al.,

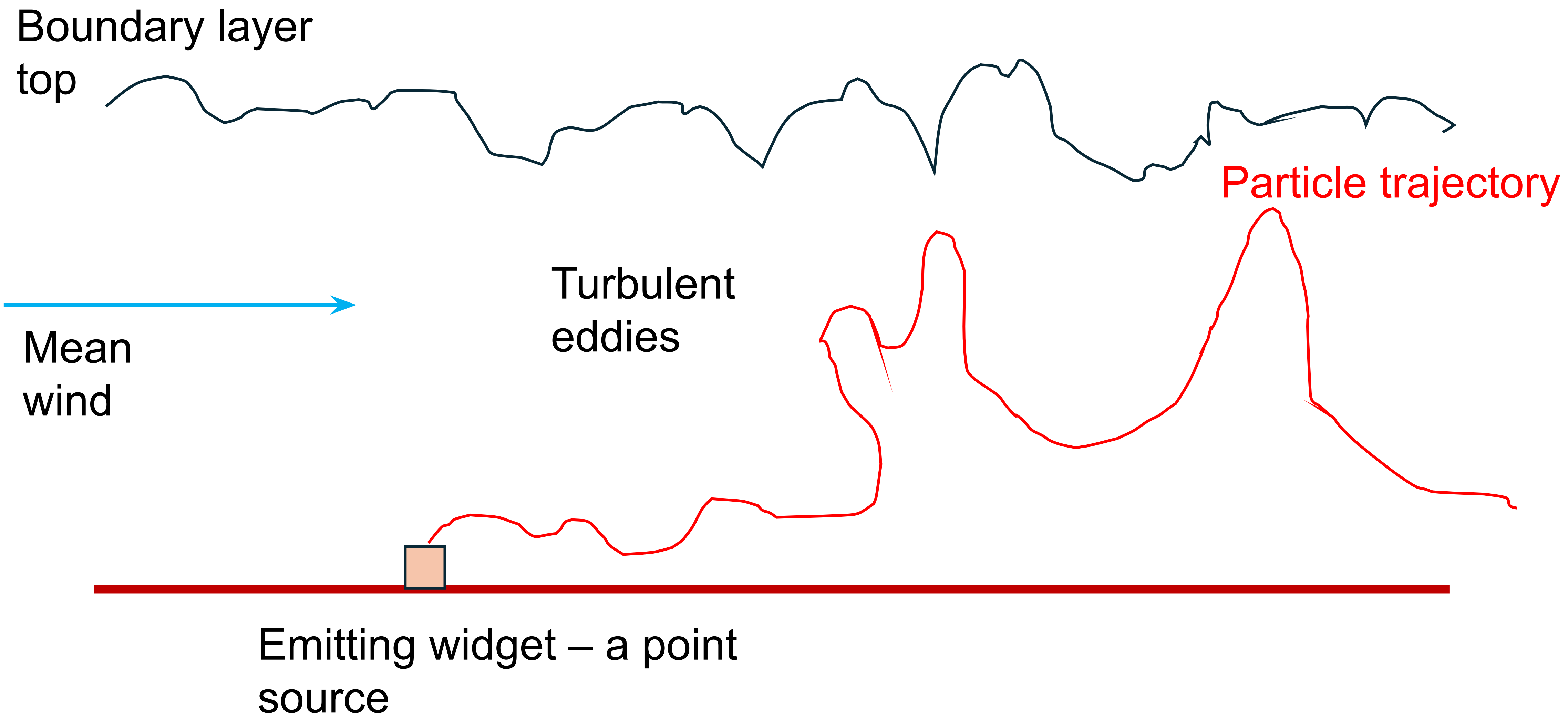
Meteorological range for turbulent (eddy covariance and plume-based) flux measurements

