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Vigilada Mineducación

Ensemble-based Data Assimilation For High-uncertainty systems: Case of study, PM10 and PM2.5 in the Aburrá Valley

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Introduction

Aburrá Valley Landscape in a Contingency Day.
www.elcolombiano.com

MAUI: Medellín Air qUality Initiative

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Introduction

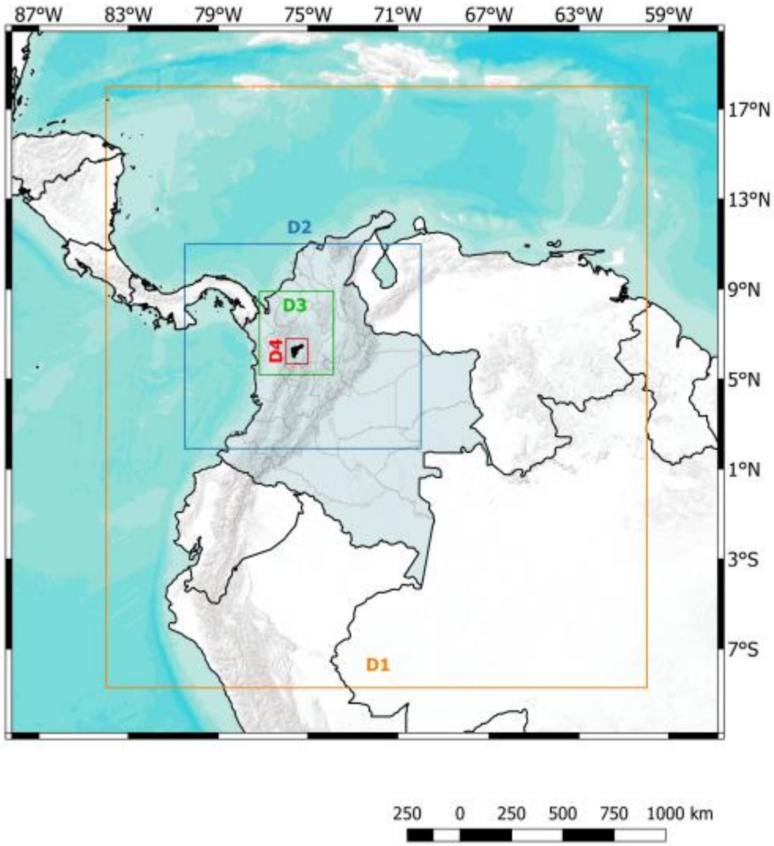
Why is this application interesting?

- A high resolution model implementations is required.

- There are different sources of high uncertainty:
  - Emissions inventory
  - Meteorology

- A low-cost sensor network is available with a high spatial representation (221 measurement points).

Preliminary Results



Domain	Longitude	Latitude	Cell size
D1	84°W-60°W	8.5°S-18°N	0.27°
D2	80.5°W-70°W	2°N-11°N	0.09°
D3	77.2°W-73.9°W	5.2°N-8.9°N	0.03°
D4	76°W-75°W	85.7°N-6.8°N	0.01°

Table 1: Nested domain specifications

Period	From 31-March-2016 to 25-April-2016
Time resolution	1 hour
Domain	[-76 to -75] west x [5.7 to 6.8] north
Spatial resolution	$0.01^\circ \times 0.01^\circ \sim 1km \times 1km$
Metereology	ECMWF. Temp.Res:3 h. Spat.Res: $0.07^\circ \times 0.07^\circ$
Initial and boundary conditions	LOTOS-EUROS (D3). Temp.Res: 1h. Spat.Res: $0.03^\circ \times 0.03^\circ$
Nominal Emissions	EDGAR V4.2

