The potential of a LEO satellite imager to quantify fossil fuel CO_2 emissions

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poster (C4.5) by Franck Lespinas

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Universität Bremen

European Commission
Joint Research Centre

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European Space Agency

"Can we achieve regional-scale CO_2 fluxes over time from current passive space-based obs"?

- Impact of algorithmic-biases on fluxes
- Impact of instrument-biases on fluxes (imperfect calibration)
- Impact of transport errors on fluxes
- Impact of observing system sampling on fluxes.

Perfect Transport	Perfect Prior Fluxes	Perfect Met (L2)	Perfect Spectroscopy (L2)	Perfect Instrument	Perfect XCO2	Done Before?
Y	Y	-	-	-	Y	Yes
Y	Y	-	-	-	N	Partial
N	Y	-	-	-	Y	Partial
Y	Y	Y	Y	Y	N	No
Y	Y	Y	Y	N	N	No
Y	Y	N	N	N	N	No
Y	N	N	N	N	N	No
N	N	N	N	N	N	No

Not assessed for fossil fuel CO_2 emissions globally yet

Courtesy C. W. O'Dell

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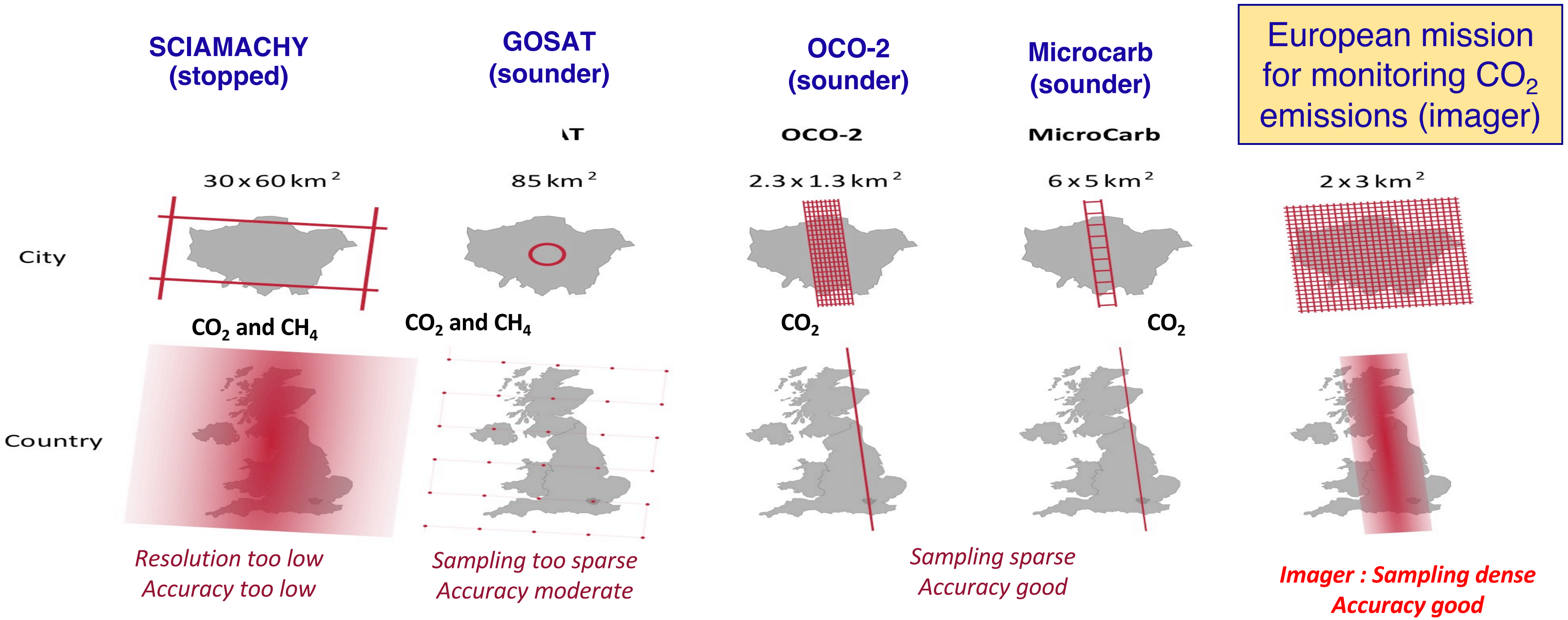
Towards an operational monitoring system of anthropogenic CO_2 emissions

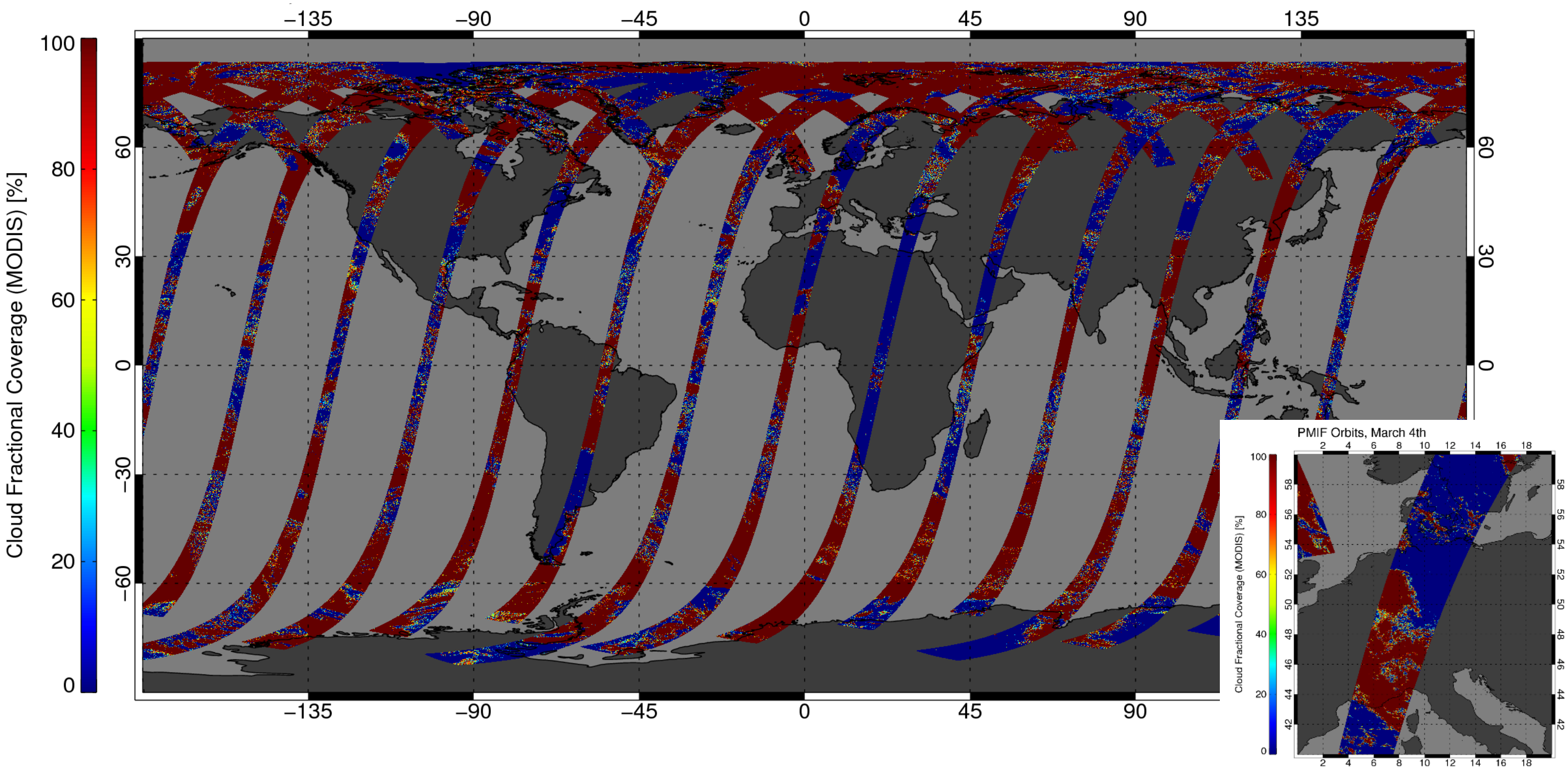
Needed attributes of space observations of column CO_2 for emission monitoring

