Changes in tropospheric NO_2 over megacities: A multi-instrument approach

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Institut für Umweltphysik / Universität Bremen

PRESCRIBE-Workshop / 15 May 2013

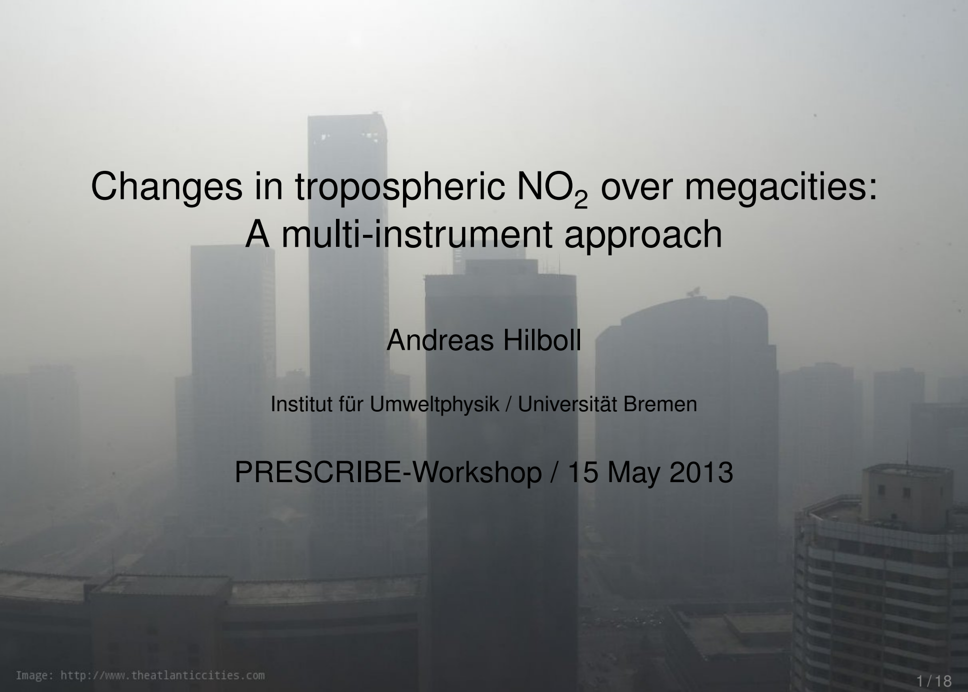

Image: http://www.theatlanticcities.com

Nitrogen dioxide (NO_2)

Why study NO_2?

- harmful to human respiratory system
- O_3 precursor
- leads to acid rain precipitation
- in a megacity setting: almost purely anthropogenic sources

NO_2 is a rewarding species:

- Strong absorption + concentrations ⟶ good signal-to-noise
- Short lifetime ⟶ observation close to source
- Estimation of stratospheric signal feasible

Long-term monitoring is important ⟶ combine several instruments

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Long-term monitoring is important $\longrightarrow$ combine several instruments

Instrumental differences

Tropospheric NO_2 is available from five instruments:

- GOME
- SCIAMACHY
- OMI
- GOME-2 on Metop-A & Metop-B

The instruments differ in

- available time period
- # meas. / location / month
- measurement local time
- spatial resolution

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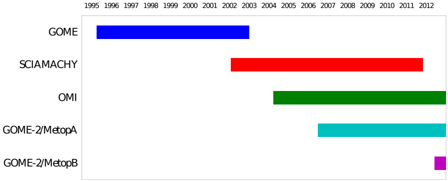

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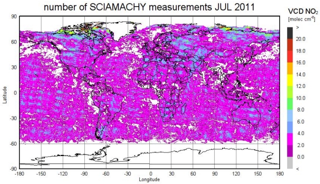