Table 2: Experimental setup

Preliminary Results

We used a LEKF and a stochastic model for parameter estimation

$$x_t = M(x_{t-1})$$
$$\delta e_t = \alpha \delta e_{t-1} + \sqrt{1-\alpha^2}\, w_t$$

where w_t is a white noise and δe_t is the emission correction factor

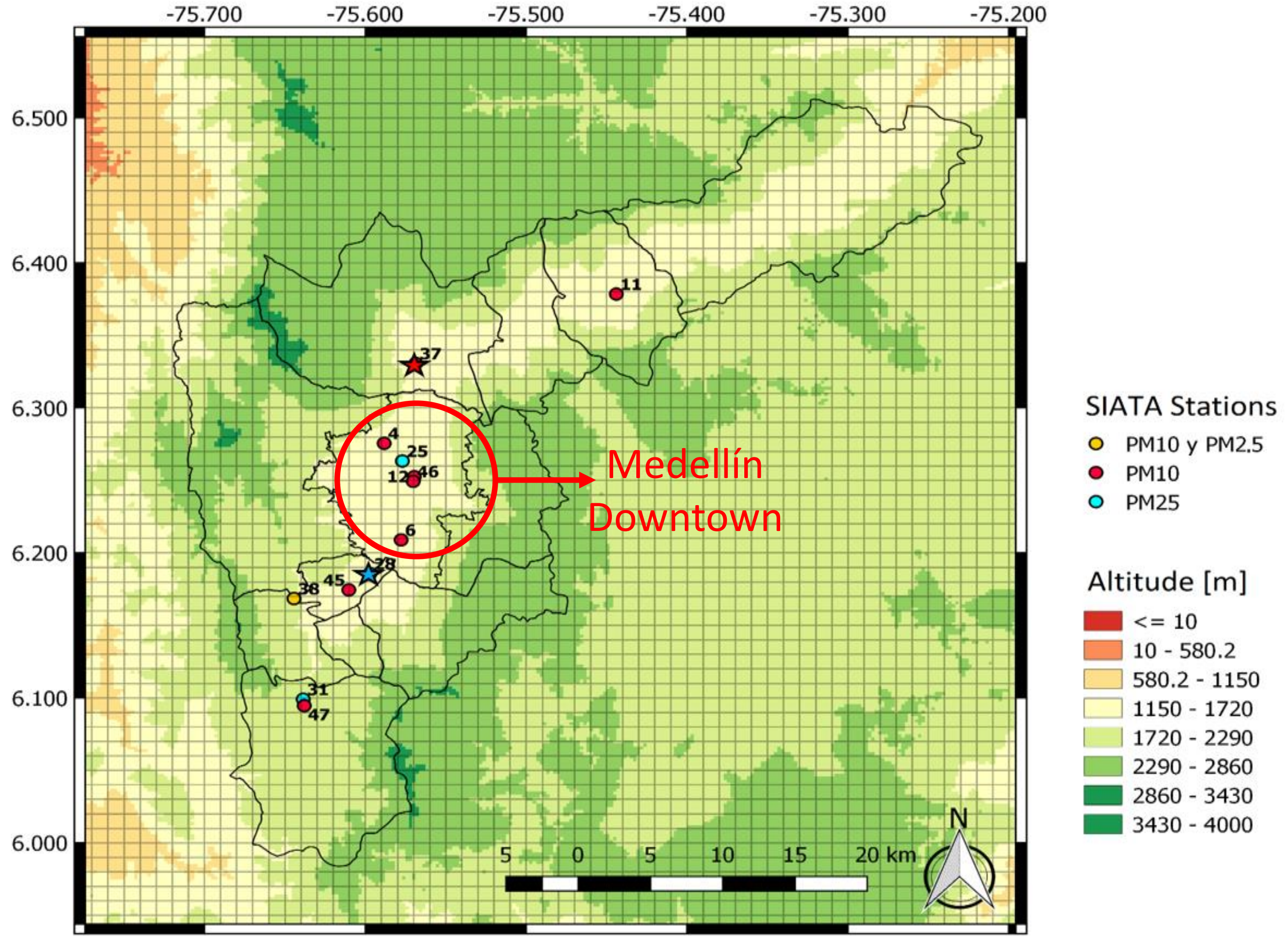
$$\begin{bmatrix} x_t \\ \delta e_t \end{bmatrix} = \begin{bmatrix} M(x_{t-1}) \\ \alpha \delta e_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ \sqrt{1-\alpha^2} \end{bmatrix} w_t$$

The coefficient α represents the time correlation parameter. Using the parameterization $\alpha = exp(-1/\tau)$ for a given time correlation length τ.