- **Dense sampling (imagery)** : images of CO_2 plumes produced by emitting areas
- **High spatial resolution** : capture emission hotspots and avoid clouds, pixel size < 3 km
- **High accuracy** : resolve the small atmospheric gradients, individual precision ≈ 1 ppm
- **Global coverage**



The Copernicus vision is a constellation of ‘sentinel CO_2 imagers’

Simulation of the sampling of one LEO satellite imager



- MODIS Terra 1km x 1km MOD35 L2 cloud mask as baseline for the orbit
- Year: 2008
- Swath: 350 km
- Spatial resolution: 2km × 2km
- Precision: 0.7 ppm

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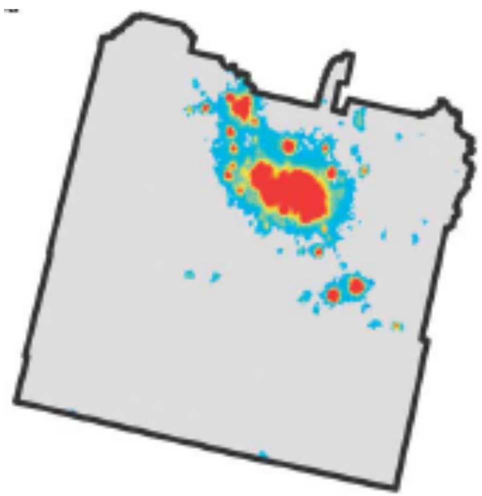
Clumping emission pixels

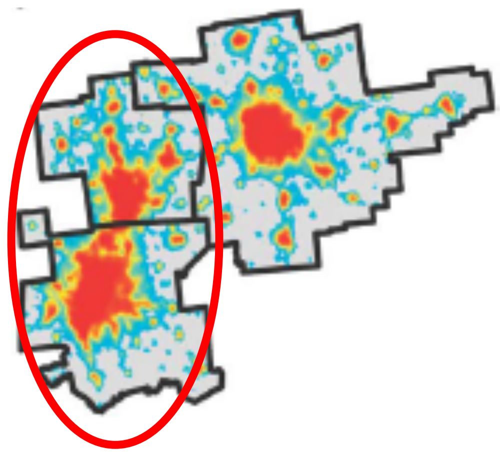
Cities cover 2% of the land surface, but emit 70% of worlds fossil fuel CO_2 emissions

A Clump : "a cluster of emitting pixels whose CO_2 emissions can be detected from space"

- Principle : adjacent high emitting pixels are grouped together
- The plume of a clump can be detected even if plumes of component pixels may not
- Clumps approximately correspond to cities and power plants
- Difficult problem : cannot use simply administrative boundaries (e.g. cities) because of hot-spots near urban areas and complex patterns of urban emissions



Too large "empty" area



One or two target?