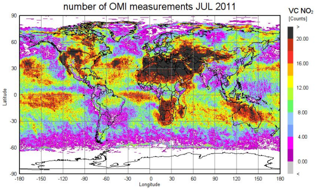

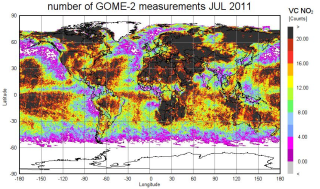

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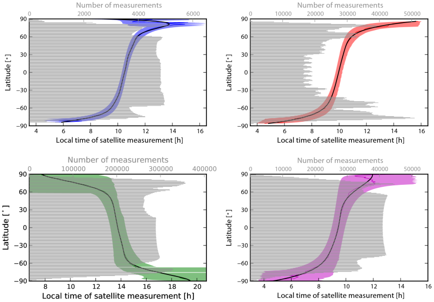

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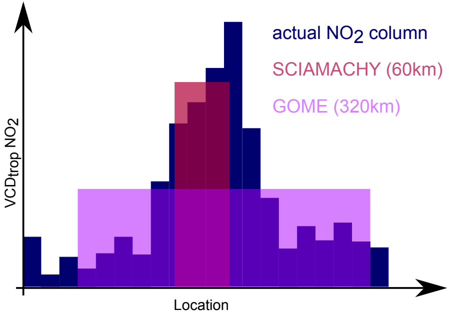

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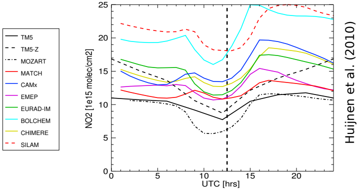
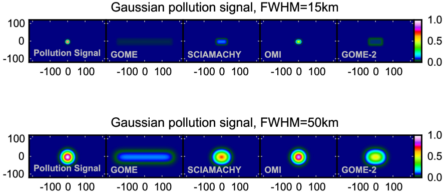
$\Longrightarrow$ **All this influences the retrieved timeseries!** $\Longleftarrow$

Influence on the retrieved data

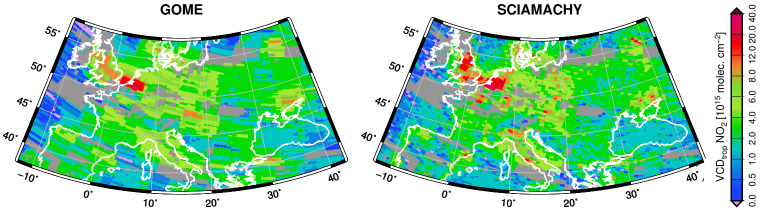
Measurement time



Spatial resolution

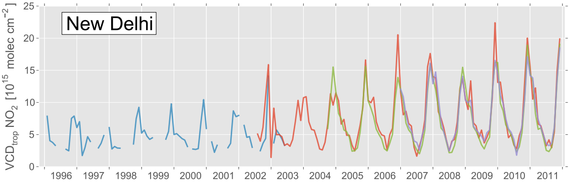


Combined effect



Influence on timeseries

- good agreement
- GOME values lower
- SCIA: peaks higher



- strong instr. dep.
- OMI values lower!
- similar seasonality

- strong instr. dep.
- irregular seasonality in morning orbits

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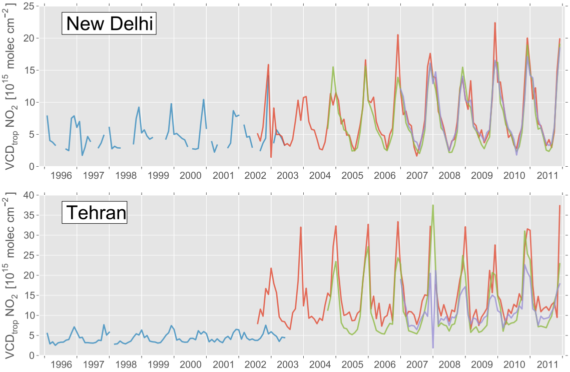