We are considering Uncertainties in:

- PM10+BC Emissions
- NH3 Emissions
- SOx Emissions

Preliminary Results



Preliminary Results

We implemented the method proposed in (Desroziers, Berre, Chapnik, & Poli, 2005) to estimate ***R.***

$$E[d_a^o(d_b^o)^T] = \boldsymbol{R}$$

$$\boldsymbol{HK} = \boldsymbol{HBH^T}\left(\boldsymbol{HBH^T} + \boldsymbol{R}\right)^{-1}$$

If matrix $\boldsymbol{HK} = \boldsymbol{HBH^T}\left(\boldsymbol{HBH^T} + \boldsymbol{R}\right)^{-1}$ are the true covariances for background and observation error. d_a^o is the difference between observations and analysis state in observation space, and d_b^o is the difference between observations and forecast state in observation space. One application of this relationship is to estimate observation error covariance matrix (Li, Kalnay, & Miyoshi, 2009).

Preliminary Results

First period (2 weeks)

- Calibration of the localization radius.
- Calibration of the correlation time *τ.*
- Estimation of matrix ***R.***
- First emissions estimation

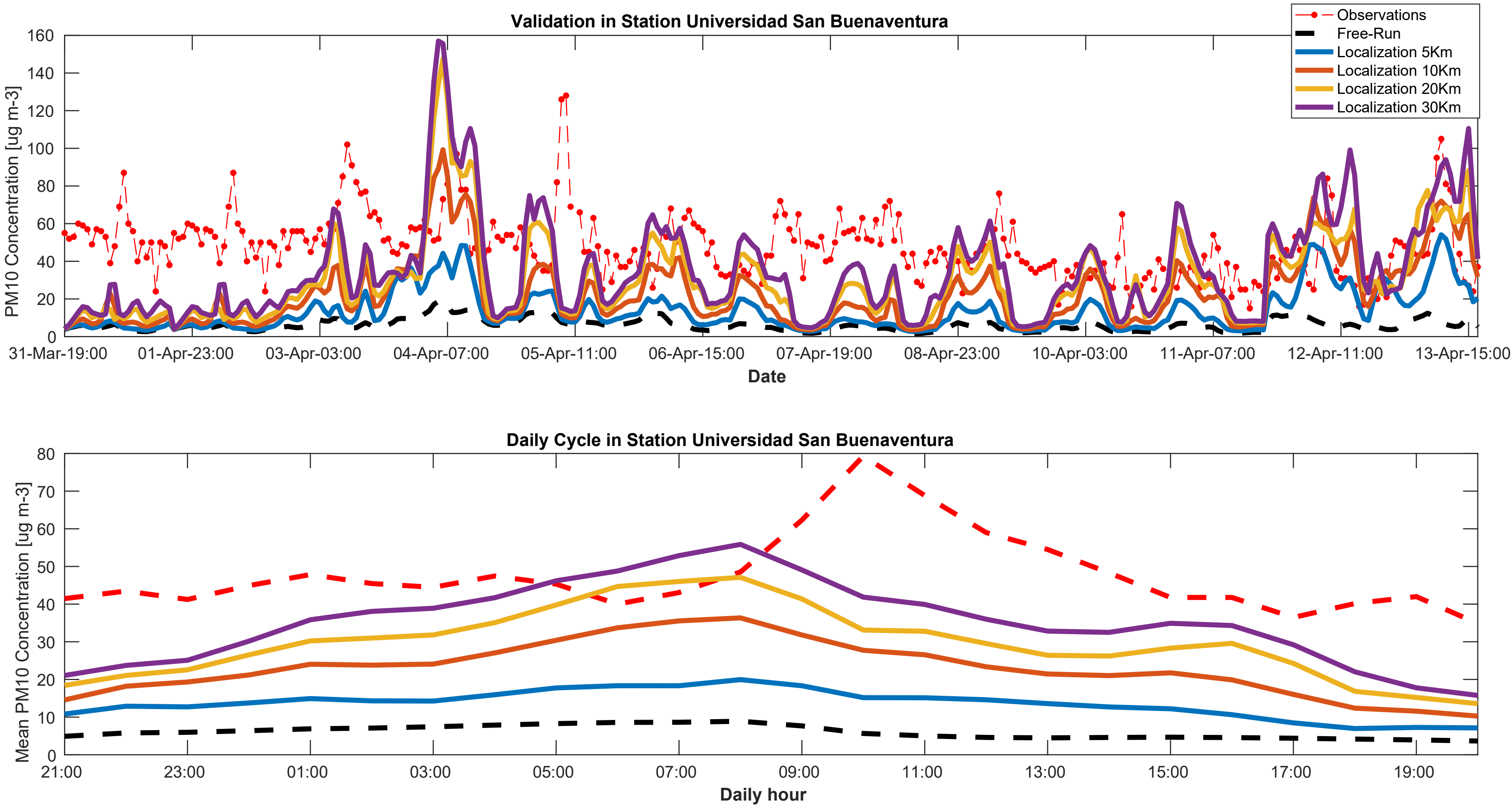
Calibrated DA method
Estimated ***R***
*E*stimated emissions as nominal emissions.