Clumping emission pixels

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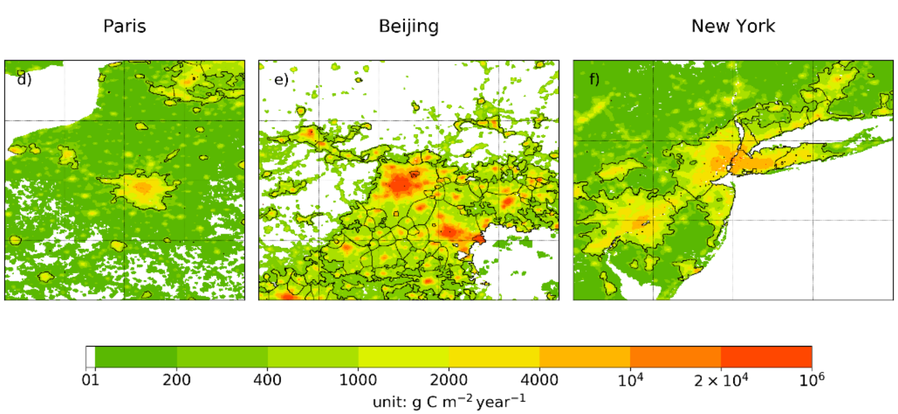
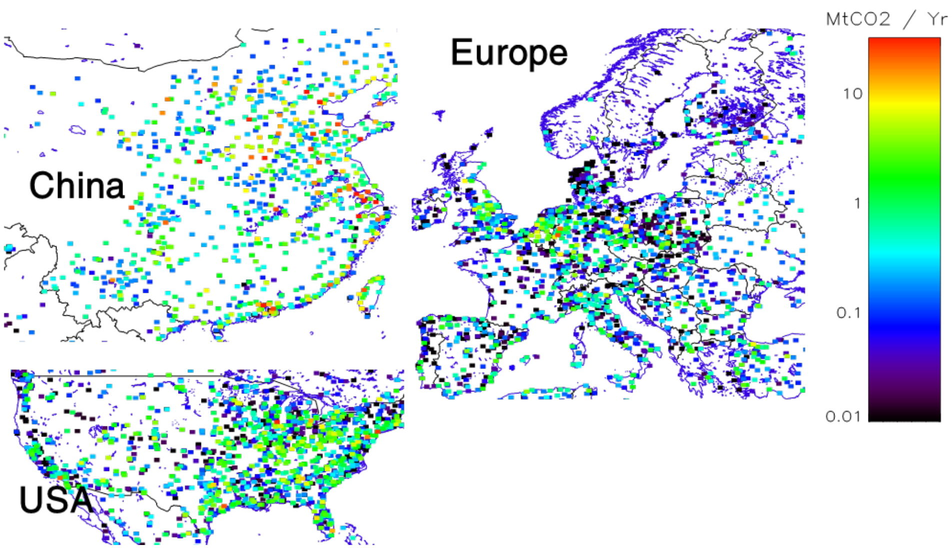
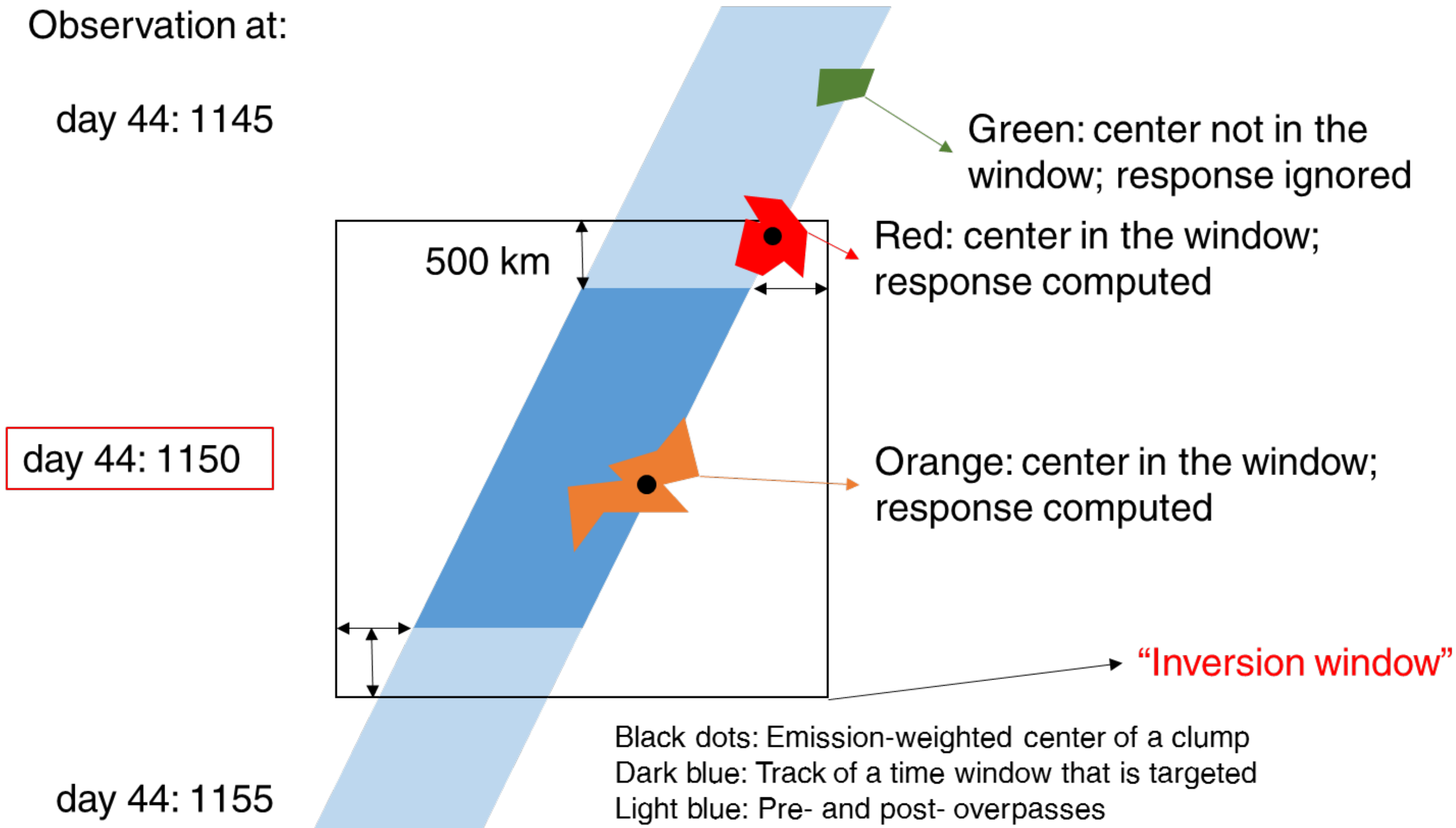
Aggregation : based on thresholds and image processing algorithm applied to the spatial gradients of emissions (emission field: ODIAC, 1km × 1km)





A global 1 km inversion system



- Strategy: global coverage of all emitting clumps, Bayesian inversion

  $A = (B^{-1} + H^T R^{-1} H)^{-1}$ (uncertainty reduction: $UR=1-\sigma_A/\sigma_B$)