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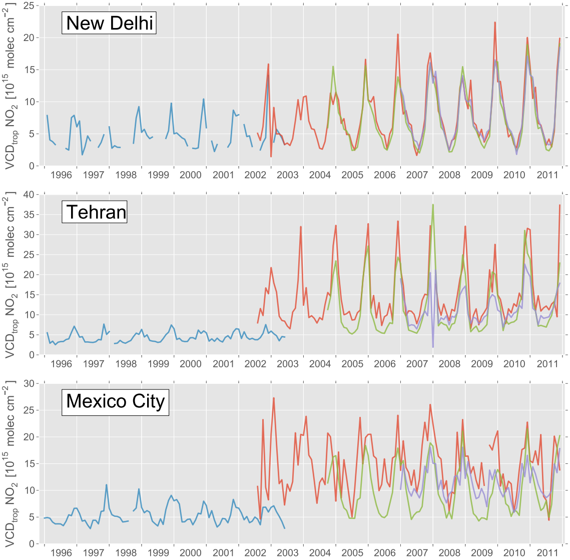

Possible solutions

easy: artificially reduce spatial resolution $\longrightarrow$ not optimal for megacities

Possible solutions

Calculate correction factors (for GOME↔SCIAMACHY):

- average five adjacent SCIAMACHY pixels
- calculate correction factor climatology ($t' = 2003/01, ..., 2011/12$)
  $\Gamma'(t', \vartheta, \varphi) = \frac{VCD^{SCIA}(t', \vartheta, \varphi)}{VCD^{SCIA}_{red.res.}(t', \vartheta, \varphi)}$
- apply correction factors to yield resolution-corrected
  $VCD^{GOME}_{corr}(t', \vartheta, \varphi) = \Gamma(t, \vartheta, \varphi) \times VCD^{GOME}(t', \vartheta, \varphi)$
- often works quite well:

- Quantitative analysis challenging (no sound error estimate)
- Does not account for changing spatial distribution

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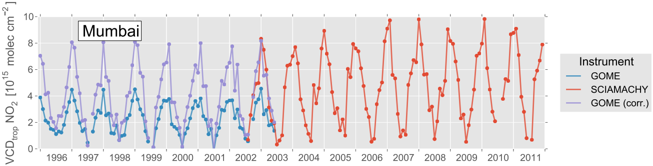

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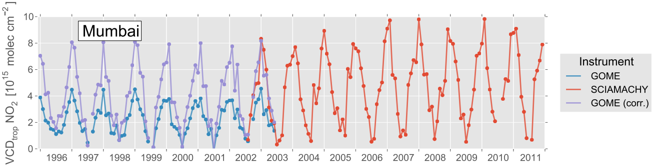

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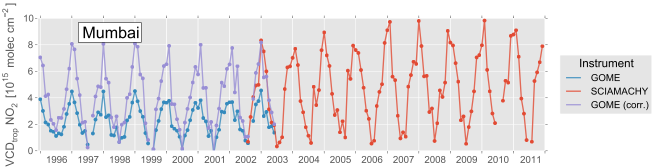

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Including instrumental differences in the trend model

Determine annual growth rates by fitting a trend model:

- One linear growth rate spanning all instruments i
- One reference value (offset) per instrument
- One harmonic seasonality component spanning all instruments,
- ... with instrument-dependent amplitude.

$$X_{trend}(t,i) = \qquad N(t,i)$$

- Apply weights to account for number of measurements
- Minimize squared residuals using optimization strategies
- Determine uncertainties via bootstrapping

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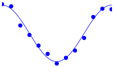
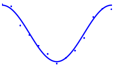
Results

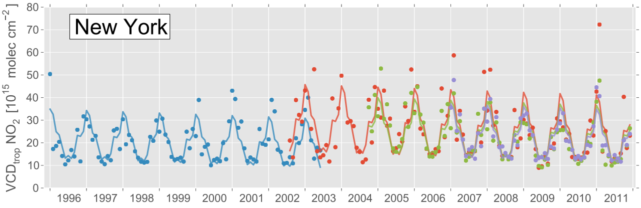


measured monthly averages



fitted trend function

Example I: Megacities in the developed world



- $-2.6 \pm 1.0\ \%\,\mathrm{yr}^{-1}$
- strong difference GOME $\leftrightarrow$ S/O/G2
- almost constant, “spiky” seasonal cycle