Second period (2 weeks)

- Second emissions estimation.
- Forecast.

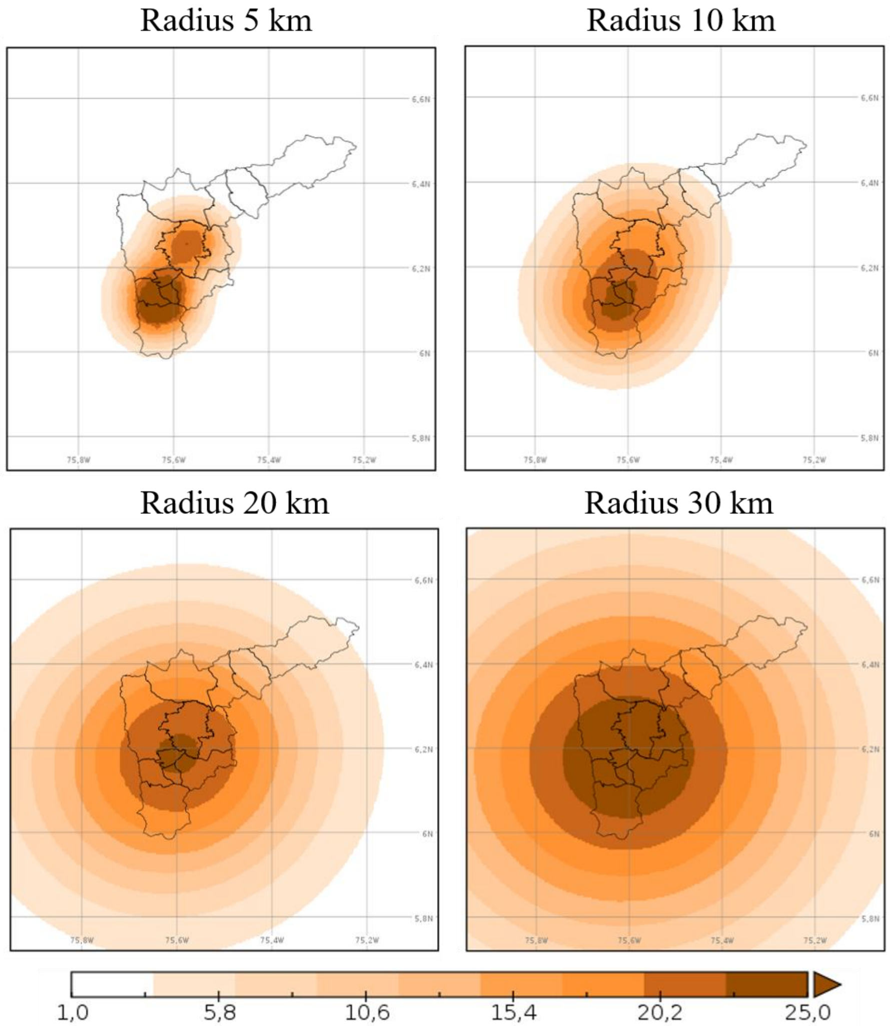
Preliminary Results

First period PM10



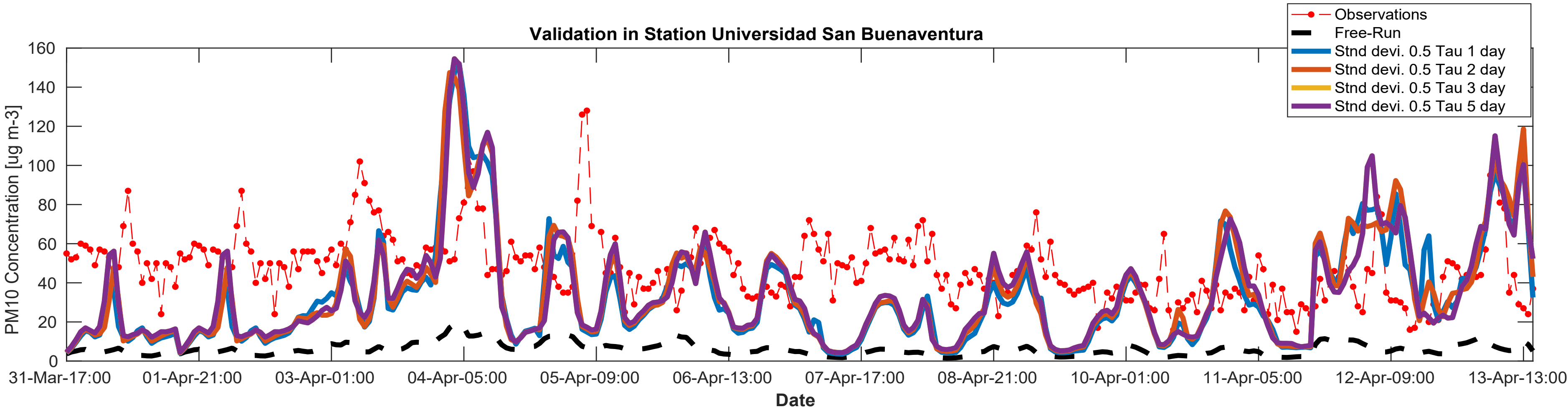