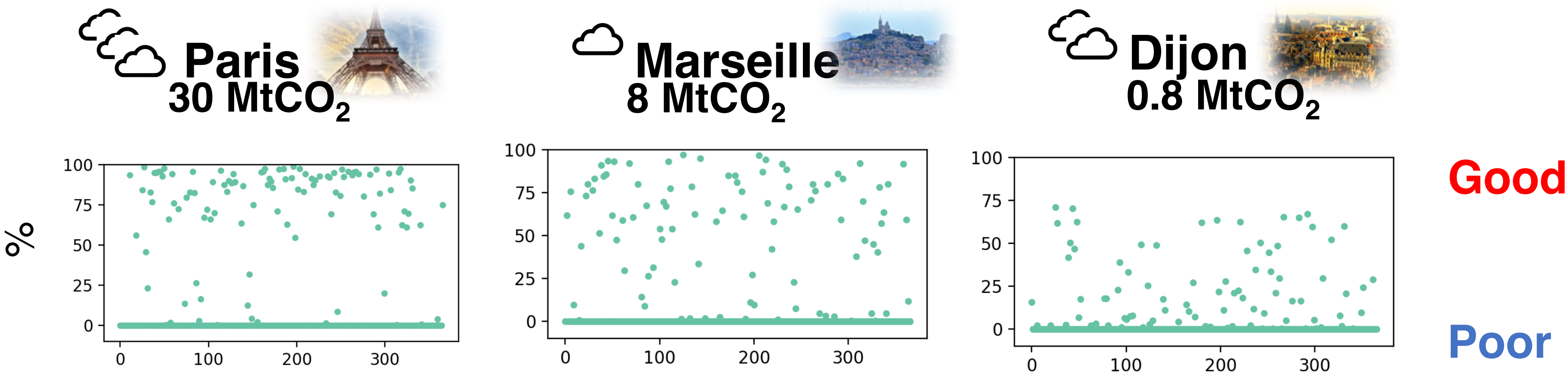
- **Simple transport model (Gaussian plume model)**
- Preserve high spatial resolution of emission fields

100 billions of plumes forming H
Numerically optimized
Full OSSE takes ≈ 1 week CPU

How many days can we see the signals of a city from space?

with one space-borne imager and assuming 100% uncertainty before inversion and no correlation in prior uncertainties

Three cities in France



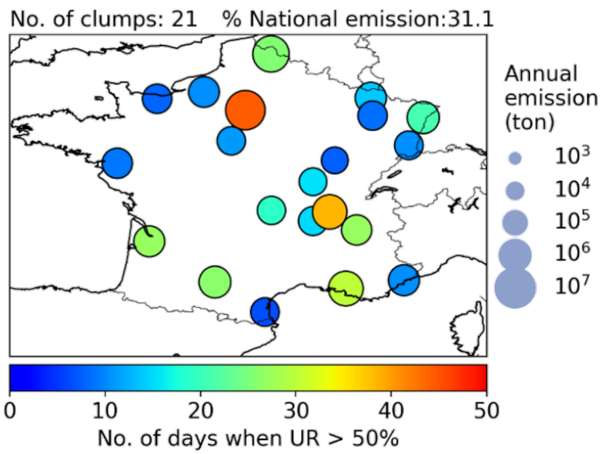
Number of days with an uncertainty reduction better than:	Paris	Marseille	Dijon
20%	94 days	75	40
50%	89	60	15
80%	65	27	0

Number of “good days” with an uncertainty reduction of at least 50%

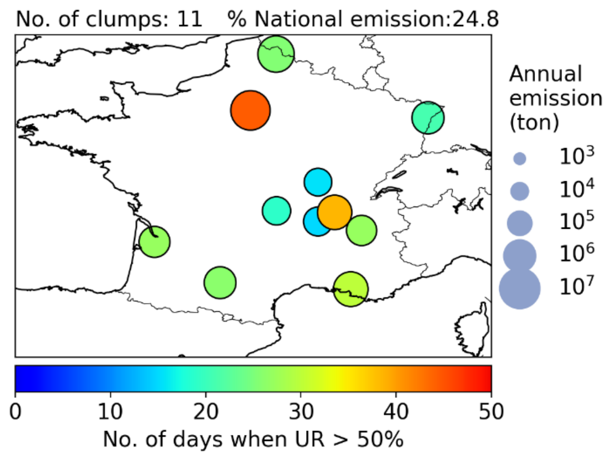
with one space-borne imager and assuming 100% uncertainty before inversion and no correlation in prior uncertainties

Clumps that have >12 days

21 clumps / 110
Σ=27 Mt C
31% of national emission



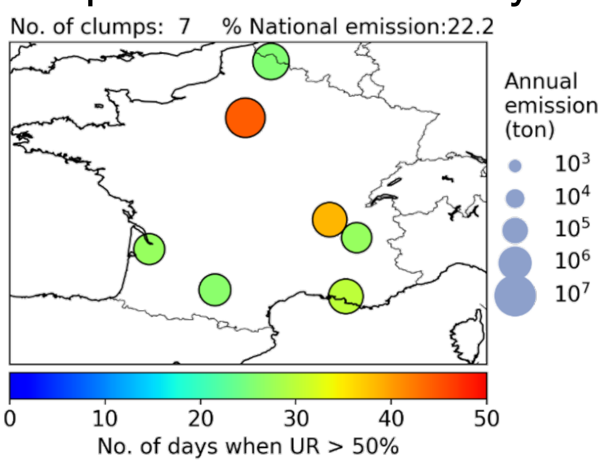
Clumps that have >30 days



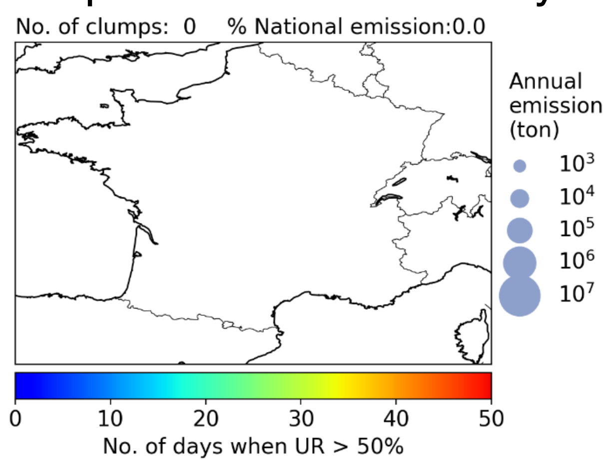
11 clumps / 110
Σ=23 Mt C
26% of national emission