Atmospheric boundary layer top ~ 1 km above ground

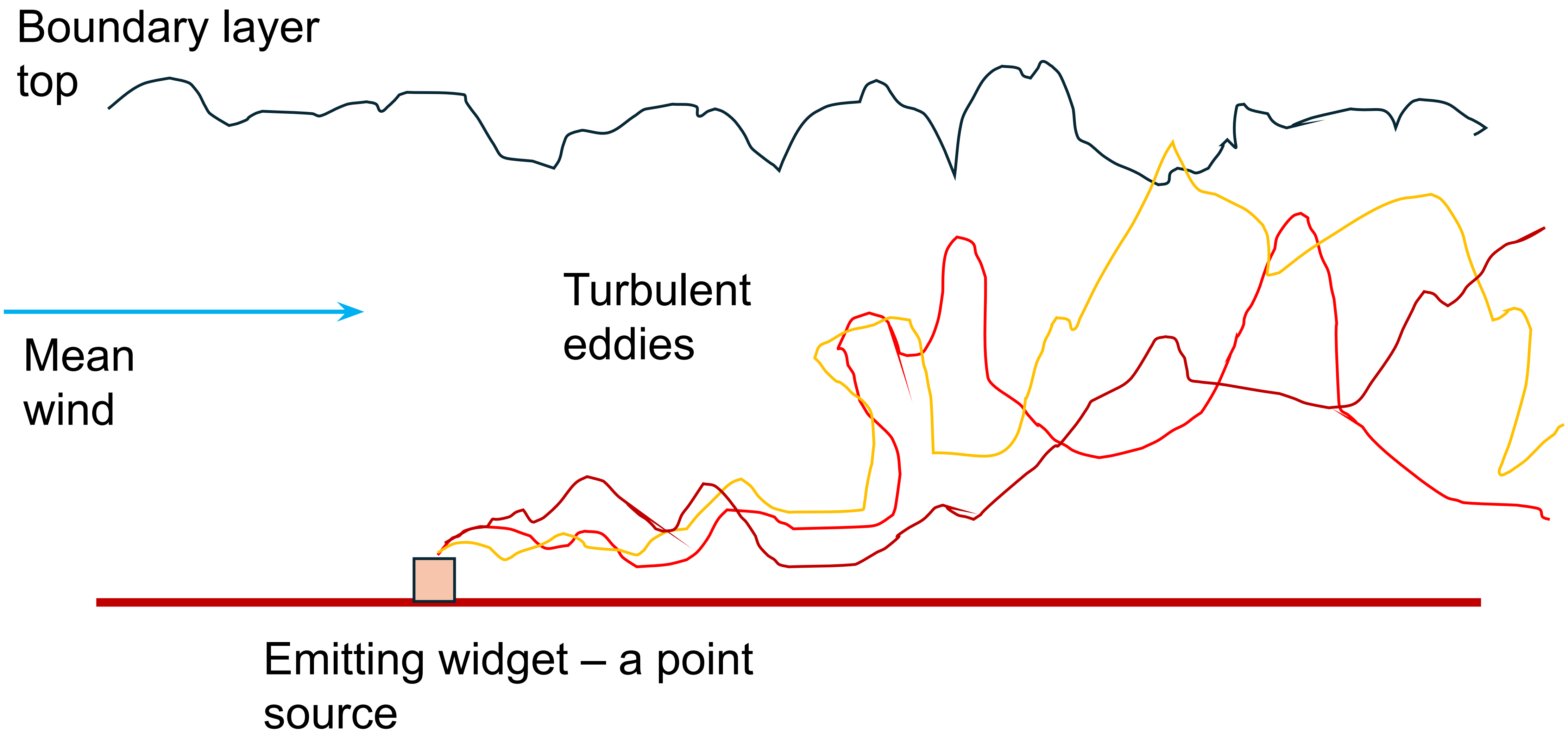


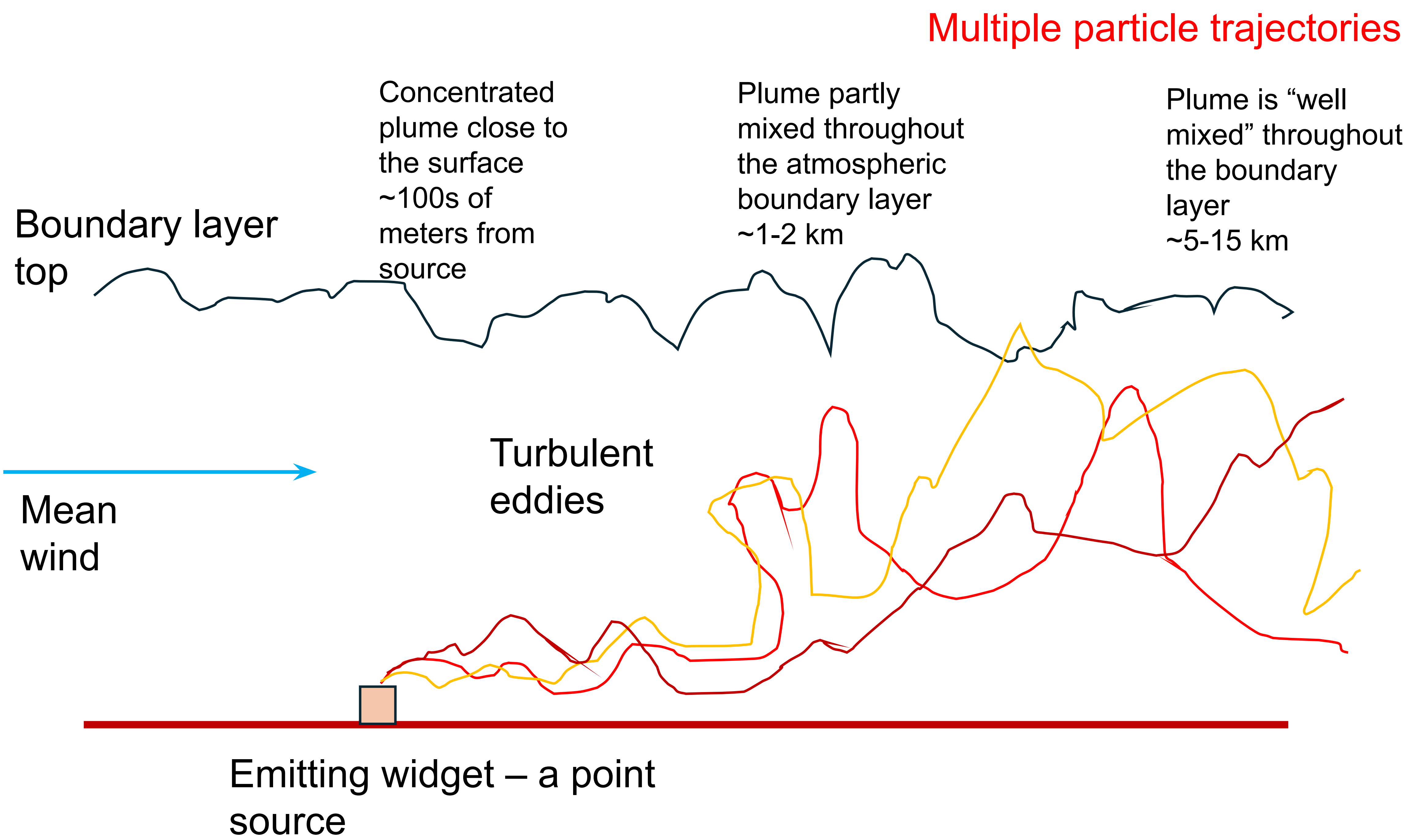
Emitting widget – a point source

Meteorological range for eddy covariance and plume-based flux measurements

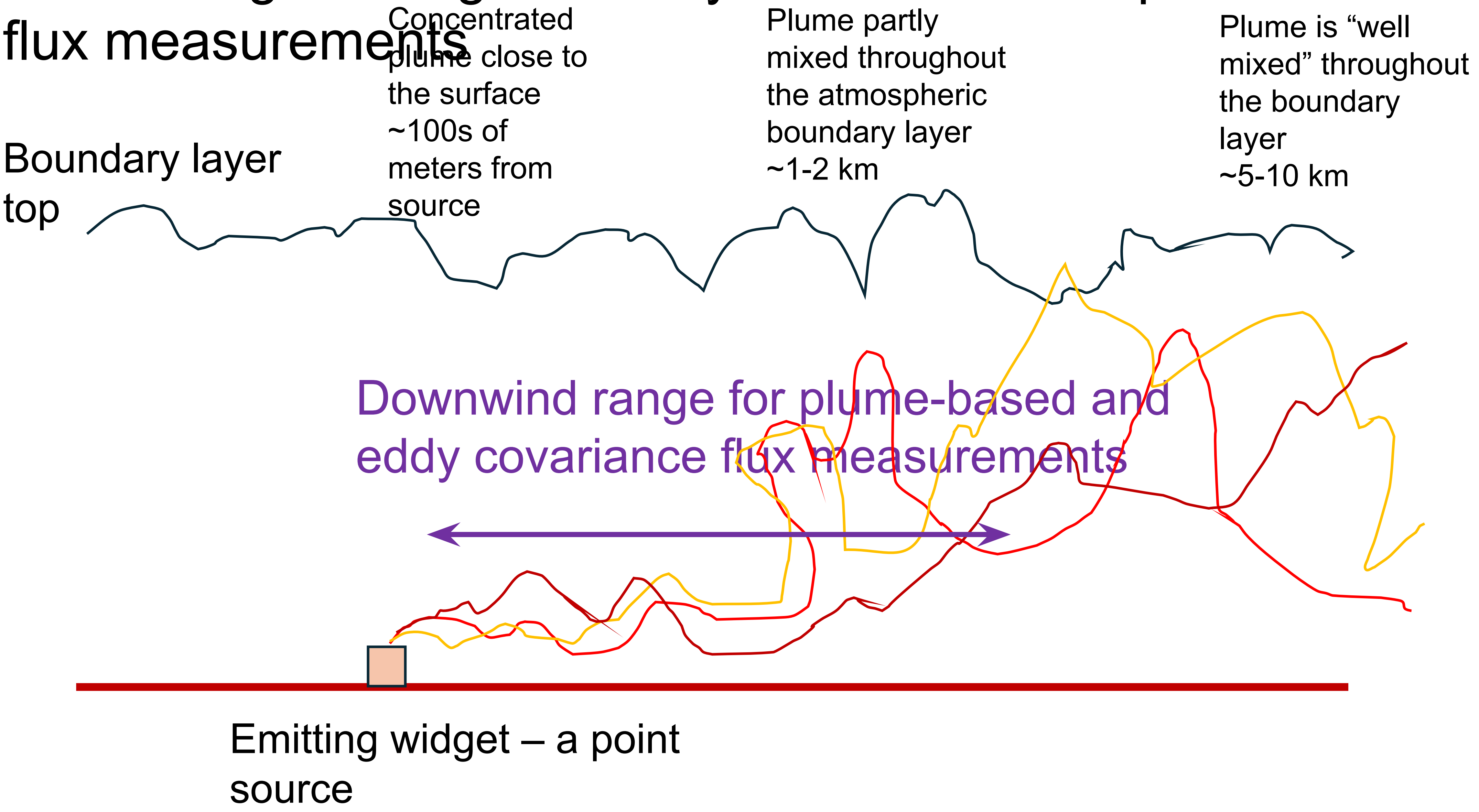


Multiple particle trajectories

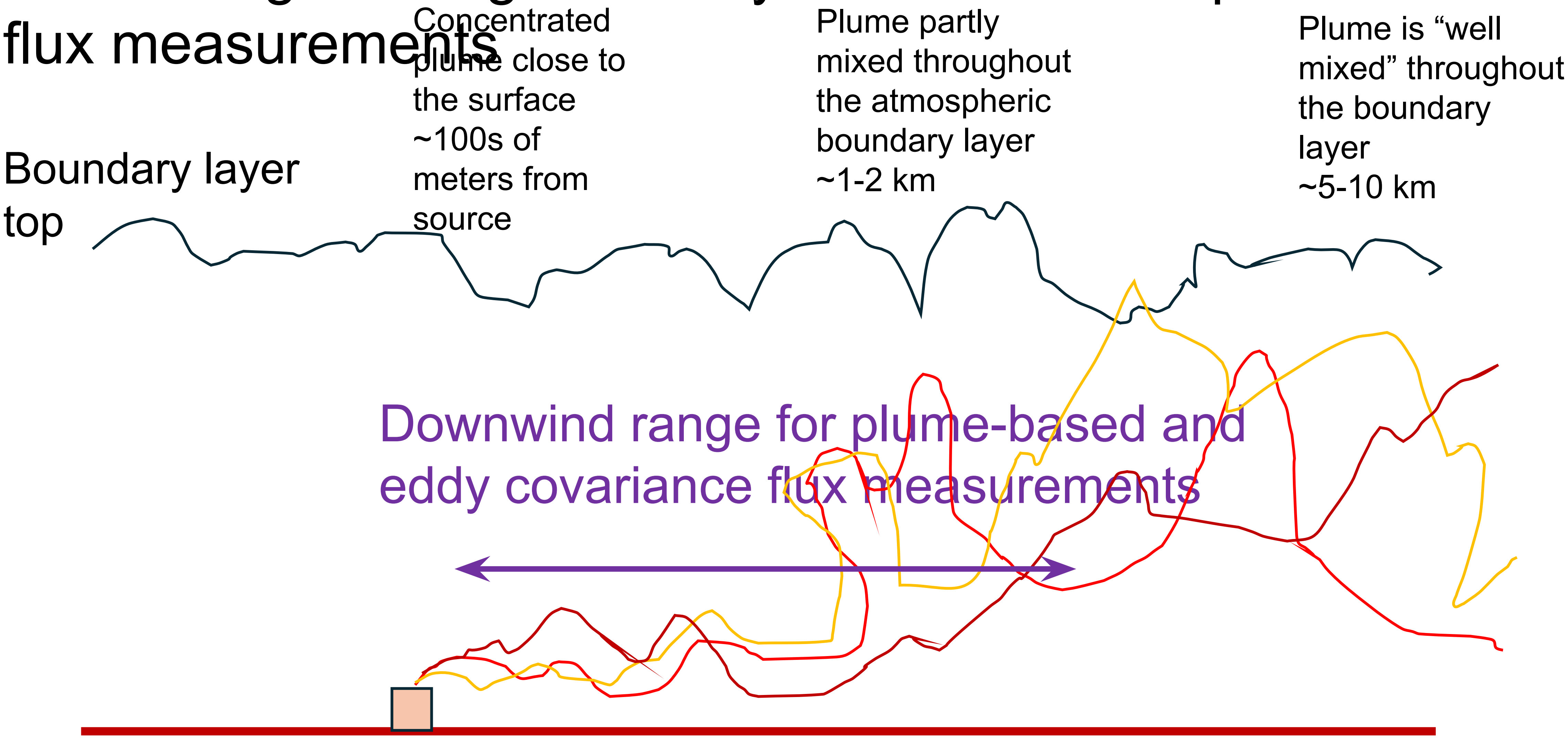



Multiple particle trajectories
Concentrated plume close to the surface ~100s of meters from source
Plume partly mixed throughout the atmospheric boundary layer ~1-2 km
Plume is “well mixed” throughout the boundary layer ~5-15 km
Boundary layer top
Turbulent eddies
Mean wind
Emitting widget – a point source

Meteorological range for eddy covariance and plume-based flux measurements



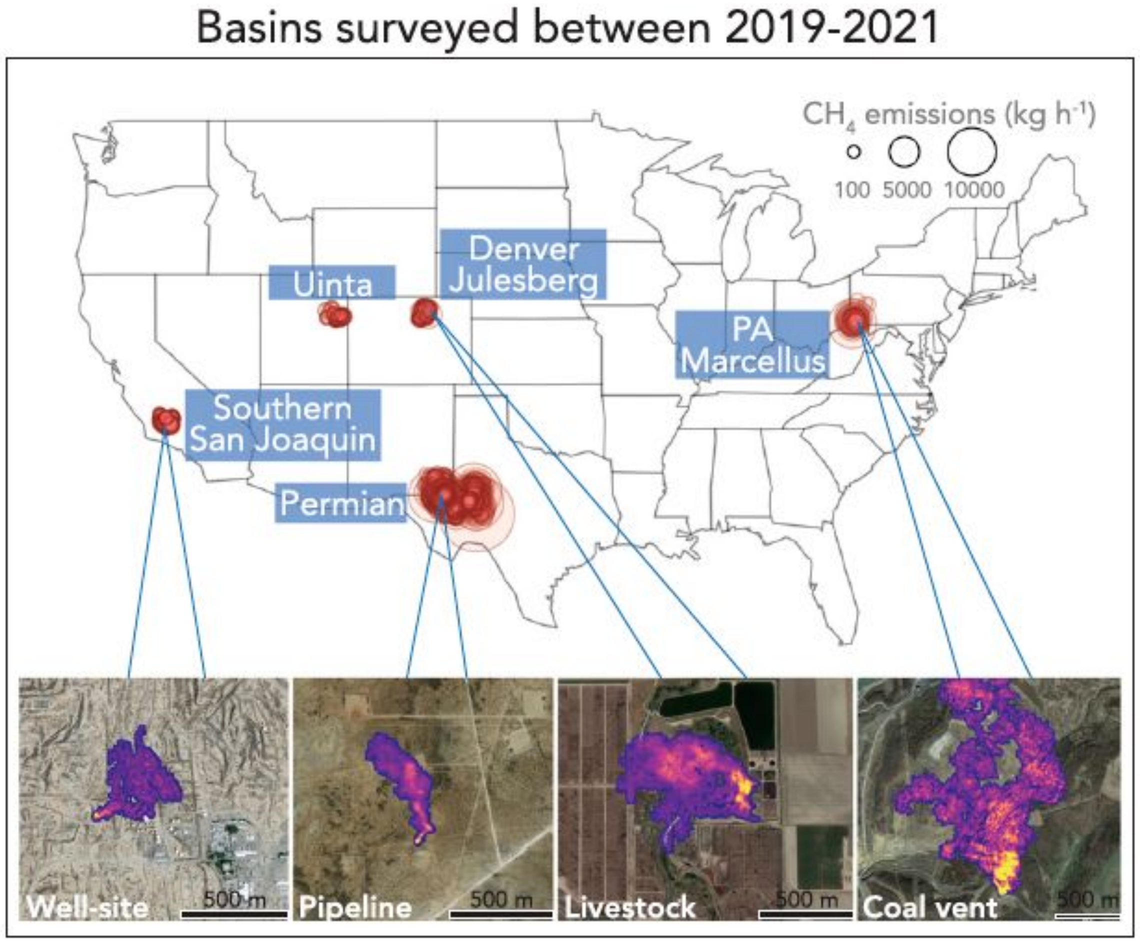
Meteorological range for eddy covariance and plume-based flux measurements

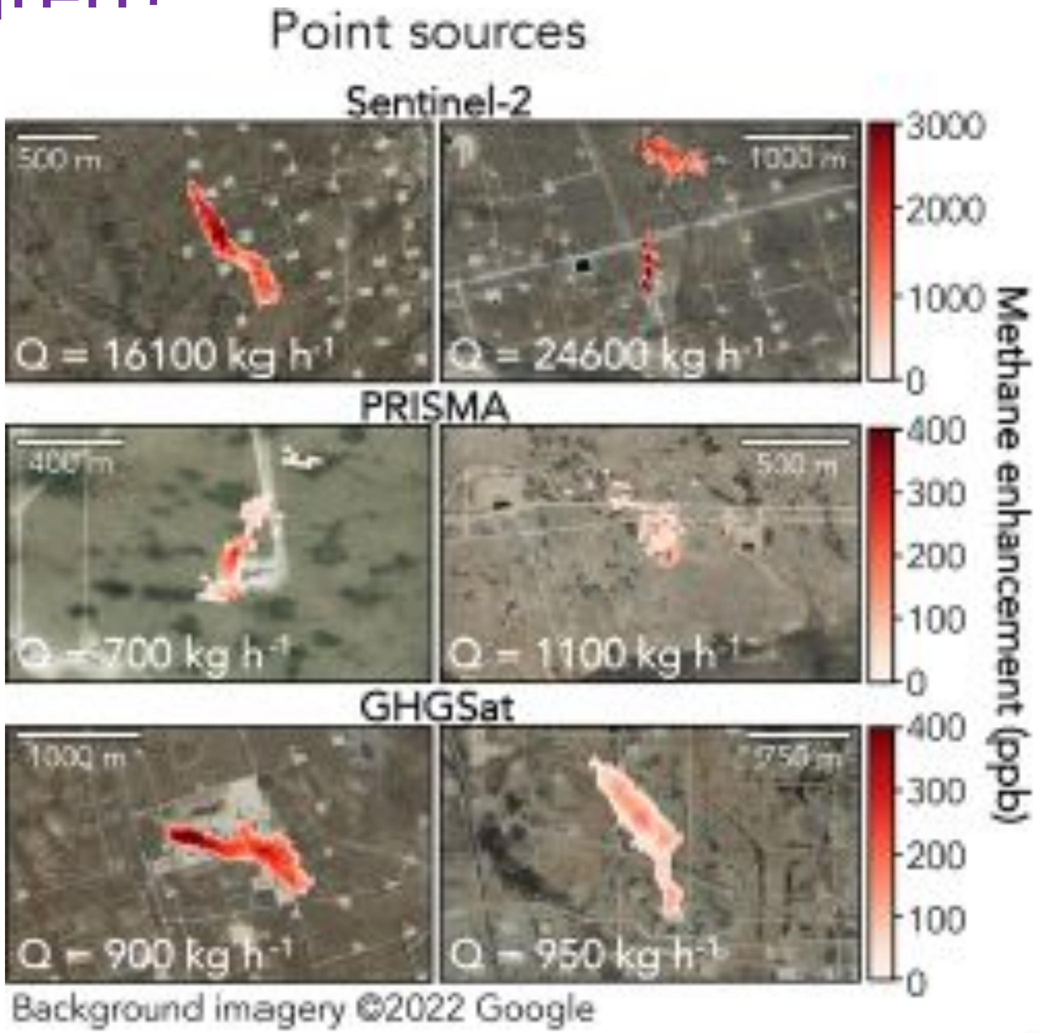


Emitting widget – a point source

Can space-based remote sensing help?

Remote sensing can pick out individual point sources. Can the surface layer winds also be measured?





Aircraft (CarbonMapper)

Satellite (various)

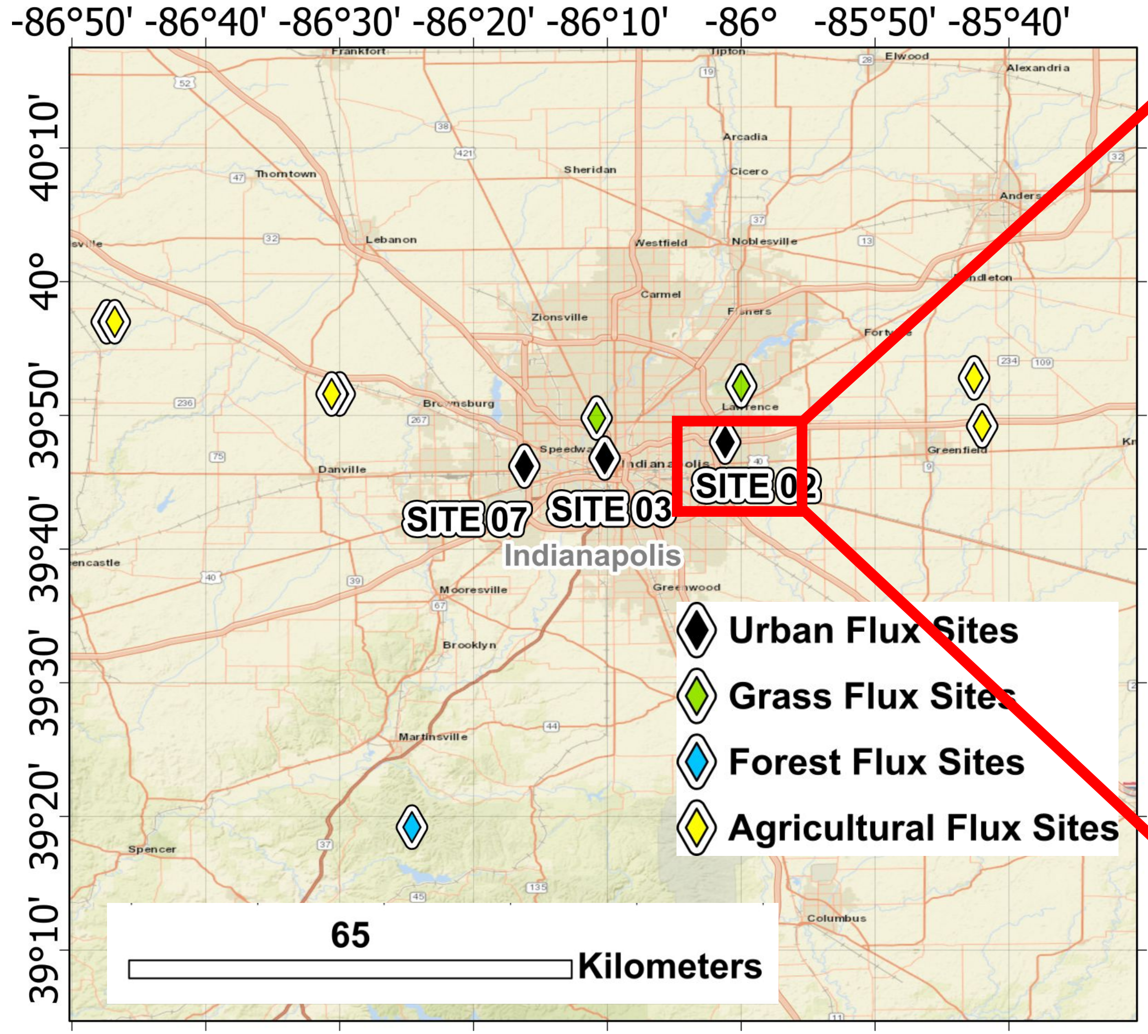
Cusworth et al.,

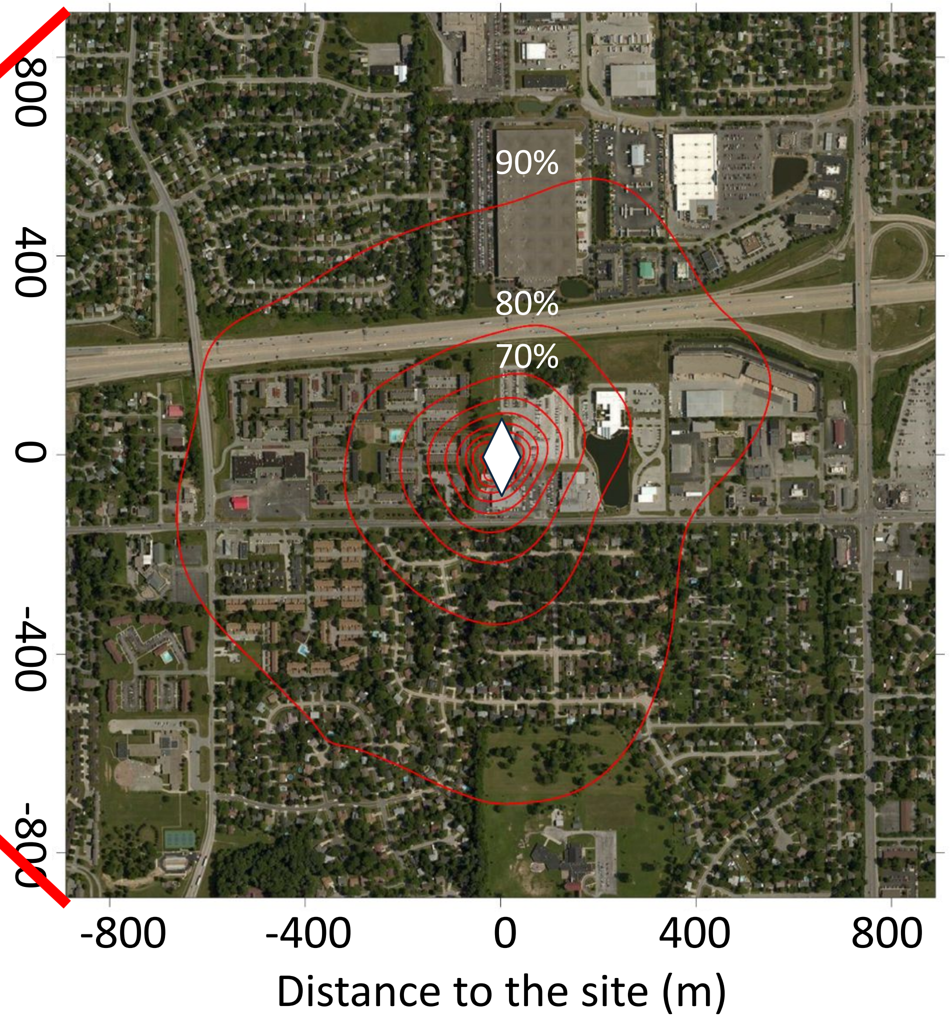
Jacob et al.,

Eddy covariance

- Great method for area-source flux measurements.
- Regularly applied to test and improve process models.
- Should be used for ensemble calibration as well.
- Unlikely that we’ll be doing this from space any time soon.