Preliminary Results

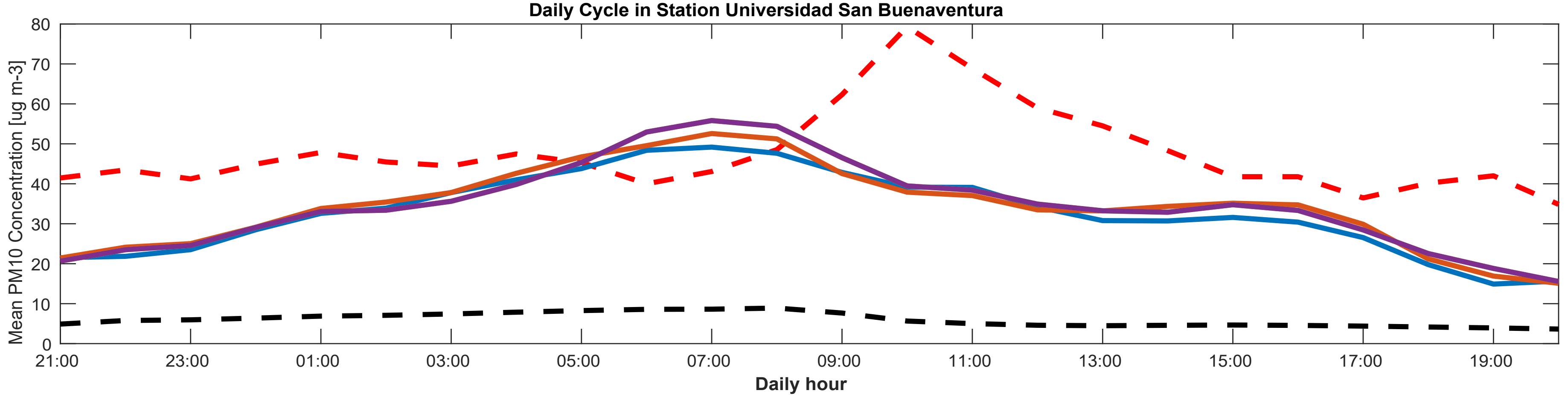
First period



Preliminary Results

First period PM2.5





Preliminary Results

First period (2 weeks)