Clumps that have >50 days

7 clumps / 110
Σ=20 Mt C
23% of national emission



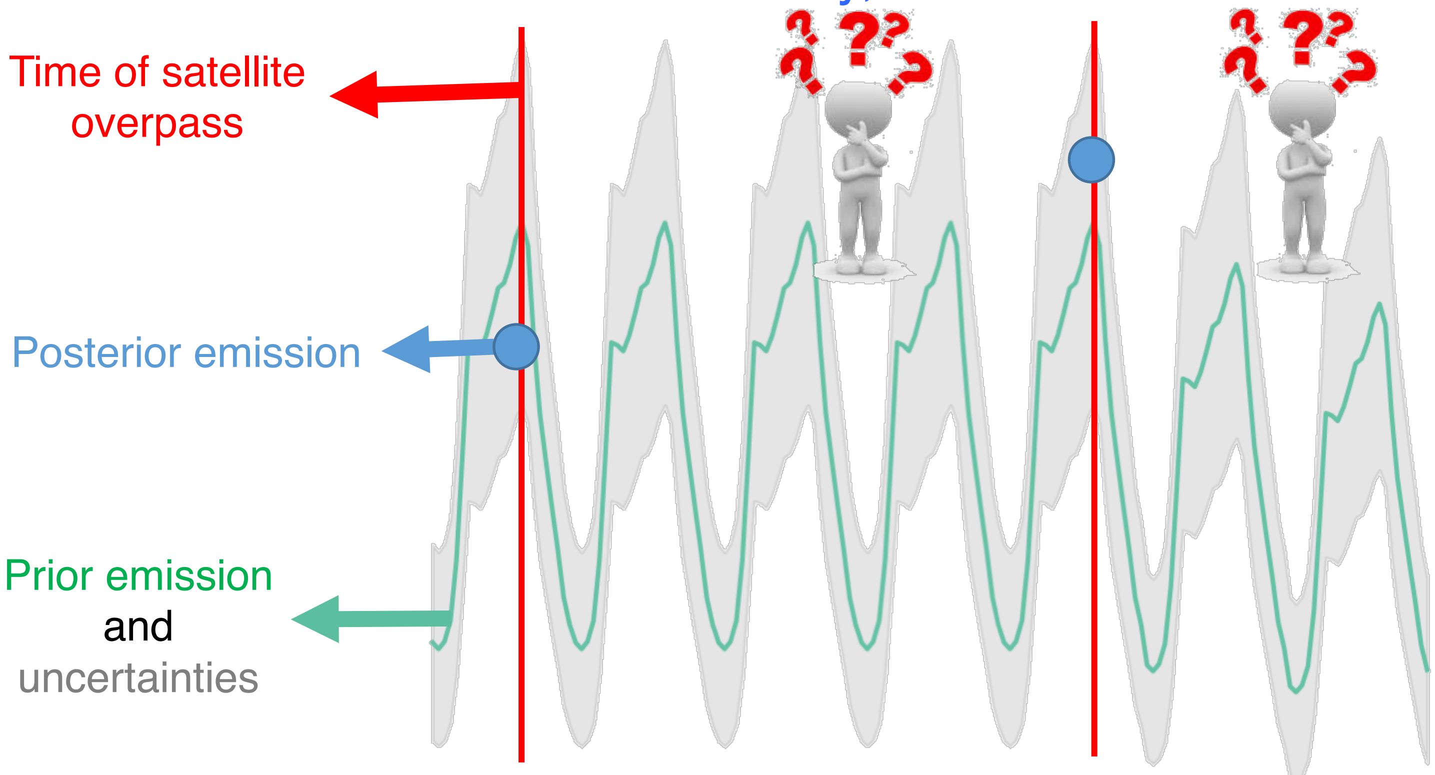
Clumps that have >100 days



0 clumps / 110

Upscaling to annual budget

If we know emission from one day, do we know emission from other days?

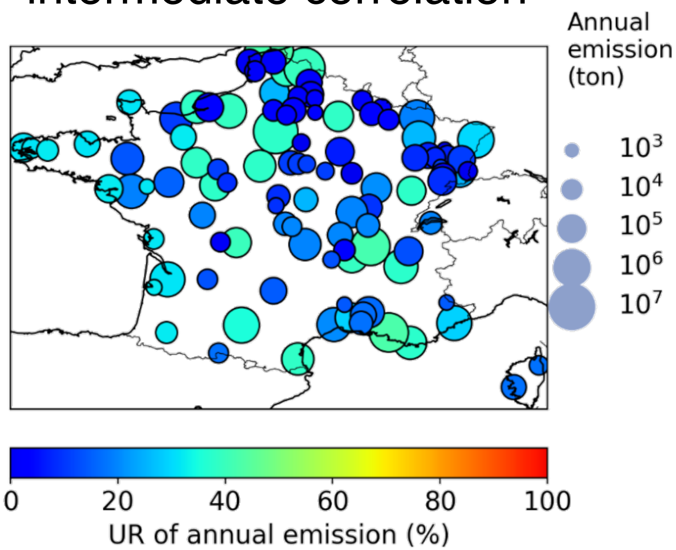


- Rely on the correlations between the uncertainties in the prior estimate of emissions
  - Intermediate correlation:
    - between hours within one day $r=e^{-\Delta H/12}$
    - between different days $r=e^{-\Delta D/7}$
  - Strong correlation:
    - between hours within one day r=1
    - between different days $r=e^{-\Delta D/20}$

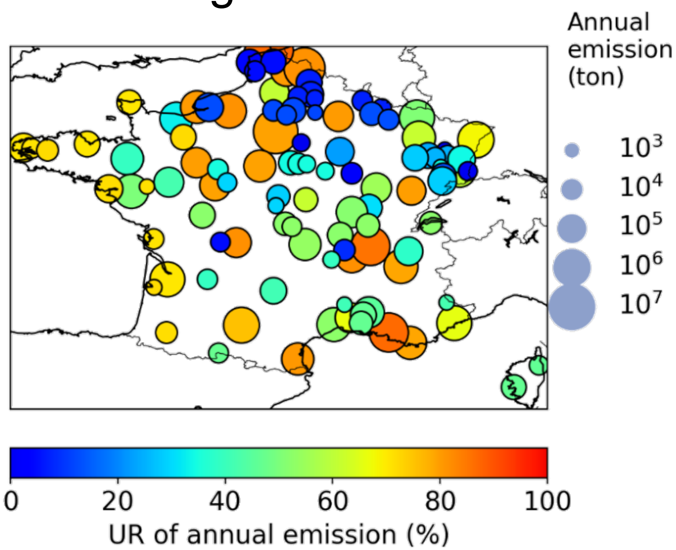
Upscaling to annual budget

		Paris	Marseille	Dijon
intermediate correlation	Prior uncertainty	19%	19%	19%
	Posterior uncertainty	12%	11%	15%
	Uncertainty reduction	38%	43%	21%
strong correlation	Prior uncertainty	32%	32%	32%
	Posterior uncertainty	7%	4%	15%
	Uncertainty reduction	80%	87%	55%