Decomposition of flux measurements: Essential for heterogeneous environments





- Mixed suburban environment
- Communications tower
- Three-level CO/CO_2/CH_4 profile (10, 40, 136m AGL)
- Flux instrumentation at 30 m AGL
- Flux system operated for about seven months.

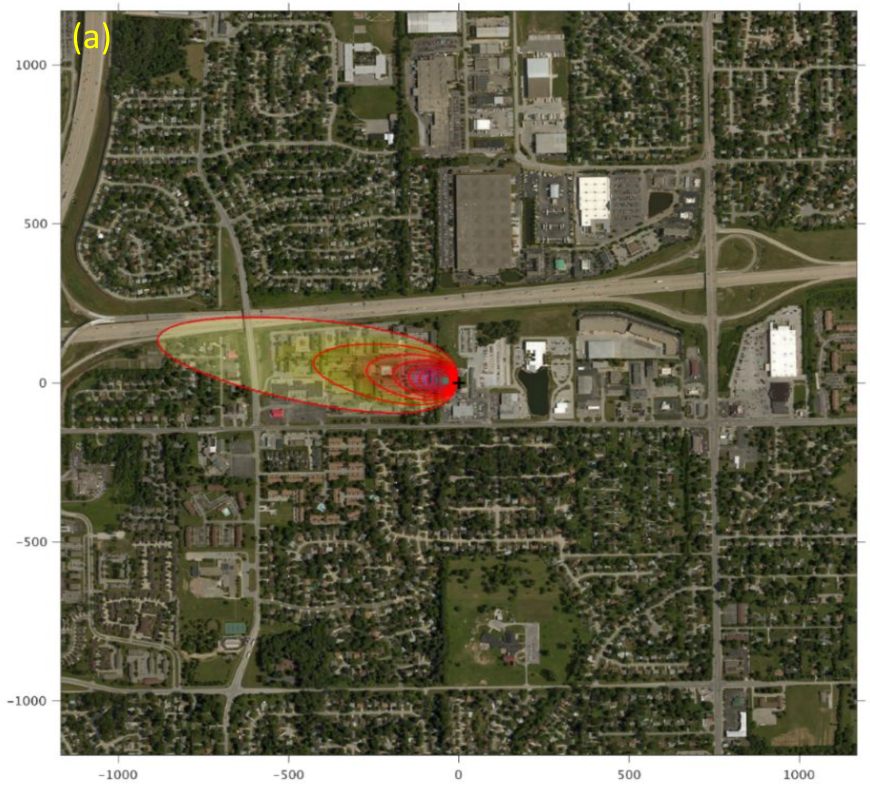
PennState

Wu et al, 2022.

NIST

Match every half-hourly flux footprint in space to the Hestia emissions map

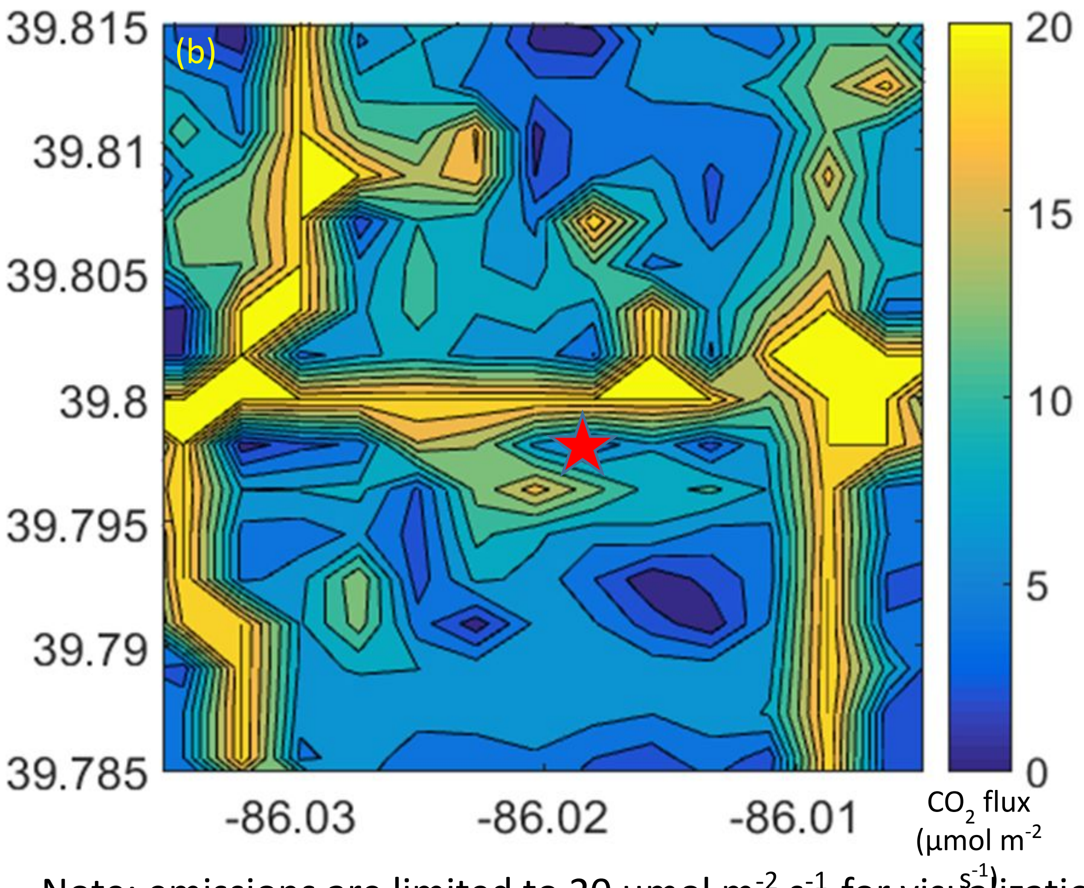
Flux footprint from one half-hourly data



Distance to the site (m)

- Flux footprint is related to instrument height, atmospheric stability and surface roughness.
- Tower measurements were used to calculate input parameters of flux footprint model.

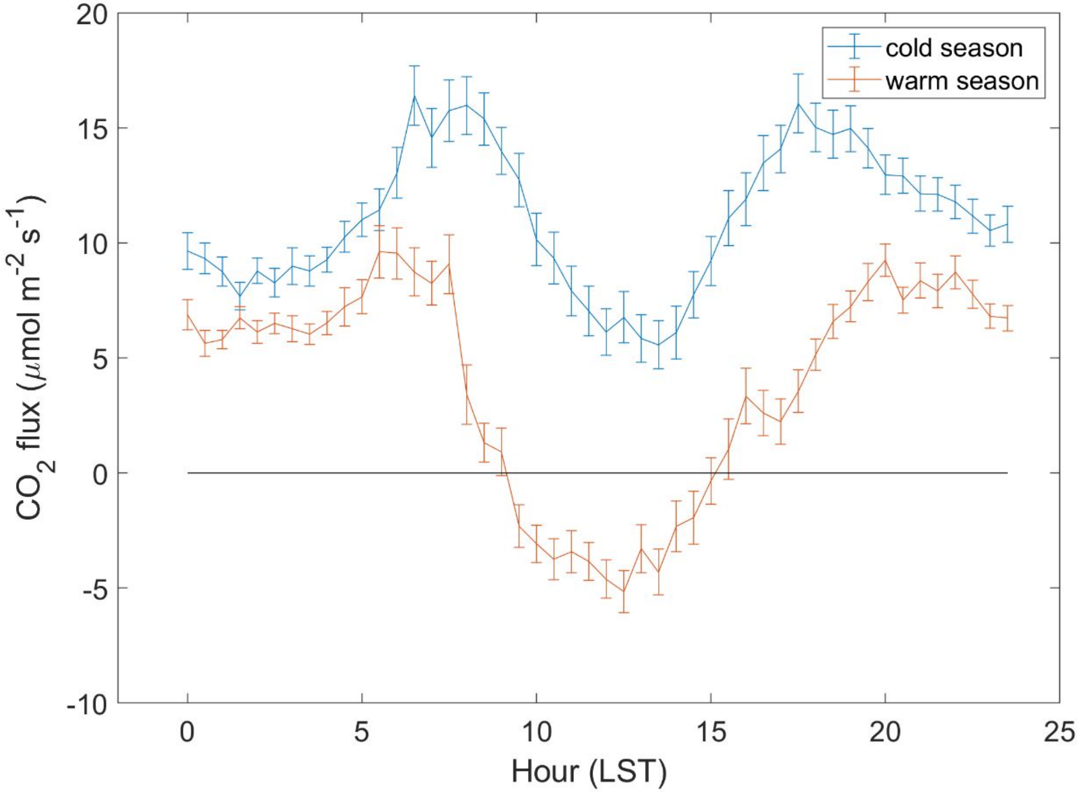
Annual mean of high-resolution (200m) Hestia emissions inventory



Note: emissions are limited to 20 μmol m^{-2} s^{-1} for visualization.

- Hestia has fine-scale spatial structure in urban CO_2 emissions, complementary to flux data.
- High emissions are correlated to the distribution of roads.

Flux data show expected patterns for mixed biological and anthropogenic CO_2 fluxes



Cold season (JFM): traffic emissions and domestic heating

Warm season (AMJJ): photosynthesis, respiration, and CO_2ff emissions.

Total CO_2 fluxes look very reasonable in time:

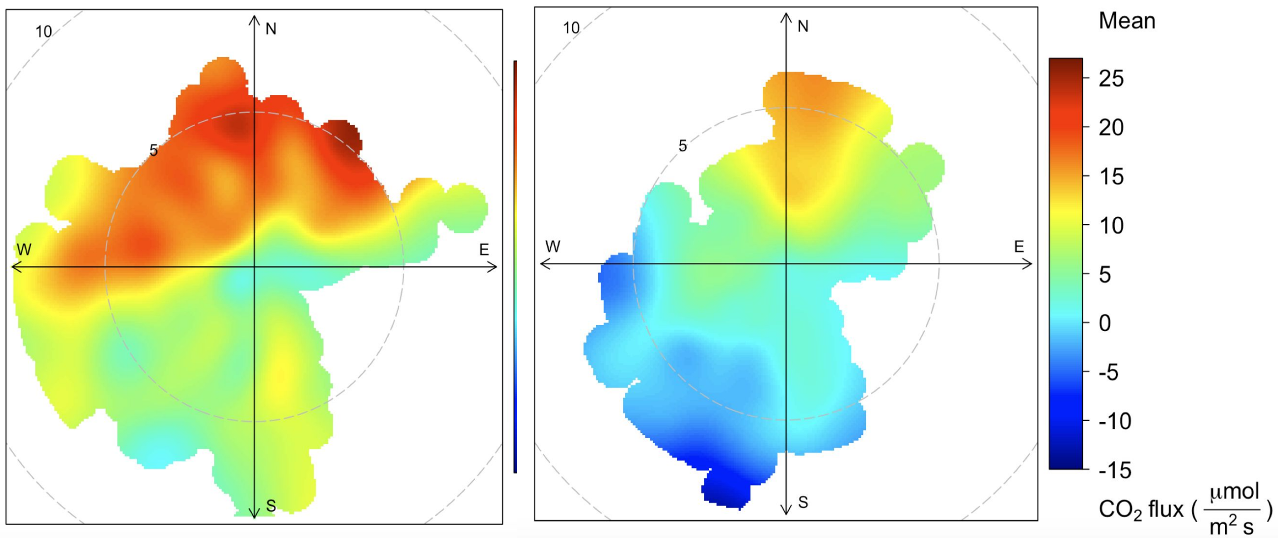
- Traffic peaks at rush hours
- Biological flux contributions in the summer.

And in space:

- Fluxes are large and positive from the north (highway), and
- smaller, sometimes negative from the south (suburban, vegetation).

Cold season (JFM)

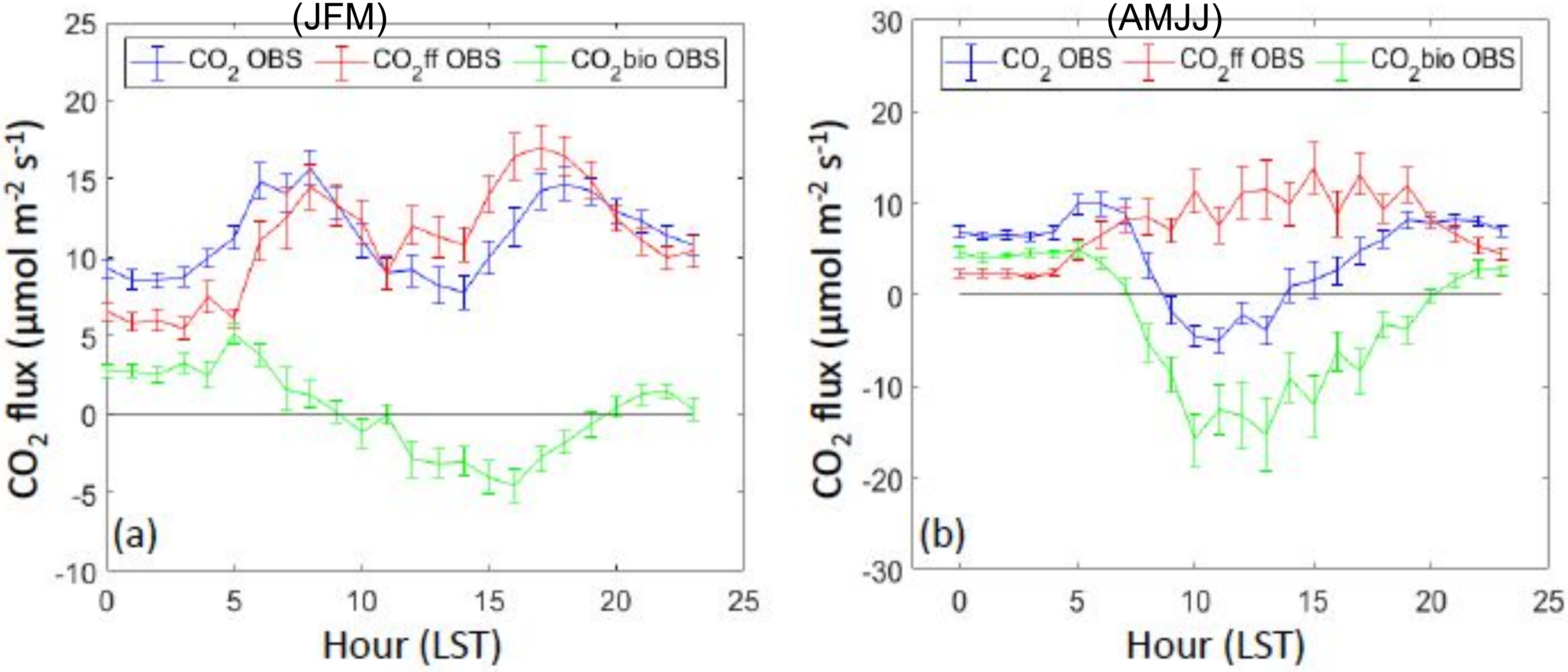
Warm season (AMJJ)