- Calibration of the localization radius.
- Calibration of the correlation time *τ*.
- Estimation of matrix ***R*.**
- First emissions estimation

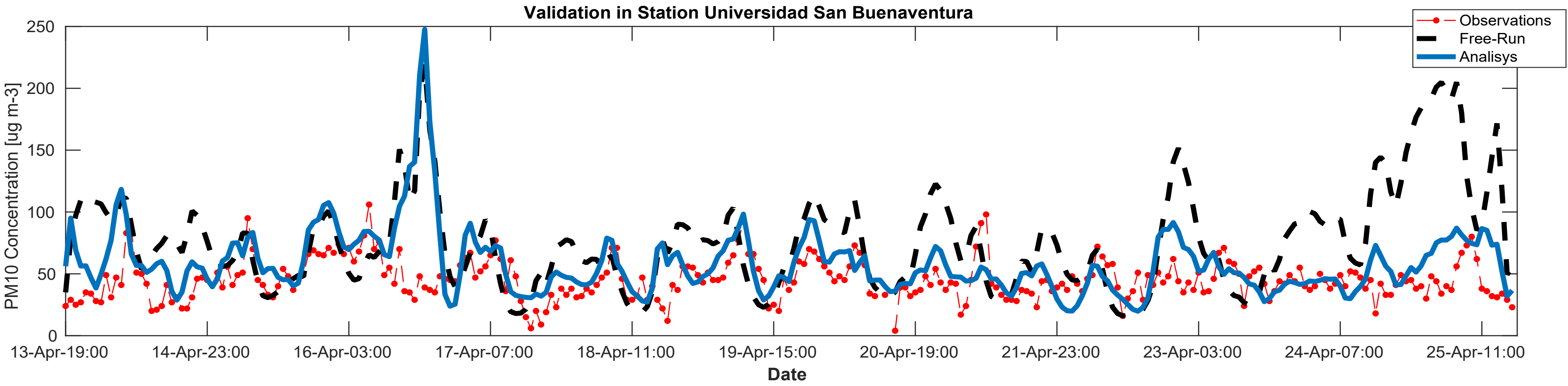
Calibrated DA method
Estimated ***R***
*E*stimated emissions as nominal emissions.

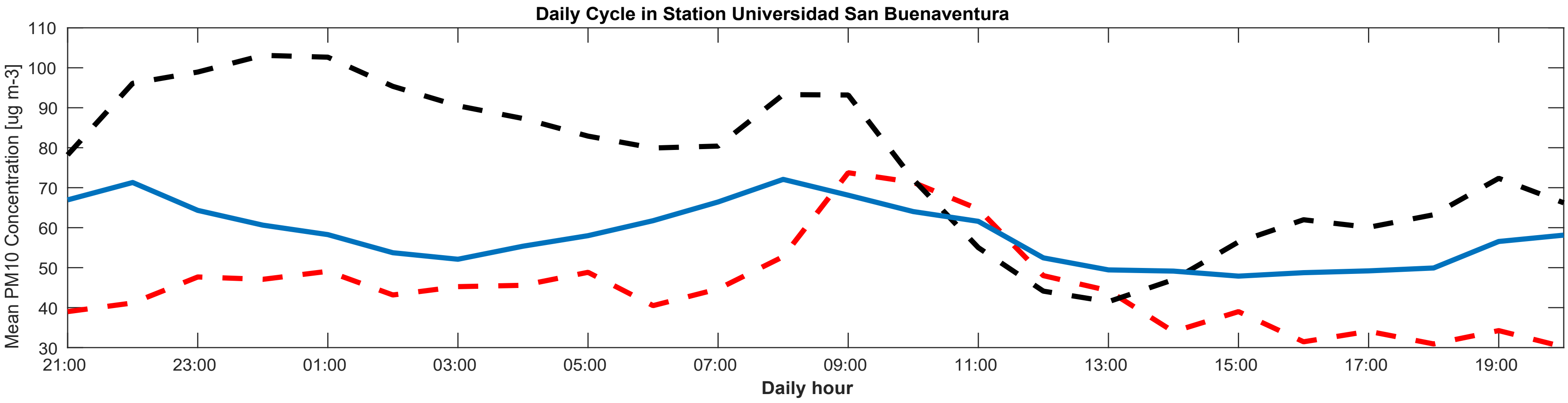
Second period (2 weeks)

- Second emissions estimation.
- Forecast.