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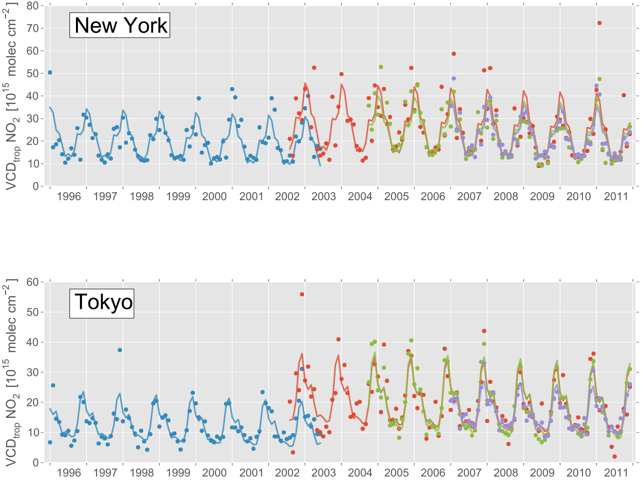

- -2.6 ± 1.0 % yr^{-1}
- strong difference GOME $\leftrightarrow$ S/O/G2
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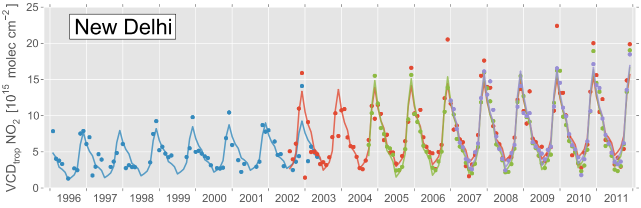
- -3.77 ± 0.97 % yr^{-1}
- very low summer values in 2011/SCIA

Example II: Megacities in the developing world



- $+7.4 \pm 1.7\ \%\,\mathrm{yr}^{-1}$
- no large differences (S/O/G2)
- very low scatter
- strong increase in seasonality (not accounted for)

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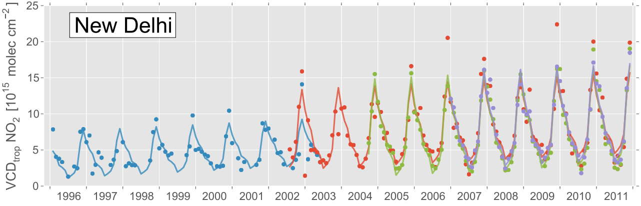

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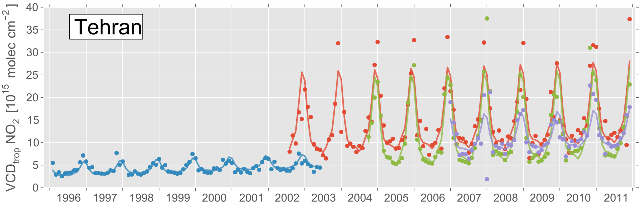
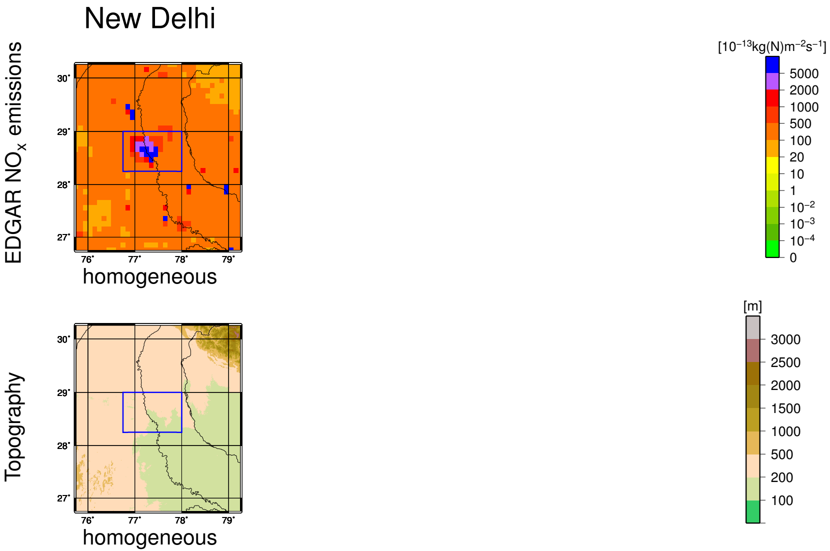