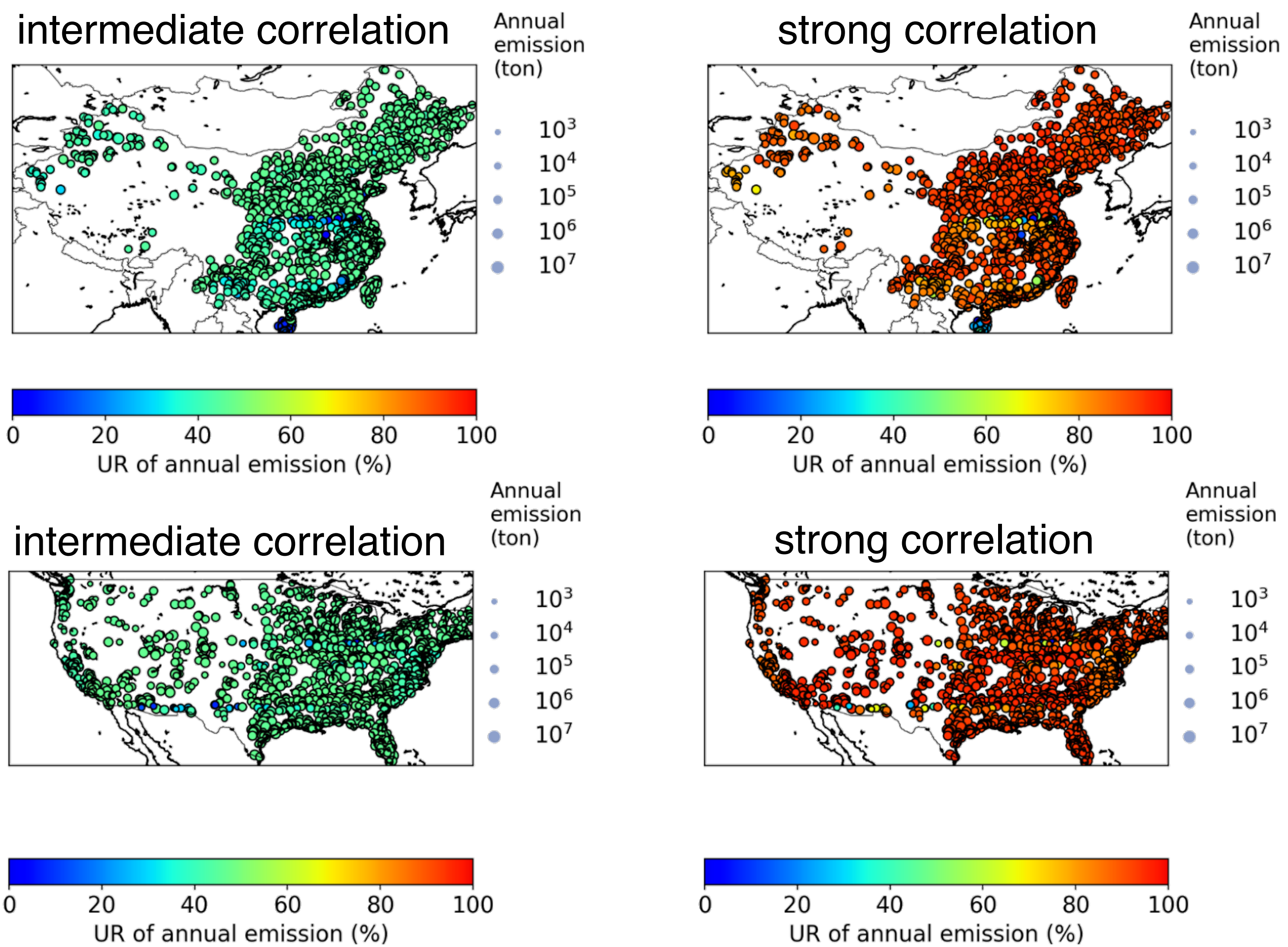
intermediate correlation



strong correlation



Upscaling to annual budget



First conclusion

1. Not too bad **number of days with significant improvement of emissions estimates**-for medium to big cites, even with one imager

2. Scaling to **annual budget of cities** depends critically on temporal error correlations of emissions

3. Scaling to **national scale** proves more complicated, with negative and positive correlations if national totals are already known rather accurately

4. A constellation of satellite imagers can further improve the potential to constrain fossil fuel CO_2 emissions

   -> poster (C4.5) by Franck Lespinas:

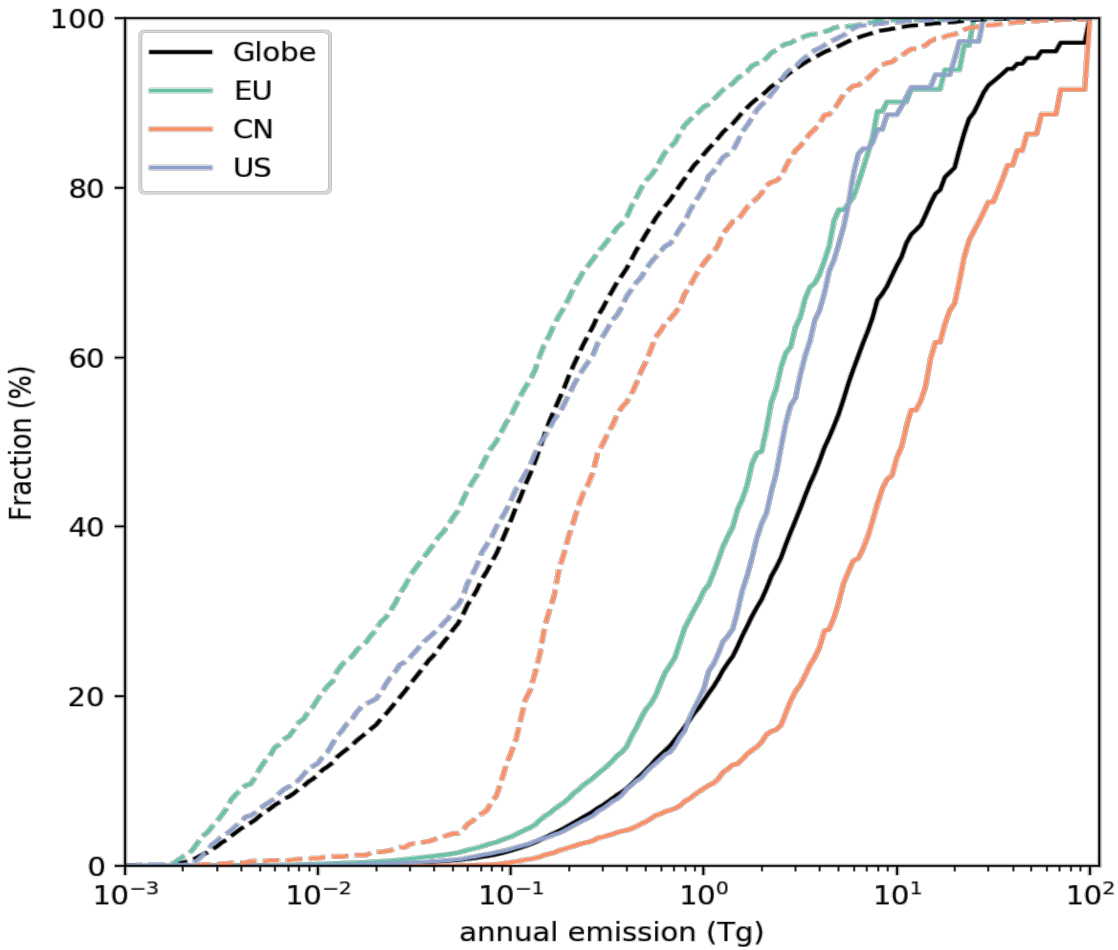
"The potential of a constellation of LEO satellite imagers to monitor worldwide fossil fuel CO2 emissions from large cities and industrial sites"