Flux decomposition yields fossil and bio CO_2 fluxes

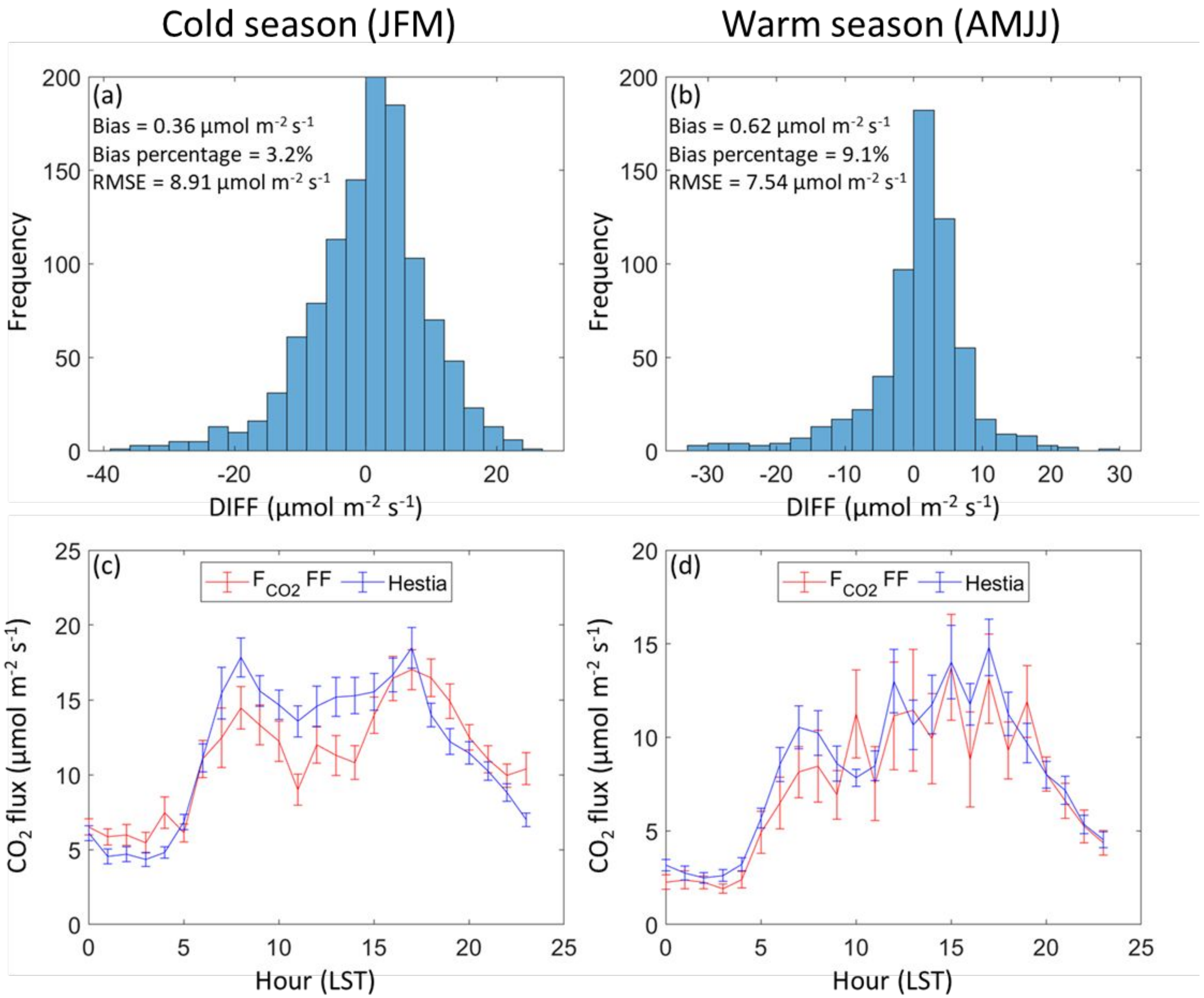
Cold season (JFM)

Warm season (AMJJ)



Photosynthesis in the winter?

Hestia - Eddy Covariance bias and temporal pattern comparisons



Very small percentage bias (3%, 9%) in the seasonal averaged CO_2ff emissions.

Modest RMSE, probably dominated by sampling error from the eddy covariance methods.

Shockingly close agreement in the seasonal temporal pattern of CO_2ff emissions.

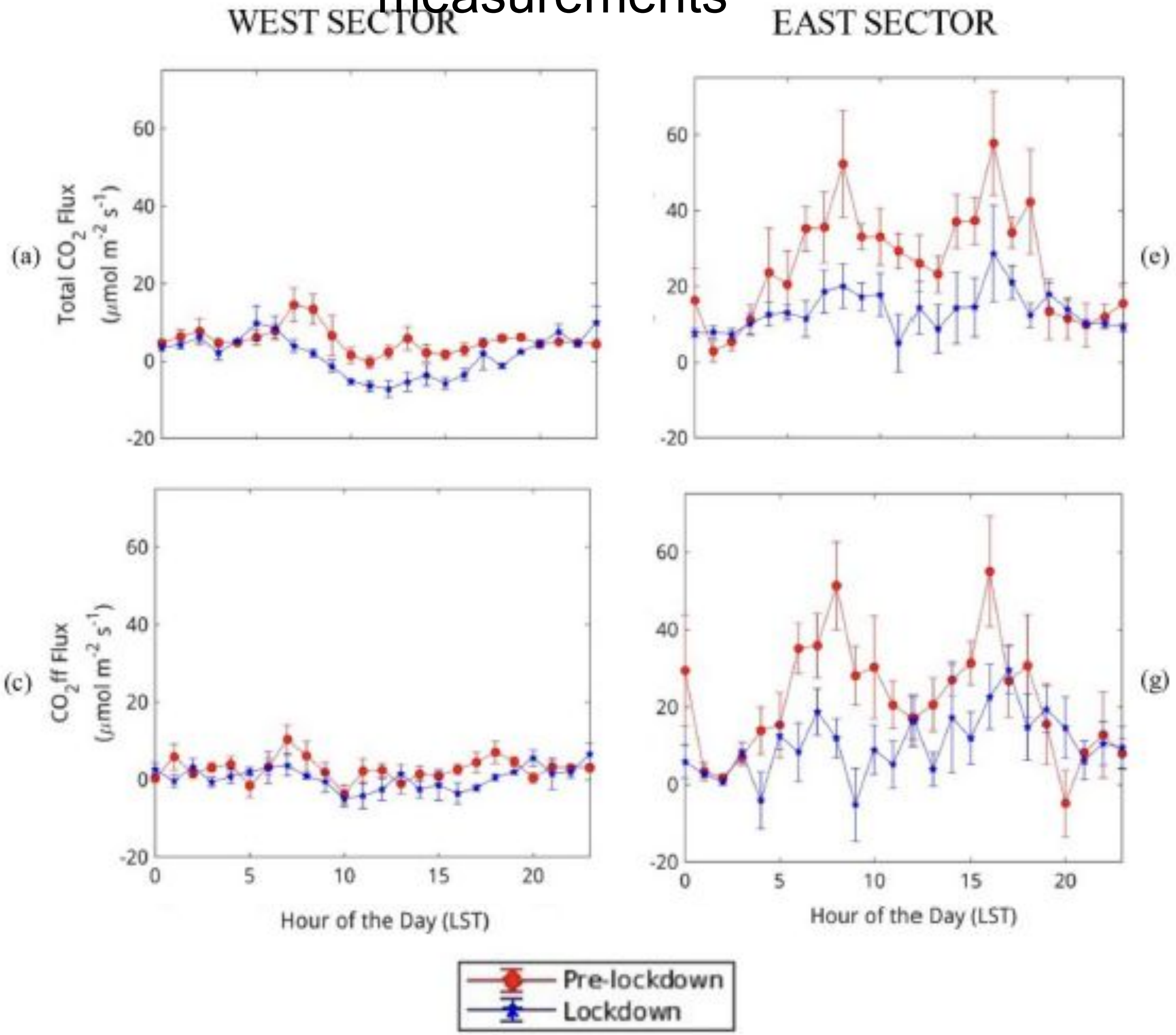
Wu et al, 2022

COVID lockdown impact on Indianapolis neighborhood fluxes.

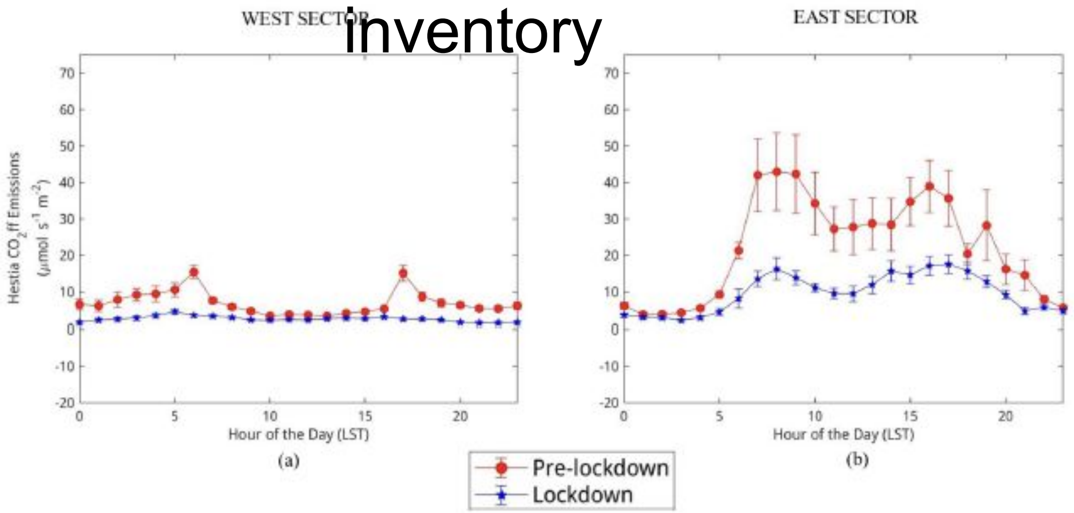
Used to test Hestia.

Vogel et al., 2024

Flux tower measurements



Hestia inventory



Multi-scale flux measurements require multi-scale atmospheric data

- Turbulent scales
- Small regions
- Large regions

“Small” regions

- What are some examples?
  - Cities
  - Oil and gas basins
- Why are they “small?”
  - Air flows across the region without significant exchange between the atmospheric boundary layer and the remainder of the atmosphere

Question: What makes air leave the atmospheric boun

- Fronts!
- Convective clouds!
- Weather!

Stull, 1988.

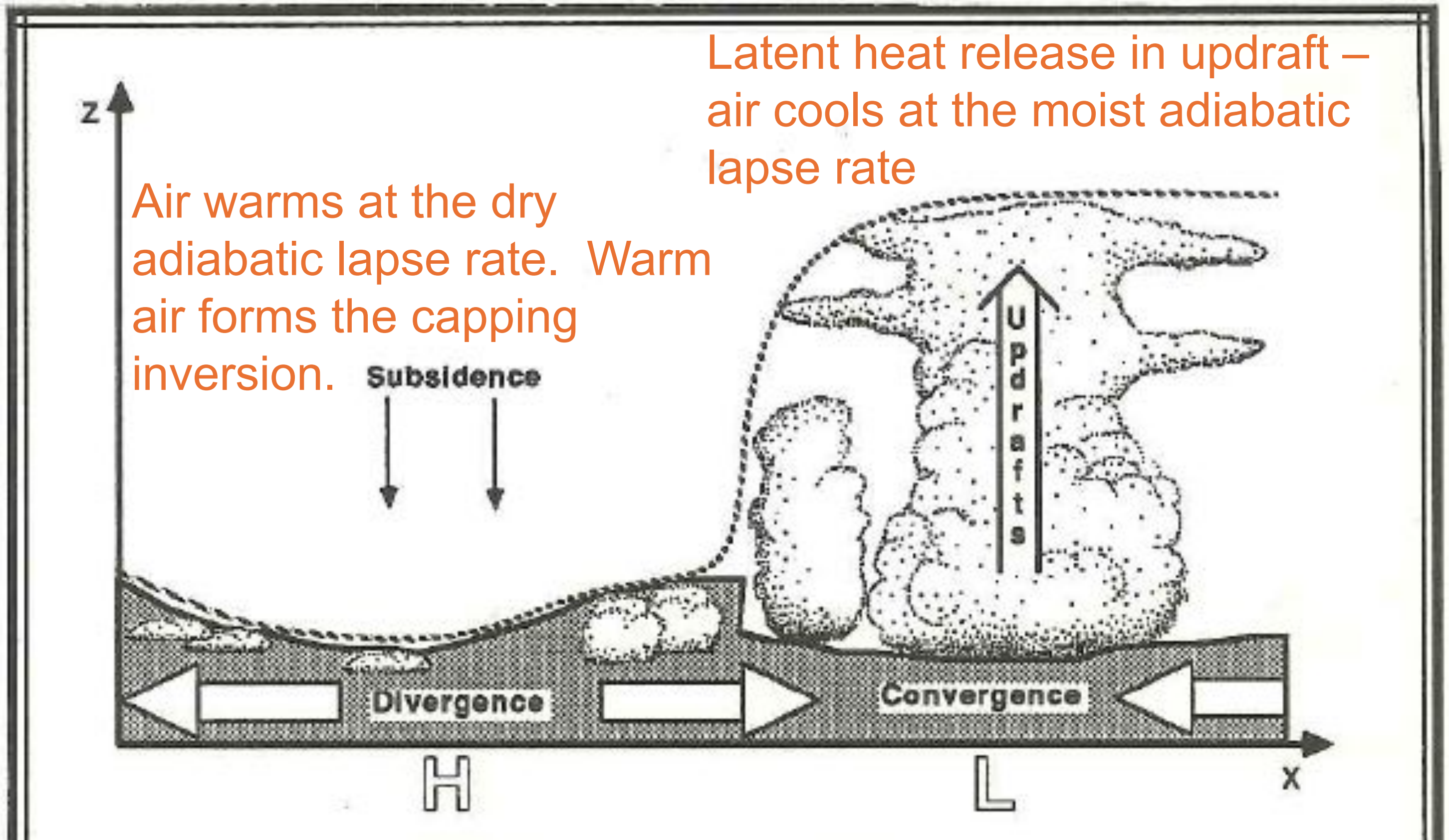
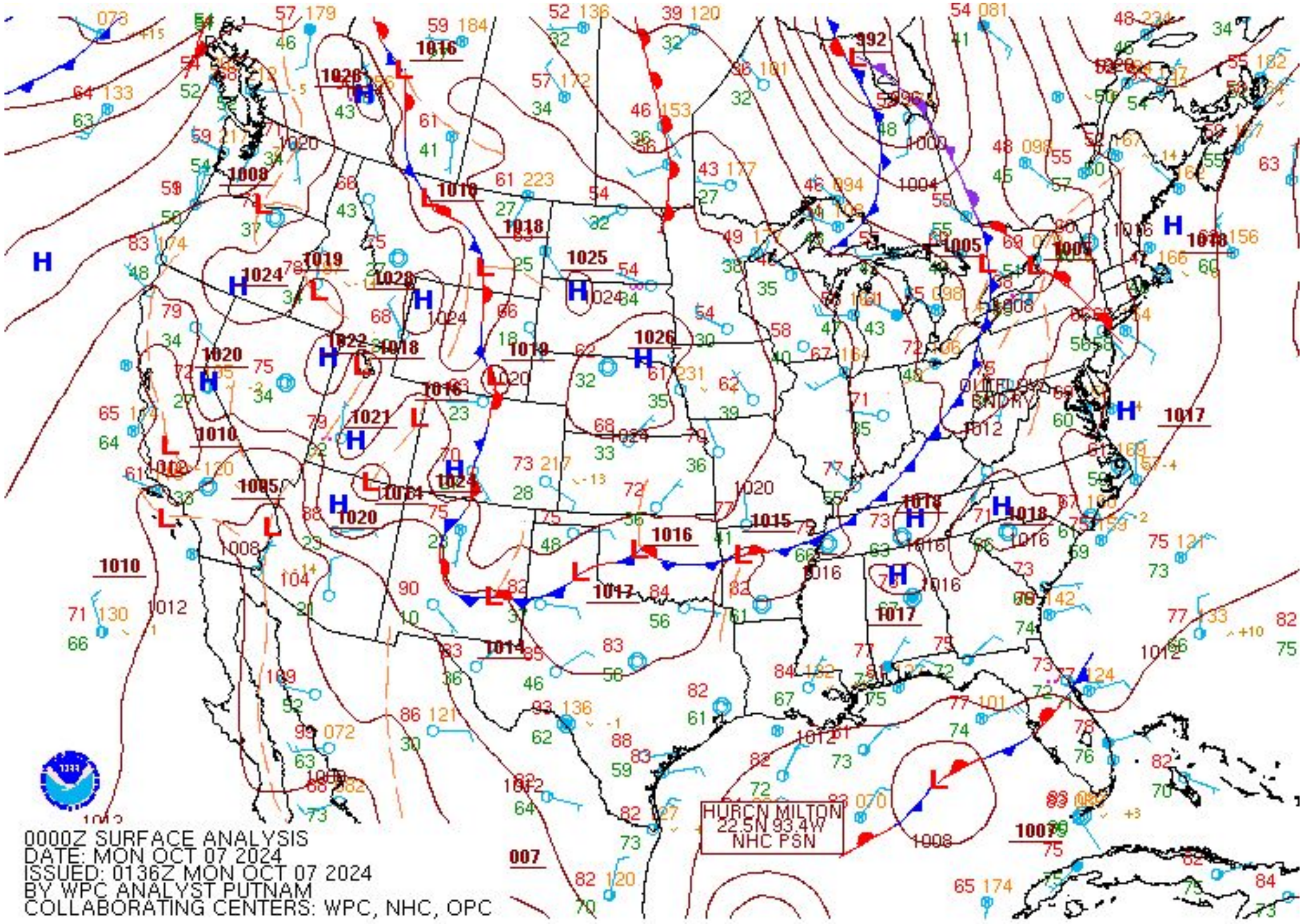


Fig. 1.6 Schematic of synoptic - scale variation of boundary layer depth between centers of surface high (H) and low (L) pressure. The dotted line shows the maximum height reached by surface modified air during a one-hour period. The solid line encloses the shaded region, which is most studied by boudary-layer meteorlogists.