- $+7.8 \pm 2.7$ % yr^{-1}
- strong dependence on instrument
- strongly varying seasonality

Impact of the spatial resolution



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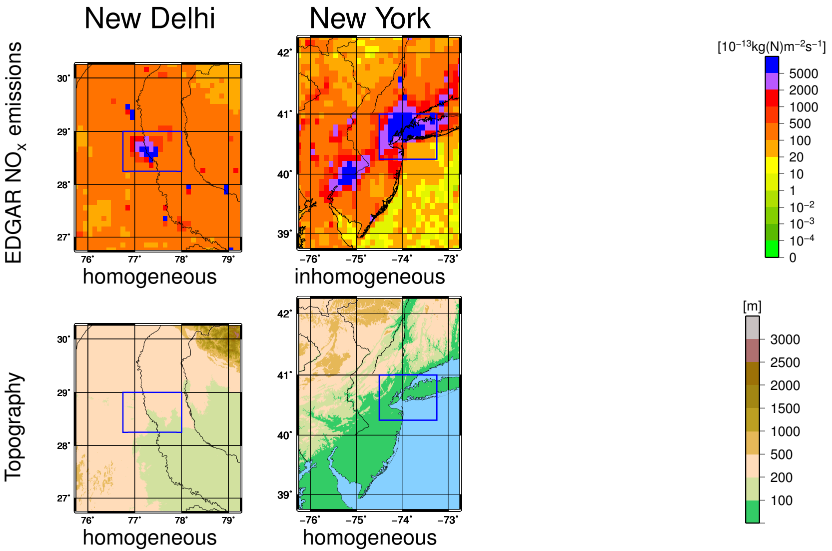

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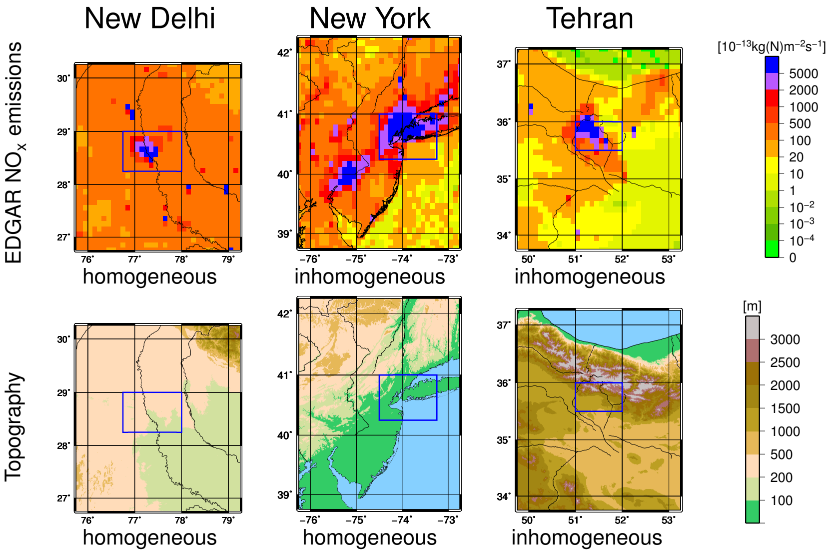