5. This system can be potentially used to evaluate the potential of other imagers, e.g. OCO3, GeoCARB, etc.

6. Investigate the impact of other error components on fluxes and prepare for an operational inversion system to be used with real data

Thank you!

Distribution of emissions from different emission clumps



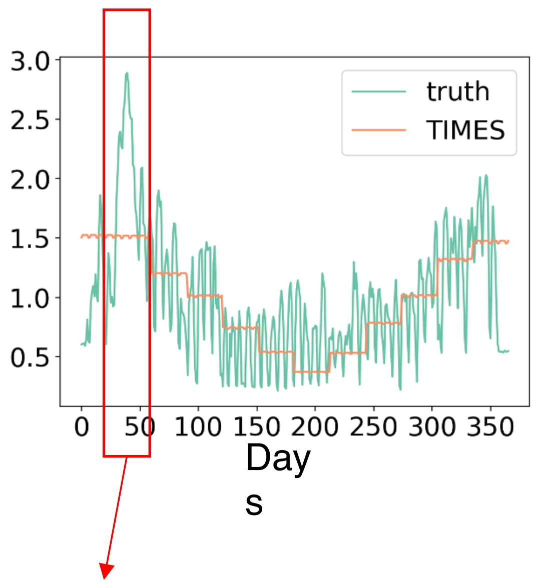
Dashed line: fraction of cumulative number of emission clumps
Solid line: fraction of cumulative emissions

Analysis of temporal correlation

Temporal auto-correlation for prior uncertainties in emissions from electricity production

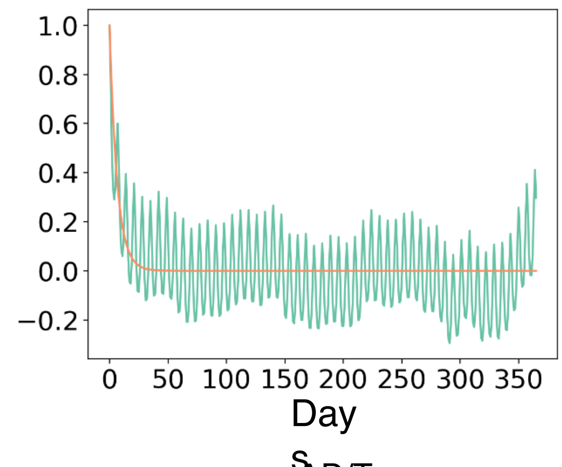
- Comparison between profiles from actual France electricity production data (5 years) and TIMES at daily scale

Time series of electricity production



cold weather

Temporal auto-correlation in errors in TIMES profile



$r=e^{-\Delta D/T}$

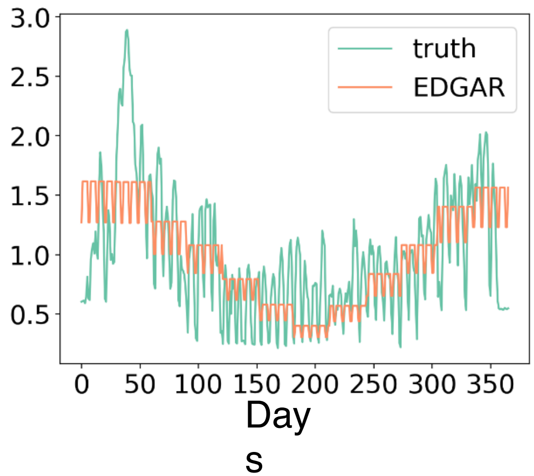
T=6.5d

Analysis of temporal correlation

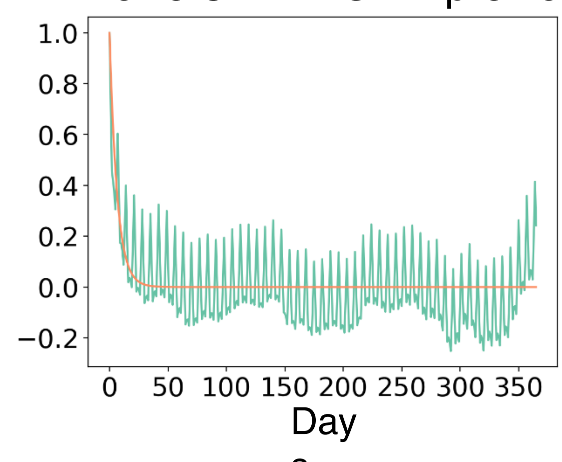
Temporal correlation for prior uncertainties in emissions from electricity production

- Comparison between profiles from actual France electricity production data and EDGAR at daily scale