Question: How long does it take for weather systems to pass by?

- How long will the weather stay sunny and lovely in Illinois?
- A few days.
- So…Small regions are those where the air passes through in less than a few days.



“Small” regions

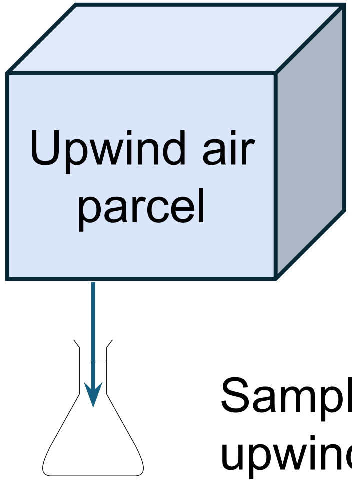
- How far does the air travel in a day?
  - Wind speed * a day = 5 m/s * 3600s * 24 h/d = 400+ km.

  - Bigger than a city or a gas basin.
  - Smaller than the Corn Belt or the Amazon.

“Small” regions

- In this case, our “box of air” can be limited to the atmospheric boundary layer.
  - How deep is the ABL?
  - What is the wind speed and direction within the ABL?

Multi-scale, multi-state observations of earth-atmosphere interactions

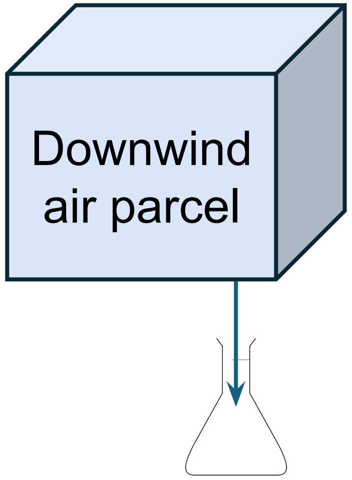


Sample air
upwind

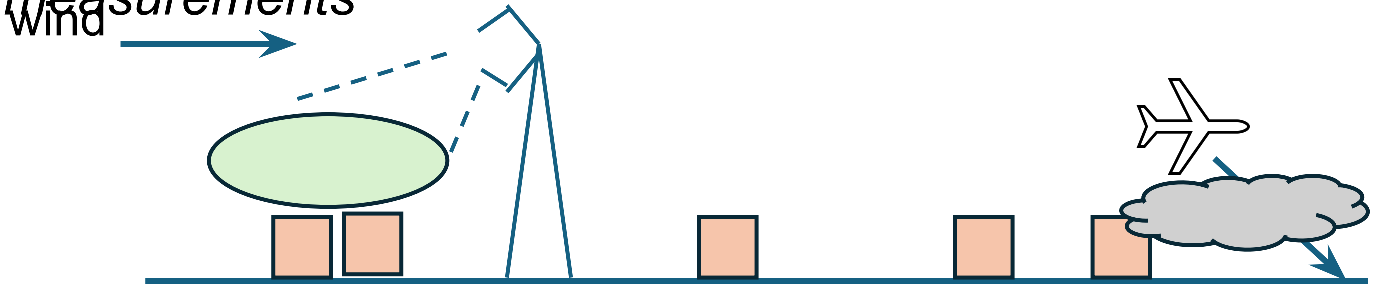
Measure regional flux to test the process model when aggregated over space.

wind

Sample air
downwind



Test and improve the process model using "local" flux measurements



Example:
US GHG
MMIS

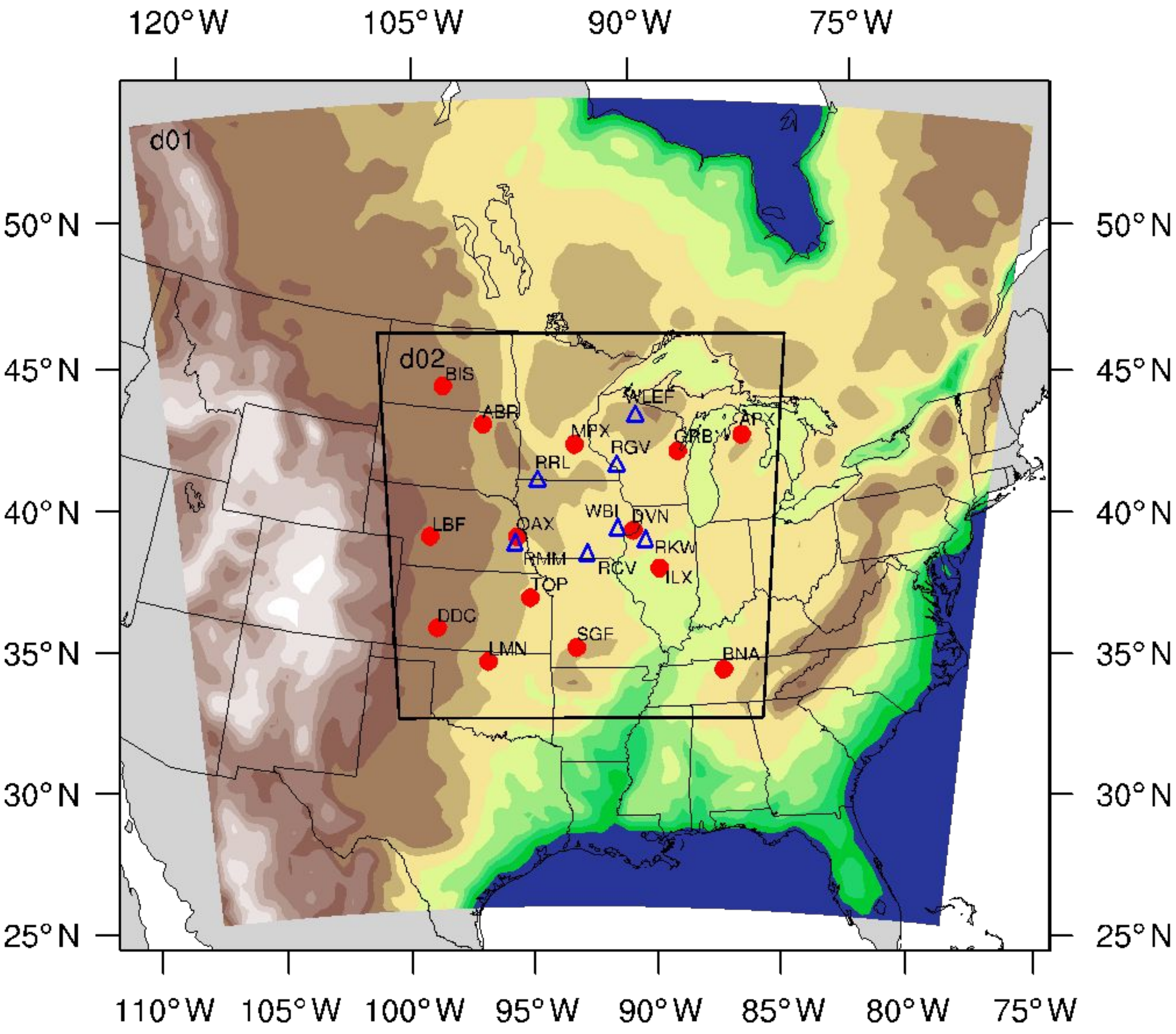
Observations are needed to drive the process model that predicts fluxes.

“Small” regions

- In this case, our “box of air” can be limited to the atmospheric boundary layer.
  - How deep is the ABL?
  - What is the wind speed and direction within the ABL?

- We simulate the ABL fairly well in instrumented regions but we still need to evaluate and improve our atmospheric models.
- And we should develop uncertainty assessments. Model ensembles are one way to do this.

Evaluation of WRF-Chem CO_2 simulations in the up Midwest, summer



Evaluation of *mid-afternoon* CO_2, *ABL depth, and ABL winds*.

Blue are tower-based CO_2 observation points (PSU, NOAA).

Red are rawinsonde stations (NOAA).

Boxes show the model domains (interior at 10 km).

Diaz-Isaac et al, ACP, 2018

Table 1. Different model configurations used in this study.

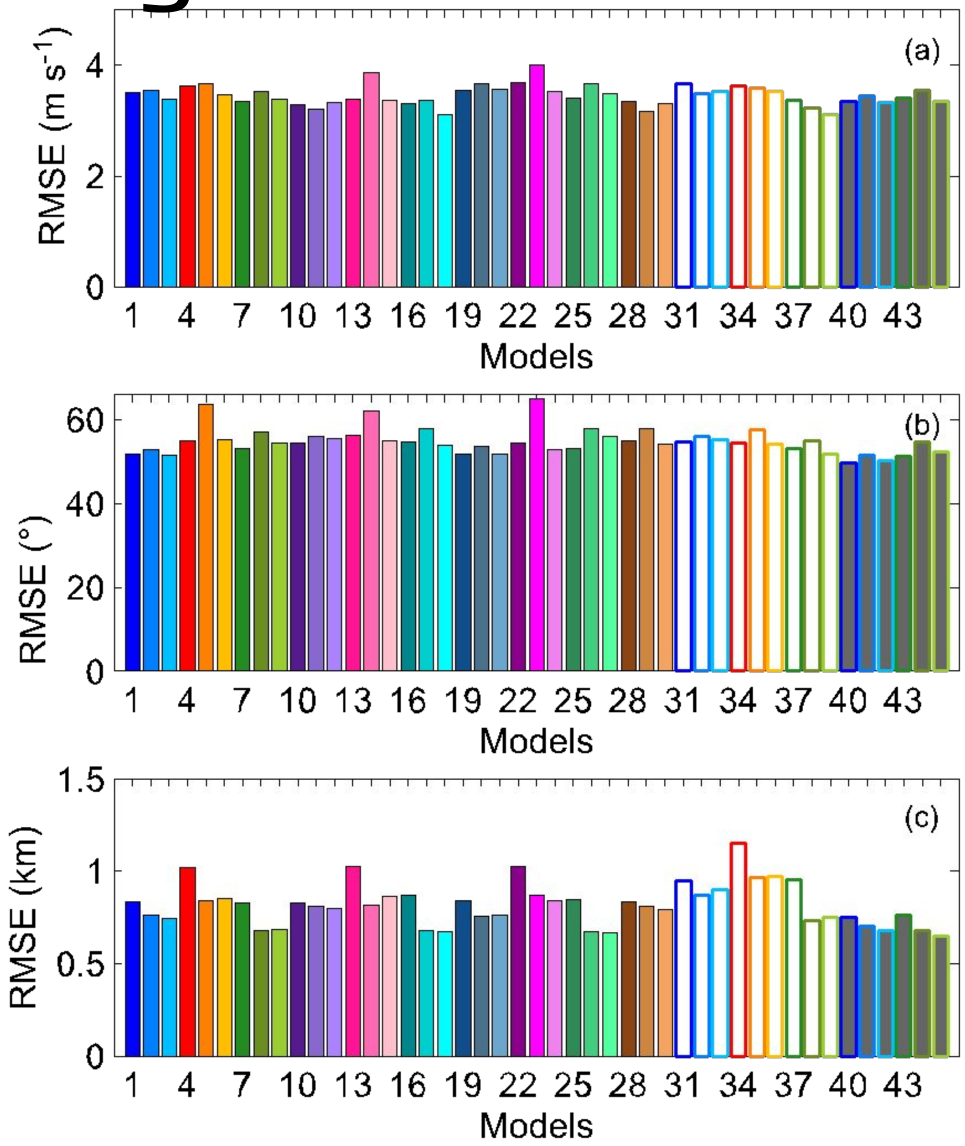
Model number	Reanalysis	LSM scheme	PBL scheme	Cumulus scheme	Microphysics schemes
1	NARR	Noah	YSU	Kain-Fritsch	WSM 5-class
2	NARR	Noah	MYJ	Kain-Fritsch	WSM 5-class
3	NARR	Noah	MYNN	Kain-Fritsch	WSM 5-class
4	FNL	RUC	YSU	Kain-Fritsch	WSM 5-class
5	FNL	RUC	MYJ	Kain-Fritsch	WSM 5-class
6	FNL	RUC	MYNN	Kain-Fritsch	WSM 5-class
7	NARR	Thermal dif.	YSU	Kain-Fritsch	WSM 5-class
8	NARR	Thermal dif.	MYJ	Kain-Fritsch	WSM 5-class
9	NARR	Thermal dif.	MYNN	Kain-Fritsch	WSM 5-class
10	NARR	Noah	YSU	Grell-3D	WSM 5-class
11	NARR	Noah	MYJ	Grell-3D	WSM 5-class
12	NARR	Noah	MYNN	Grell-3D	WSM 5-class
13	FNL	RUC	YSU	Grell-3D	WSM 5-class
14	FNL	RUC	MYJ	Grell-3D	WSM 5-class
15	FNL	RUC	MYNN	Grell-3D	WSM 5-class
16	NARR	Thermal dif.	YSU	Grell-3D	WSM 5-class
17	NARR	Thermal dif.	MYJ	Grell-3D	WSM 5-class
18	NARR	Thermal dif.	MYNN	Grell-3D	WSM 5-class
19	NARR	Noah	YSU	Kain-Fritsch	Thompson
20	NARR	Noah	MYJ	Kain-Fritsch	Thompson
21	NARR	Noah	MYNN	Kain-Fritsch	Thompson
22	FNL	RUC	YSU	Kain-Fritsch	Thompson
23	FNL	RUC	MYJ	Kain-Fritsch	Thompson
24	FNL	RUC	MYNN	Kain-Fritsch	Thompson
25	NARR	Thermal dif.	YSU	Kain-Fritsch	Thompson
26	NARR	Thermal dif.	MYJ	Kain-Fritsch	Thompson
27	NARR	Thermal dif.	MYNN	Kain-Fritsch	Thompson
28	NARR	Noah	YSU	Grell-3D	Thompson
29	NARR	Noah	MYJ	Grell-3D	Thompson
30	NARR	Noah	MYNN	Grell-3D	Thompson
31	NARR	Noah	YSU	No CP	WSM 5-class
32	NARR	Noah	MYJ	No CP	WSM 5-class
33	NARR	Noah	MYNN	No CP	WSM 5-class
34	FNL	RUC	YSU	No CP	WSM 5-class
35	FNL	RUC	MYJ	No CP	WSM 5-class
36	FNL	RUC	MYNN	No CP	WSM 5-class
37	NARR	Thermal dif.	YSU	No CP	WSM 5-class
38	NARR	Thermal dif.	MYJ	No CP	WSM 5-class
39	NARR	Thermal dif.	MYNN	No CP	WSM 5-class
40	FNL	Noah	YSU	Kain-Fritsch	WSM 5-class
41	FNL	Noah	MYJ	Kain-Fritsch	WSM 5-class
42	FNL	Noah	MYNN	Kain-Fritsch	WSM 5-class
43	FNL	Thermal dif.	YSU	Kain-Fritsch	WSM 5-class
44	FNL	Thermal dif.	MYJ	Kain-Fritsch	WSM 5-class
45	FNL	Thermal dif.	MYNN	Kain-Fritsch	WSM 5-class

45-member atmospheric transport ensemble

Varied the:
boundary and initial conditions (2),
land surface model (3),
boundary layer parameterization (3),
cumulus convection parameterization (3) and
cloud microphysics parameterization (2).