Impact of spatial heterogeneity

- Homogeneous, high-emission areas with no topographic boundaries
  $\longrightarrow$ instrument resolution has negligible impact
- Areas with inhomogeneous, partly high emissions and no topographic boundaries: NO_2 pollution can spread
  $\longrightarrow$ small impact of instrument resolution
- Emission point sources with topographic barriers (e.g. mountains): NO_2 cannot spread throughout the whole area
  $\longrightarrow$ instrument resolution is very important

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Results: annual trends

City	relative (%)	absolute ($\times 10^{14}$)
Baghdad	**+18.0±2.1**	**+3.24±0.37**
Beijing	**+7.3±2.2**	**+9.5±2.9**
Buenos Aires	+1.7±1.6	+0.55±0.51
Cairo	**+6.4±1.0**	**+1.73±0.28**
Dhaka	**+24.0±3.8**	**+3.41±0.54**
Los Angeles	**-5.8±1.2**	**-13.2±2.6**
Mexico City	+1.0±1.6	+0.51±0.82
Mumbai	**+3.6±1.1**	**+0.70±0.21**
New Delhi	**+7.4±1.7**	**+2.57±0.60**
New York	**-2.6±1.0**	**-5.7±2.3**
Seoul	+0.7±1.2	+1.0±1.8
Tehran	**+7.8±2.7**	**+2.68±0.93**
Tokyo	**-3.77±0.97**	**-5.4±1.4**

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Los Angeles	**-5.8±1.2**	**-13.2±2.6**	**-9.6±2.6**
Mexico City	+1.0±1.6	+0.51±0.82	-2.9±1.9
Mumbai	**+3.6±1.1**	**+0.70±0.21**	**+1.4±0.8**
New Delhi	**+7.4±1.7**	**+2.57±0.60**	**+2.0±1.1**
New York	**-2.6±1.0**	**-5.7±2.3**	**-9.8±2.4**
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Tokyo	**-3.77±0.97**	**-5.4±1.4**	**-12.3±2.7**

Non-linear changes

- Timeseries are long enough to show varying change rate

Possible solutions:

- piece-wise linear trends (Russell et al.)
- Break-point regression (break-points determined by regression, not by a-priori)
- Non-parametric analysis, e.g. STL/LOESS

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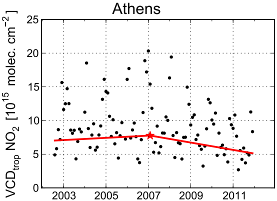

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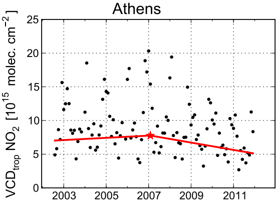

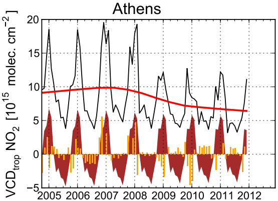

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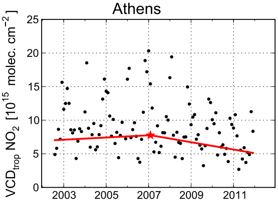

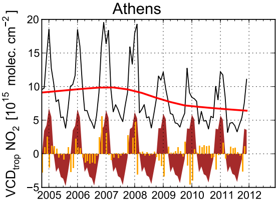

⟶ But: hard to extend to multiple instruments ⟵

Summary

- Long-term changes in tropospheric NO_2 from satellite
- Different instruments' spatial resolutions result in differences in the behavior of the four datasets
- Trend model using all available data
- pos. trends in emerging, neg. trends in developed regions
- Effect of spatial resolution depends on local surroundings of cities
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Acknowledgements

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- ESSReS for funding my PhD (http://earth-system-science.org)
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- Thank you for your attention!!!