Time series of electricity production



Temporal-autocorrelation in errors in EDGAR profile

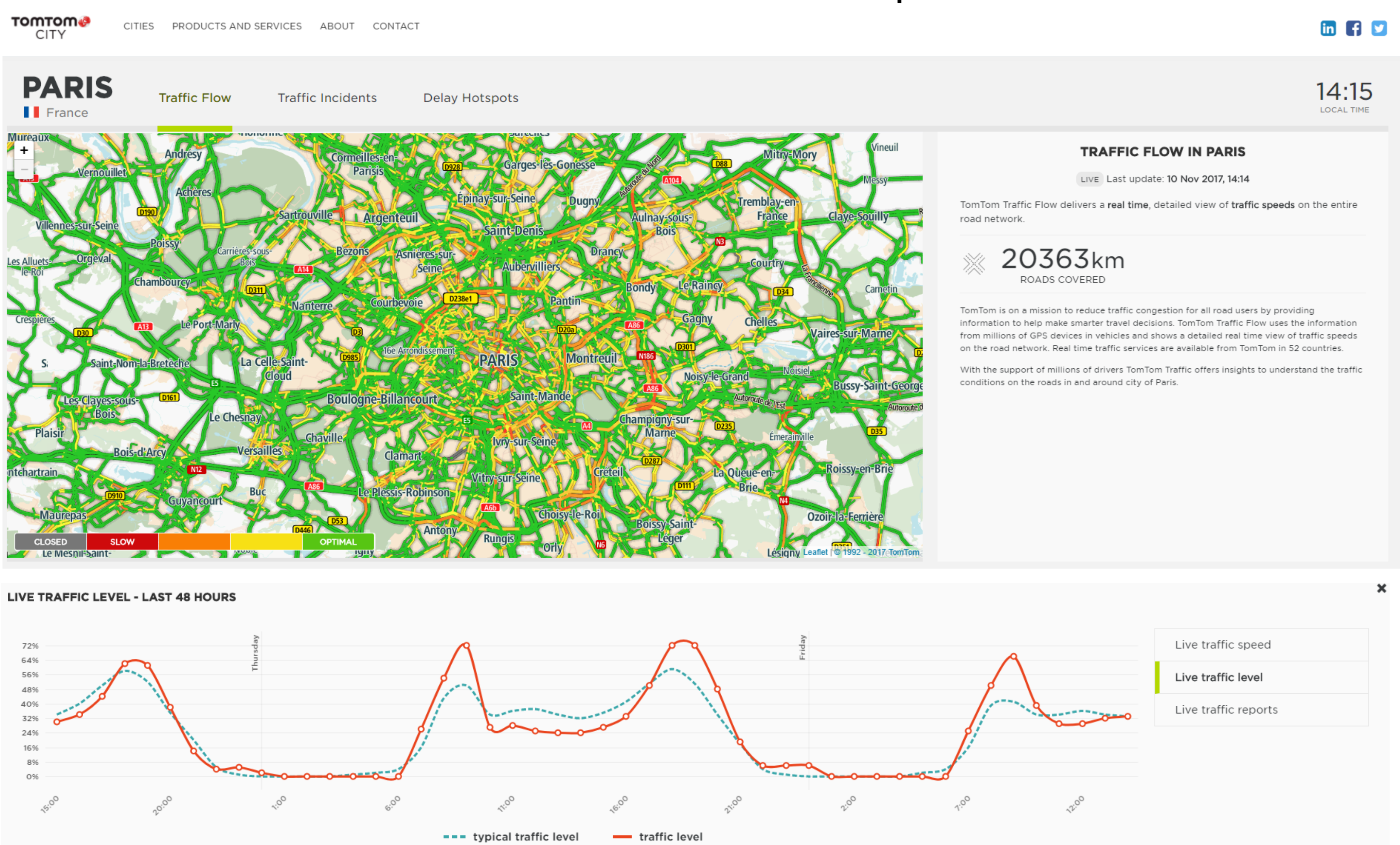


$r=e^{-\Delta D/T}$

T=6.5d

Results: Analysis of temporal correlation

Temporal correlation for emissions from road transport

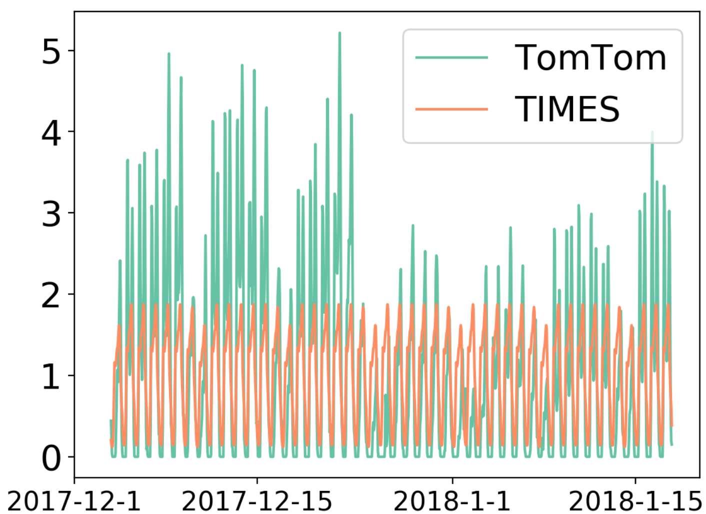


Analysis of spatial/temporal correlation

Temporal correlation for prior uncertainties in emissions from road transport

- Comparison between profiles from TomTom data and TIMES/EDGAR at daily scale

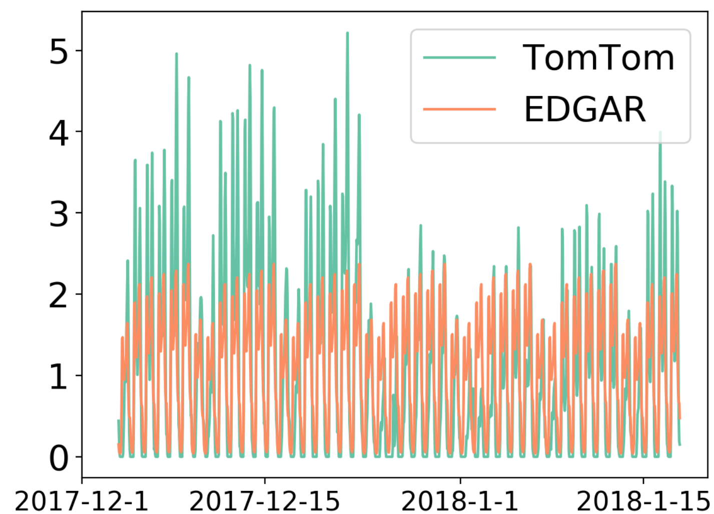
Time series of TomTom traffic index



$r=e^{-\Delta D/T}$

T=3.5d

Time series of TomTom traffic index



$r=e^{-\Delta D/T}$

T=4.3d