Diaz-Isaac et al, ACP, 2018

Random errors are significant for *all* model configurations



Afternoon conditions, daily comparison.

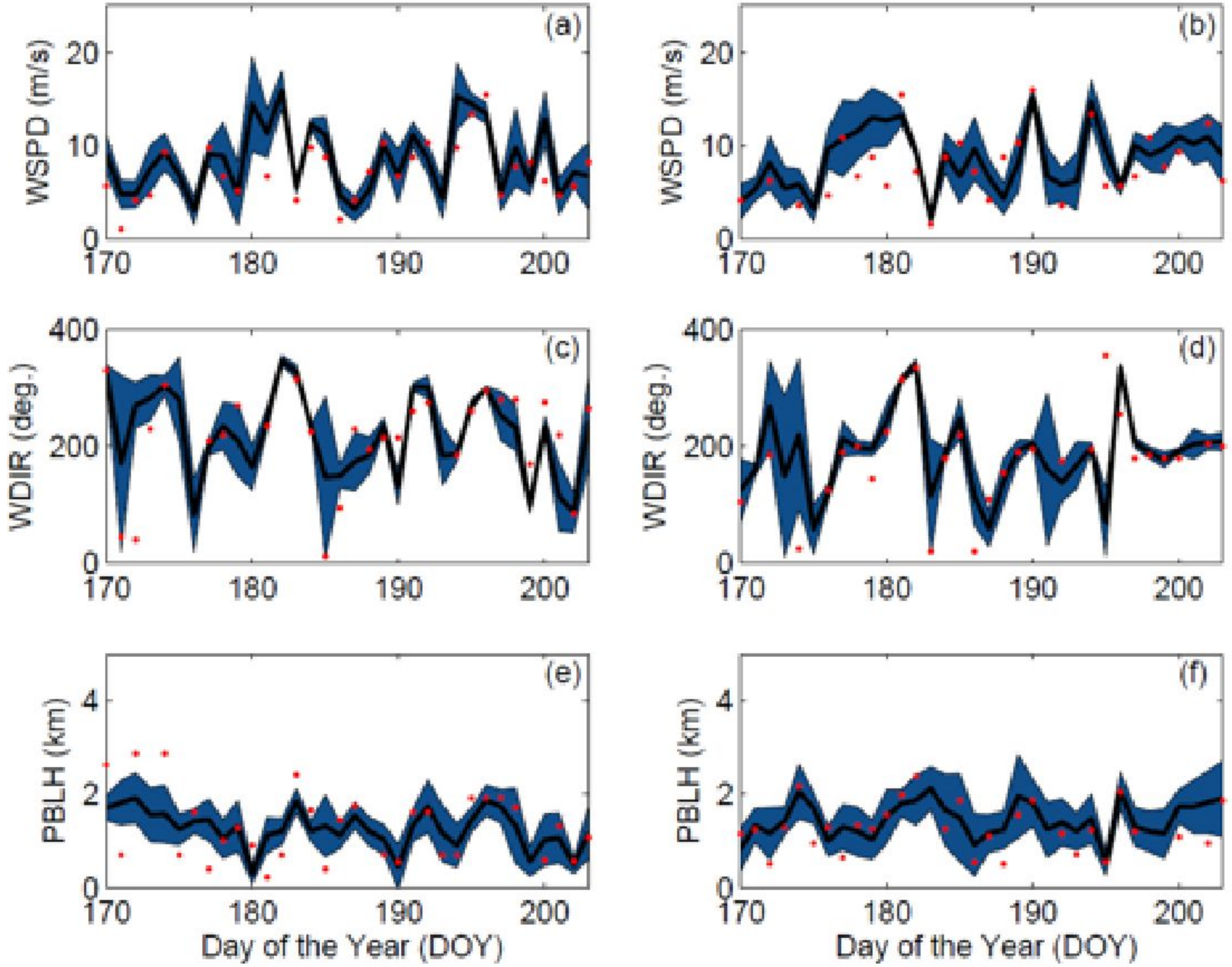
ABL wind (a) RMSE ~ 3 m/s.

ABL wind direction (b) RMSE ~ 50 degrees.

ABL depth (c) RMSE ~ 700 m.

Diaz-Isaac et al, ACP, 2018

How do you create a calibrated atmospheric transport model ensemble?



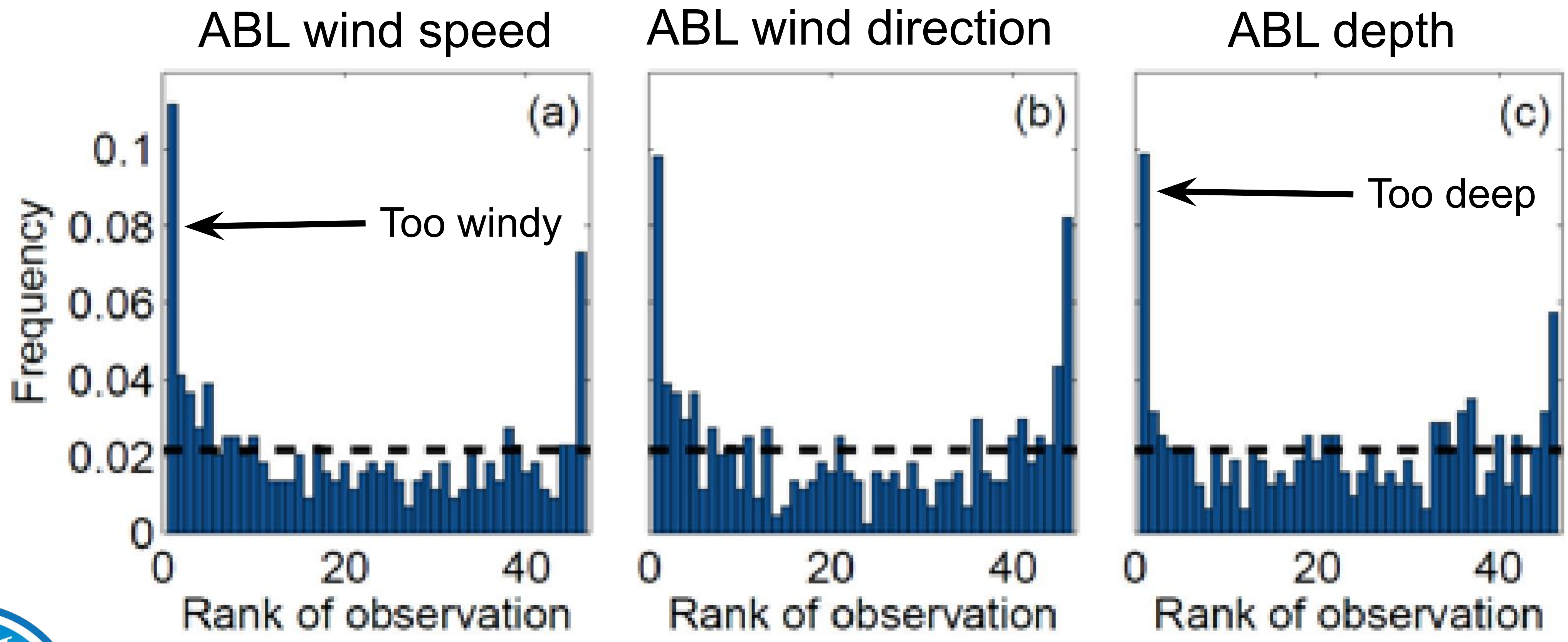
Construct a “rank histogram.”

Rank the observation with respect to its location among the members of the ensemble.

The ensemble should encompass the observations (sufficient spread), but not have too much spread.

Diaz-Isaac et al, 2019

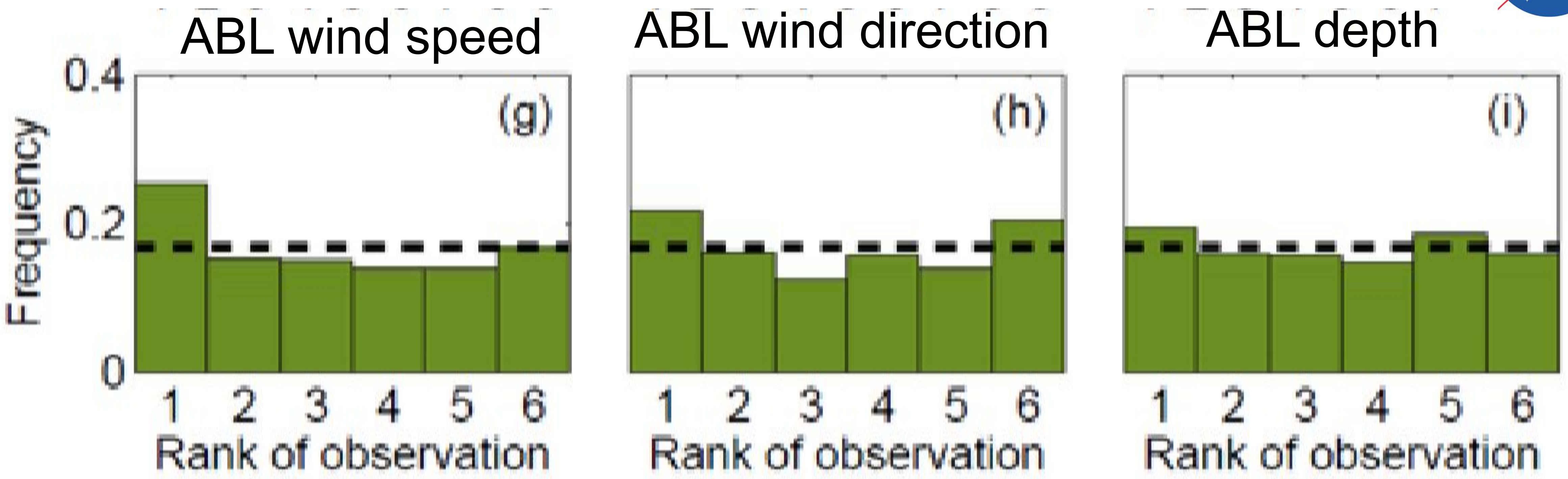
That 45-member ensemble is "under-dispersive"



We can improve the ensemble by throwing out biased members.

Diaz-Isaac et al, 2019

Pruned 5-member ensemble



- Spread among models is a good representation of atmospheric model transport uncertainty.
- Ensemble bias is small.

Diaz-Isaac et al, 2019

ACT product: Continental-Scale Ensemble Modeling Framework

MsTMIP, CASA, SiB4, CarbonTracker

CarbonTracker, FFDAS

CarbonTracker, CMS, Schuh, Baker, OCO2MIP

Zhou et al, 2020

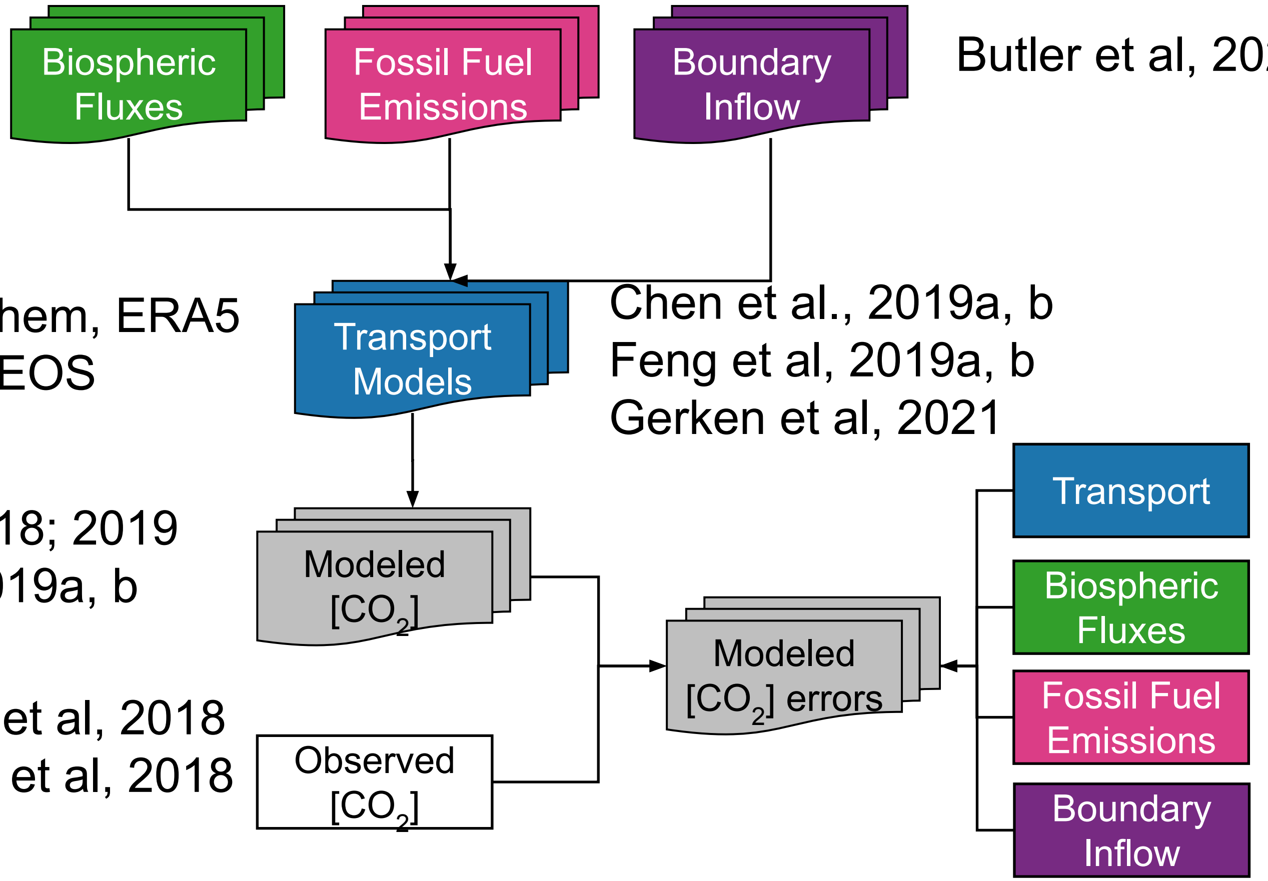
Butler et al, 2020

WRF-Chem, ERA5 TM5, GEOS

Chen et al., 2019a, b
Feng et al, 2019a, b
Gerken et al, 2021

Diaz et al, 2018; 2019
Feng et al, 2019a, b

Miles et al, 2018
Davis et al, 2018



Purpose: Quantify model uncertainty using an objective approach. Data-calibrated ensembles are necessary.

Applications: Use model ensemble to disaggregate sources of uncertainty, identify biased ensemble members.

