



# Weighting factors of satellite data in TM5-4dvar

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#### 1 Objective

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  - Intermediate Approach: "optimized" inflation
  - New approach: density-depended inflation
- 4 Open Questions for discussion

### Objective

- Target: Use TROPOMI observations in TM5-4dvar
- Problem: Sheer number of observations "breaks" cost function
- Solutions:
  - Variance inflation
  - Observation Thinning
  - Super-Observations

## Background: TROPOMI, cost function and prior work

### **TROPOMI** observations

- TROPOspheric Monitoring Instrument onboard of Sentinel-5 Precursor
- Local overpass time 13:30
- High resolution (up to  $7 \times 7 \text{ km}^2$ )



- $\rightarrow$  After quality filtering around 500.000 observations per day
  - For comparison NOAA surface flasks deliver around 12 observations per day

$$J(x) = J_{obs}(x) + J_{prior}(x)$$

- Target of inversion is finding state x (here the global CO emissions) such that J is minimized
- J is quadratic function, i.e. this is a least-squares problem with many dimensions

$$J_{obs}(x) = \frac{(F(x) - y)^2}{\sigma^2}$$

#### Only looking at observational part

- F is model and its sampling to the times and places of the observations
- *y* are the measurements
- $\blacksquare~\sigma$  is observation error and sampling error of model

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#### Variance Inflation

$$J_{obs}(x) = \frac{(F(x) - y)^2}{I^2 \sigma^2}$$

- Increase error by factor I to decrease weight in cost function
- Intended to capture various things, depending on setup e.g.:
  - Error correlation
  - Correlations between observations themselves (redundant information)
  - Model errors
  - Representativeness errors (scales not resolved by model)
- Applied in different ways: flat factor or additive value, possibly depending on other variables like latitude, observation height,...

#### Previous approach in TM5-4dvar

- Previous TM5-4dvar studies used form of variance inflation: Hooghiemstra et al. 2012, Krol et al. 2013, Nechita-Banda et al. 2018, Naus et al. 2022,..
- All used flat value of  $I = \sqrt{50}$  for IASI and/or MOPITT
- Factor mostly arbitrary, was initially intended to represent observation density
- $\blacksquare$  Satellite observations only used in zoom region  $\rightarrow$  want global
- Older satellites (MOPITT, IASI,..) have lower observation density → cannot use that inflation for TROPOMI

# New work: Extended variance inflation

- Use condition  $J_{obs,sat} = J_{obs,stations}$
- Leads to *I* ≈ 200 (note there is no square root, i.e. cost is reduced 800 times stronger compared to previous studies!)
- Single observation has virtually 0 weight
- $\rightarrow\,$  Problematic over oceans and for small scale signals e.g. from biomass burning

- Make inflation depend on actual observation density
- In preprocessing step calculate distances d between observations
- "Count" observations that are close to each other
- Calculate individual inflation factors for each observation

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#### New approach: Counting adjacent observations

"Count" observations that are close to each other, different options:

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- $\sum \exp\left(-\frac{d}{r}\right)$  exponential decay, similar to spatial correlations within emissions in TM5-4dvar
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....

Currently use r = 200 km, the spatial correlations length for biomass burning, e.g. smallest distance on which model can change emissions. Is this meaningful? How should this (weighted) count N affect the (local) cost  $J_{loc}$ :

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- Want something that grows slower, e.g.  $J \propto \sqrt{N}$
- Other possibilities:  $J \propto \ln(N)$ , ...

### **Open Questions for discussion**

- Counting function?
- Correlation length?
- Cost function behavior?
- How to do proper weighting to other datasets?
- Combine with flat factor?

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- $\blacksquare$  ... and of course thank You for your attention