Feng et al, 2019a, b; 2021

Use these uncertainty diagnoses to inform the uncertainty assumptions in inverse models.

Lauvaux et al, 2019
Wesloh et al, 2020; 2024

“Small” regions

- In this case, our “box of air” can be limited to the atmospheric boundary layer.
  - How deep is the ABL?
  - What is the wind speed and direction within the ABL?

- More abundant measurements of these quantities would be valuable.
- I think this can be done from space-based sensors.

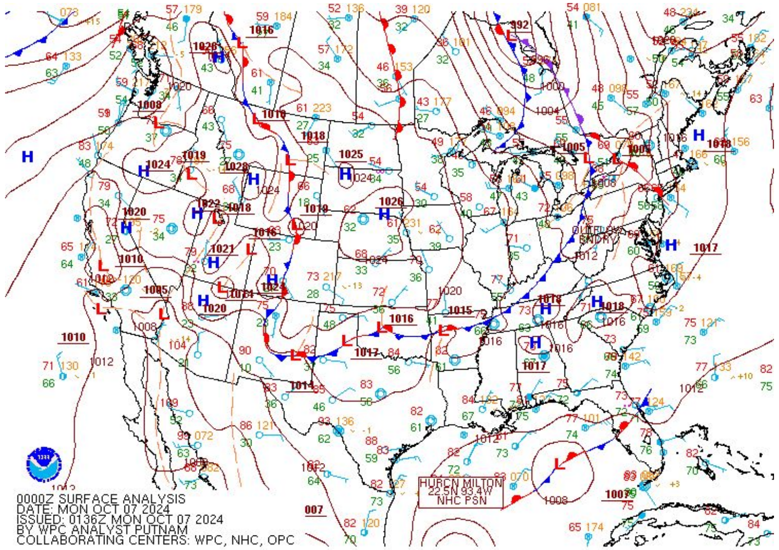
“Large” regions

- These are areas so large that we cannot ignore exchange of air between the atmospheric boundary layer and the remainder of the atmosphere.

- Examples:
  - The Corn Belt
  - Southeastern forests
  - The Amazon

“Large” regions: What do we need to measure and simulate?

- Lifting of air by weather systems.
  - Convergence and lifting at low pressure centers.
  - Frontal lifting / the “warm conveyor belt”
- Vertical mixing by convective clouds



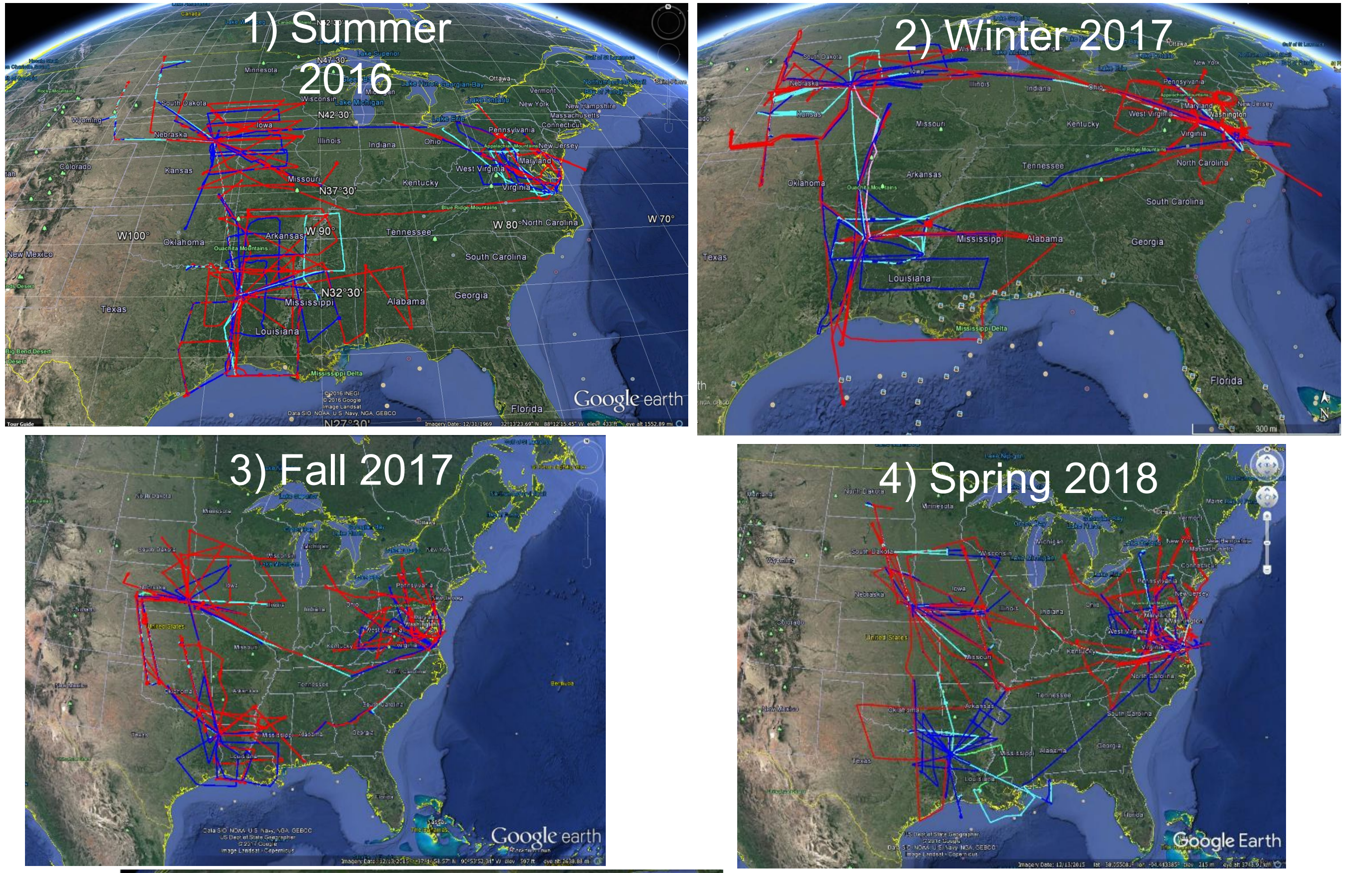
ACT America

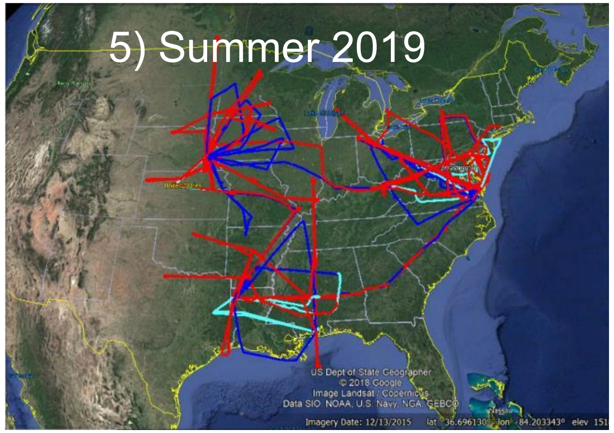
ATMOSPHERIC CARBON & TRANSPORT

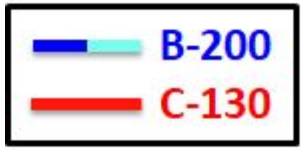
Davis et al., 2021

Flight Campaigns and Data

- Five, six-week campaigns over 3 years, covering each season and summer twice. ~25 flights / campaign.
- Each campaign: 2 weeks in each of 3 regions across US (MidAtlantic, MidWest, South Central).
- More than 30 synoptic sequences sampled.
- About 40% of the data in the atmospheric boundary layer (ABL). Data up to 9km MSL.
- **1140 total flight hours** and ~400,000 km of data collection. About 1,500 flasks and 1,000 vertical profiles.
- Aircraft data include three data flags to enable quick partitioning of the observations
  - Atmospheric level - ABL / free troposphere
  - Maneuver – spiral, en route ascent/descent, level leg
  - Air-mass – warm sector, cold sector, fair/undefined
- Extremely low instrument failure rate. Every flight returned valuable science data.

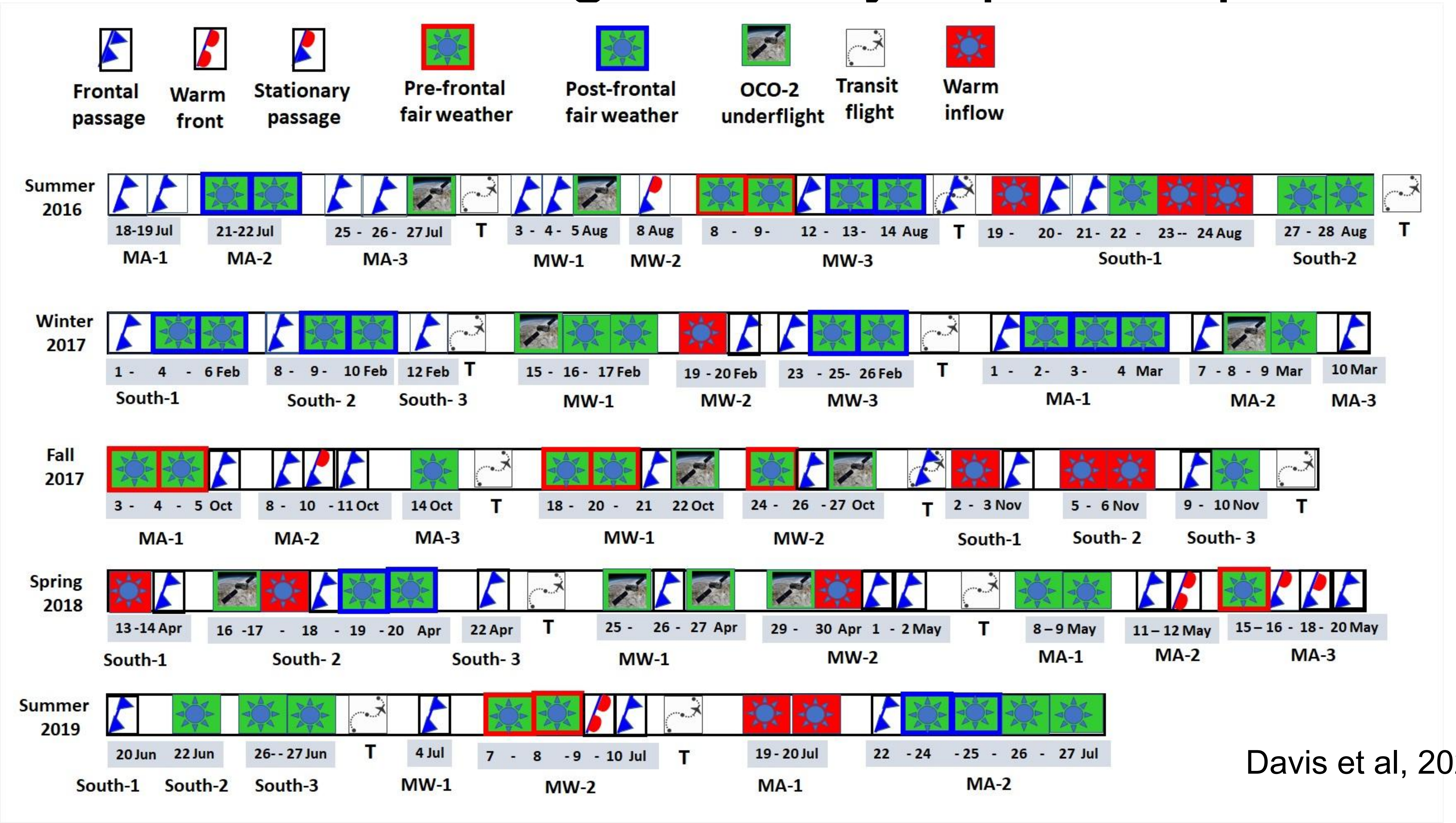




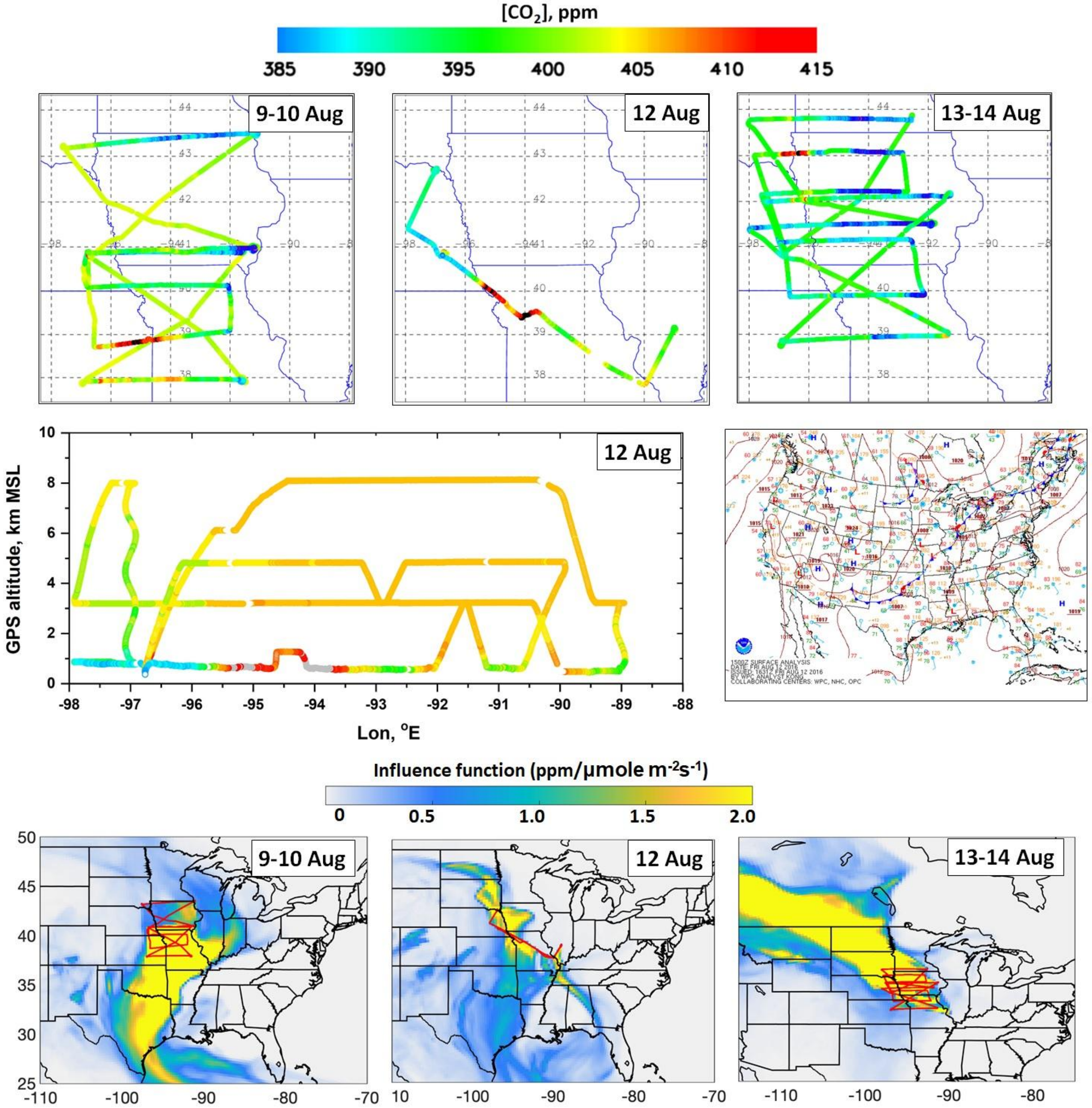


Davis et al., 2021
Wei et al, 2021

ACT-America flights as synoptic sequences



Davis et al, 2021



ACT-America synoptic sequence example.

9-14 August, 2016

Two prefrontal, one frontal and two post frontal flights.

Frontal passage on 12 August. Cross-frontal CO_2 differences evident from the ABL to the upper free troposphere.

Warm sector CO_2 higher than cold sector CO_2. Tropospheric differences largely due to continental boundary conditions. ABL differences modified by continental fluxes.

Influence functions indicate upwind areas sampled by the ABL flight data.

Davis et al, 2021

ACT-America measured the impacts of frontal weather on atmospheric greenhouse gas distributions, in addition to winds and ABL depths.

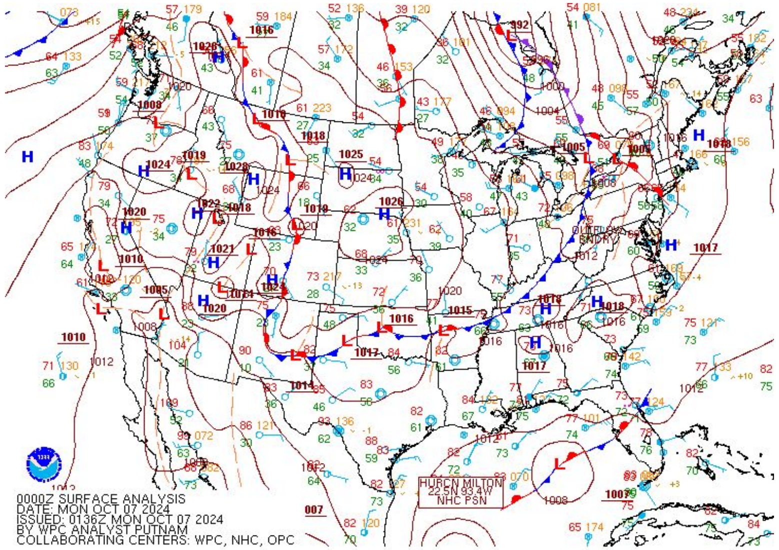
ACT-America didn’t measure cloud convective processes or frontal lifting directly.

The data set has, frankly, been largely avoided by most of today’s global inverse modeling systems.

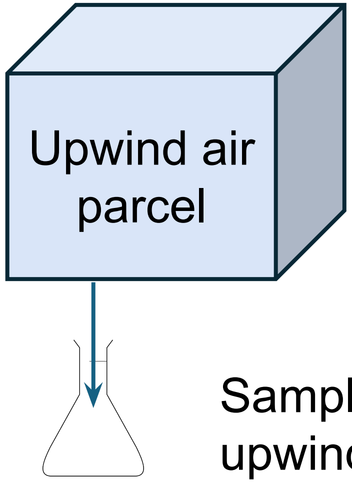
“Large” regions: What do we need to measure and simulate?

- Lifting of air by weather systems.
  - Convergence and lifting at low pressure centers.
  - Frontal lifting / the “warm conveyor belt”
- Vertical mixing by convective clouds

- This is more than just winds and ABL depth
- Can we improve quantification of these processes using space-based measurements?



Multi-scale, multi-state observations of earth-atmosphere interactions

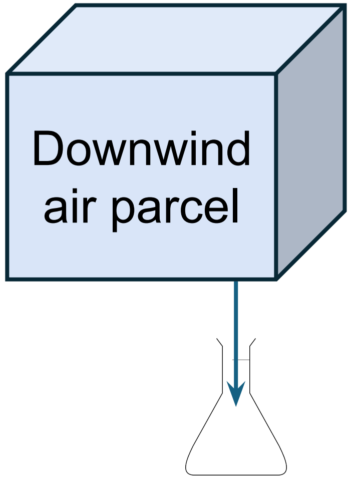


Measure regional flux to test the process model when aggregated over space.

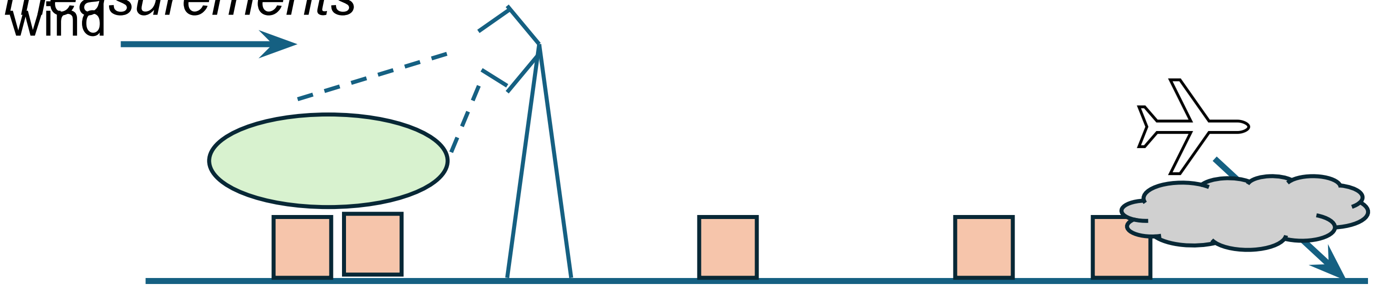
Sample air upwind

wind

Sample air downwind



Test and improve the process model using “local” flux measurements



Example:
US GHG
MMIS

Observations are needed to drive the process model that predicts fluxes.

Thanks for your attention.

Members of the Earth-Atmosphere Interactions Lab

References

Barkley, Z., K. Davis, N. Miles, S. Richardson, A. Deng, B. Hmiel, D. Lyon, and T. Lauvaux, (2023). Quantification of Oil and Gas Methane Emissions in the Delaware and Marcellus Basins Using a Network of Continuous Tower-Based Measurements, Atmos. Chem. Phys., 23, 6127 - 6144, https://doi.org/10.5194/acp-23-6127-2023

Butler, Martha P., Thomas Lauvaux, Sha Feng, Junjie Liu, Kevin W. Bowman, and Kenneth J. Davis, 2020. Atmospheric simulations of total column CO2 mole fractions from global to mesoscale within the Carbon Monitoring System Flux inversion framework. *Atmosphere*, *11*, 787; doi:10.3390/atmos11080787

Caulton et al., 2019

Chen, Hans W., Fuqing Zhang, Thomas Lauvaux, Kenneth J. Davis, Sha Feng, Martha P. Butler, and Richard B. Alley, 2019. Characterization of Regional-Scale CO_2 Transport Uncertainties in an Ensemble with Flow-Dependent Transport Errors. Geophysical Research Letters, 46, 4049–4058. https://doi.org/10.1029/2018GL081341

Chen, Hans W., Lily N. Zhang, Fuqing Zhang, Kenneth J. Davis, Thomas Lauvaux, Sandip Pal, Brian Gaudet, and Joshua P. DiGangi, 2019. Evaluation of Regional CO2 Mole Fractions in the ECMWF CAMS Real-Time Atmospheric Analysis and NOAA CarbonTracker Near-Real-Time Reanalysis With Airborne Observations From ACT-America Field Campaigns, Journal of Geophysical Research:Atmospheres, 124. https://doi.org/10.1029/2018JD029992.

Ciais et al., 2013.

Cusworth et al., 2022

Davis, Kenneth J., Aijun Deng, Thomas Lauvaux, Natasha L. Miles, Scott J. Richardson, Daniel P. Sarmiento, Kevin R. Gurney, R. Michael Hardesty, Timothy A. Bonin, W. Alan Brewer, Brian K. Lamb, Paul B. Shepson, Rebecca M. Harvey, Maria O. Cambaliza, Colm Sweeney, Jocelyn C. Turnbull, James Whetstone and Anna Karion, 2017. The Indianapolis Flux Experiment (INFLUX): A test-bed for developing urban greenhouse gas emission measurements. *Elem Sci Anth*: 2017;5:21. DOI: http://doi.org/10.1525/elementa.188

Davis, K.J., M.D. Obland, B. Lin, T. Lauvaux, C. O'Dell, B. Meadows, E.V. Browell, J.H. Crawford, J.P. DiGangi, C. Sweeney, M.J. McGill, J. Dobler, J.D. Barrick, and A.R. Nehrir. 2018. ACT-America: L3 Merged In Situ Atmospheric Trace Gases and Flask Data, Eastern USA. ORNL DAAC, Oak Ridge, Tennessee, USA. DOI: 10.3334/ORNLDAAC/1593

Davis, Kenneth J.; Edward V. Browell; Sha Feng; Thomas Lauvaux; Michael D. Obland; Sandip Pal; Bianca C. Baier; David F. Baker; Ian T. Baker; Zachary R. Barkley; Kevin W. Bowman; Yu Yan Cui; A. Scott Denning; Joshua P. DiGangi; Jeremy T. Dobler; Alan Fried; Tobias Gerken; Klaus Keller; Bing Lin; Amin R. Nehrir; Caroline P. Normile; Christopher W. O'Dell; Lesley E. Ott; Anke Roiger; Andrew E. Schuh; Colm Sweeney; Yaxing Wei; Brad Weir; Ming Xue; Christopher A. Williams, 2021. The Atmospheric Carbon and Transport (ACT) – America Mission. Bulletin of the American Meteorological Society, 102, E1714–E1734, https://doi.org/10.1175/BAMS-D-20-0300.1.

Díaz-Isaac , Liza I., T. Lauvaux, K.J. Davis: Impact of physical parameterizations and initial conditions on simulated atmospheric transport and CO2 mole fractions in the US Midwest. Atmos. Chem. Phys., 18, 14813–14835, doi.org/10.5194/acp-18-14813-2018, 2018.

Díaz-Isaac, L. I., Lauvaux, T., Bocquet, M., and Davis, K. J.: Calibration of a multi-physics ensemble for estimating the uncertainty of a greenhouse gas atmospheric transport model, Atmos. Chem. Phys., 19, 5695-5718, https://doi.org/10.5194/acp-19-5695-2019, 2019.

Dlugocenky et al., 2003.

Feng, S., T. Lauvaux, K. Davis, K. Keller, Y. Zhou, C. Williams, A. Schuh, J. Liu, I. Baker. Seasonal characteristics of model uncertainties from biogenic fluxes, transport, and large-scale boundary inflow in atmospheric CO2 simulations over North America, 2019. Journal of Geophysical Research: Atmospheres, 124, 14,325–14,346. https://doi.org/10.1029/2019JD031165

Feng, S., Lauvaux, T., Keller, K., Davis, K. J., Rayner, P., Oda, T., & Gurney, K. R. (2019). A road map for improving the treatment of uncertainties in high-resolution regional carbon flux inverse estimates. *Geophysical Research Letters*, 46. https://doi.org/10.1029/2019GL082987

Feng, S., T. Lauvaux, C. A. Williams, K.J. Davis, Y. Zhou, I. Baker, Z.R. Barkley, D. Wesloh, (2021). Joint CO2 mole fraction and flux analysis confirms missing processes in CASA terrestrial carbon uptake over North America. Global Biogeochemical Cycles, 35, e2020GB006914, https://doi.org/10.1029/2020GB006914

More references

Gerken, T., Feng, S., Keller, K., Lauvaux, T., DiGangi, J.P., Choi, Y., Baier, B., Davis, K.J., 2021. Examining model observation residuals using ACT-America data, JGR-Atmospheres, 126, e2020JD034481 https://doi.org/10.1029/2020JD034481.

Heimberger, Alexie M. F., Paul B. Shepson, Brian H. Stirm, Chloe Susdorf, Jocelyn Turnbull, Maria O. L. Cambaliza, Olivia E. Salmon, Anna-Elodie M. Kerlo, Tegan N. Lavoie, Rebecca M. Harvey, Kenneth J. Davis, Thomas Lauvaux, Anna Karion, Colm Sweeney, W. Allen Brewer, R. Michael Hardesty, Kevin R. Gurney, James Whetstone, 2017. Precision Assessment for the Aircraft Mass Balance Method for Measurement of Urban Greenhouse Gas Emission Rates. *Elem Sci Anth*. 2017;5:26. DOI: http://doi.org/10.1525/elementa.134

Jacob et al., 2022

Kiemle, C., G. Ehret, A. Giez, K. J. Davis, D. H. Lenschow and S. P. Oncley, 1997: Estimation of boundary-layer humidity fluxes and statistics from airborne DIAL. *J. Geophys. Res.*, 102, 29189-29204.

Lauvaux et al., 2019

Lauvaux, T., K.R. Gurney, N.L. Miles, K.J. Davis, S.J. Richardson, A. Deng, B.J. Nathan, T. Oda, J.A.Wang, L.R. Hutyra, and J.C.Turnbull, 2020. Policy-relevant assessment of urban greenhouse gas emissions, Environ Sci Tech. 54, 16, 10237–10245, https://doi.org/10.1021/acs.est.0c00343.

Miles, Natasha L., Scott J. Richardson, Thomas Lauvaux, Kenneth J. Davis, Aijun Deng, Jocelyn Turnbull, Anna Karion, Colm Sweeney, Kevin R. Gurney, Risa Patarasuk, Igor Razlivanov, Maria O. Cambaliza and Paul B. Shepson, 2017. Quantification of urban atmospheric boundary layer greenhouse gas dry mole fraction enhancements: Results from the Indianapolis Flux Experiment (INFLUX), *Elem Sci Anth*. 2017;5:27. DOI: http://doi.org/10.1525/elementa.127

Miles, N.L., S.J. Richardson, D.K. Martins, K.J. Davis, T. Lauvaux, B.J. Haupt, and S.K. Miller. 2018. ACT-America: L2 In Situ CO2, CO, and CH4 Concentrations from Towers, Eastern USA. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1568

Monteiro, Vanessa C., Natasha L. Miles, Scott J. Richardson, Zachary Barkley, Bernd J. Haupt, David Lyon, Benjamin Hmiel, and Kenneth J. Davis, 2022. Methane, carbon dioxide, hydrogen sulfide, and isotopic ratios of methane observations from the Permian Basin tower network, Earth Syst. Sci. Data, 14, 2401–2417. https://doi.org/10.5194/essd-14-2401-2022

Omara et al., 2016

Richardson, Scott J., Natasha L. Miles, Kenneth J. Davis, Thomas Lauvaux, Douglas K. Martins, Jocelyn C. Turnbull, Kathryn McKain, Colm Sweeney and Maria O. L. Cambaliza, 2017. CO_2, CO, and CH_4 surface in situ measurement network in support of the Indianapolis FLUX (INFLUX) Experiment. *Elem Sci Anth*. 2017;5:59. DOI: http://doi.org/10.1525/elementa.140

Stull, R.B. 1988, An Introduction to Boundary Layer Meteorology, Kluwer Academic Publishers.

Vogel, E., K. J. Davis, K. Wu, N. L. Miles, S. J. Richardson, K. R. Gurney, V. Monteiro, G.S. Roest, H.C.R. Kenion, J.P. Horne (2024) Using eddy-covariance to measure the effects of COVID-19 restrictions on CO2 emissions in a neighborhood of Indianapolis, IN, Carbon Management, 15:1, 2365900, https://doi.org/10.1080/17583004.2024.2365900

Wesloh, D., Lauvaux, T., & Davis, K. J. (2020). Development of a mesoscale inversion system for estimating continental-scale CO2 fluxes. Journal of Advances in Modeling Earth Systems, 12, e2019MS001818 https://doi.org/10.1029/2019MS001818

Wesloh, D., Keller, K., Feng, S., Lauvaux, T., & Davis, K. J. (2024). Temporal error correlations in a terrestrial carbon cycle model derived by comparison to carbon dioxide eddy covariance flux tower measurements. *Journal of Geophysical Research: Biogeosciences*, *129*, e2023JG007526. https://doi.org/10.1029/2023JG007526

Wu, Kai, Thomas Lauvaux, Kenneth J. Davis, Aijun Deng, Israel Lopez Coto, Kevin R. Gurney and Risa Patarasuk, 2018. Joint inverse estimation of fossil fuel and biogenic CO2 fluxes in an urban environment: An observing system simulation experiment to assess the impact of multiple uncertainties. Elem Sci Anth. 2018;6(1):17. DOI: http://doi.org/10.1525/elementa.138

Zhou, Y., Williams, C. A., Lauvaux, T., Davis, K. J., Feng, S., Baker, I., et al. (2020). A multiyear gridded data ensemble of surface biogenic carbon fluxes for North America: Evaluation and analysis of results. Journal of Geophysical Research: Biogeosciences,125, e2019JG005314. https://doi.org/10.1029/2019JG005314