Preliminary Results

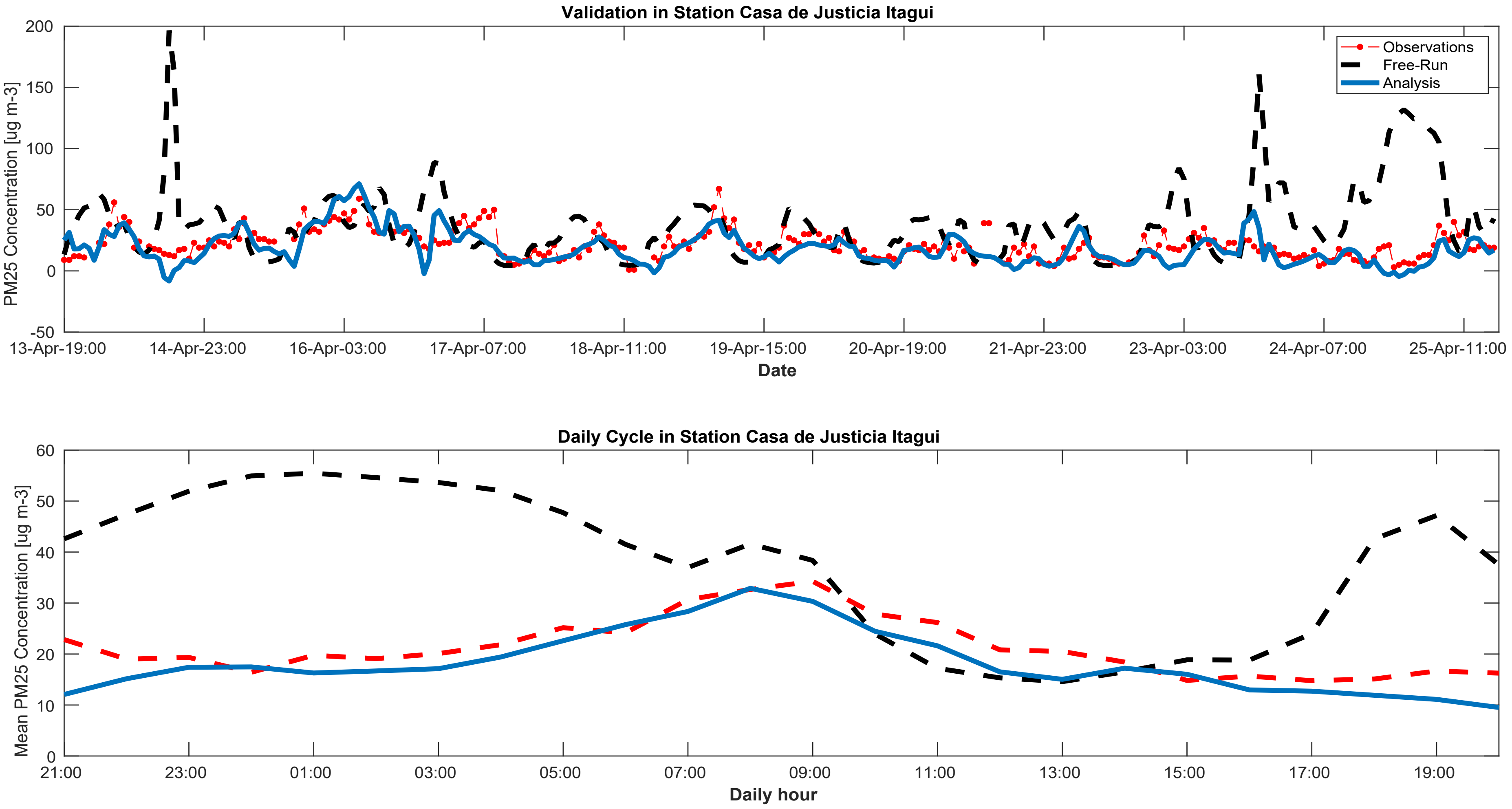
Second period PM10





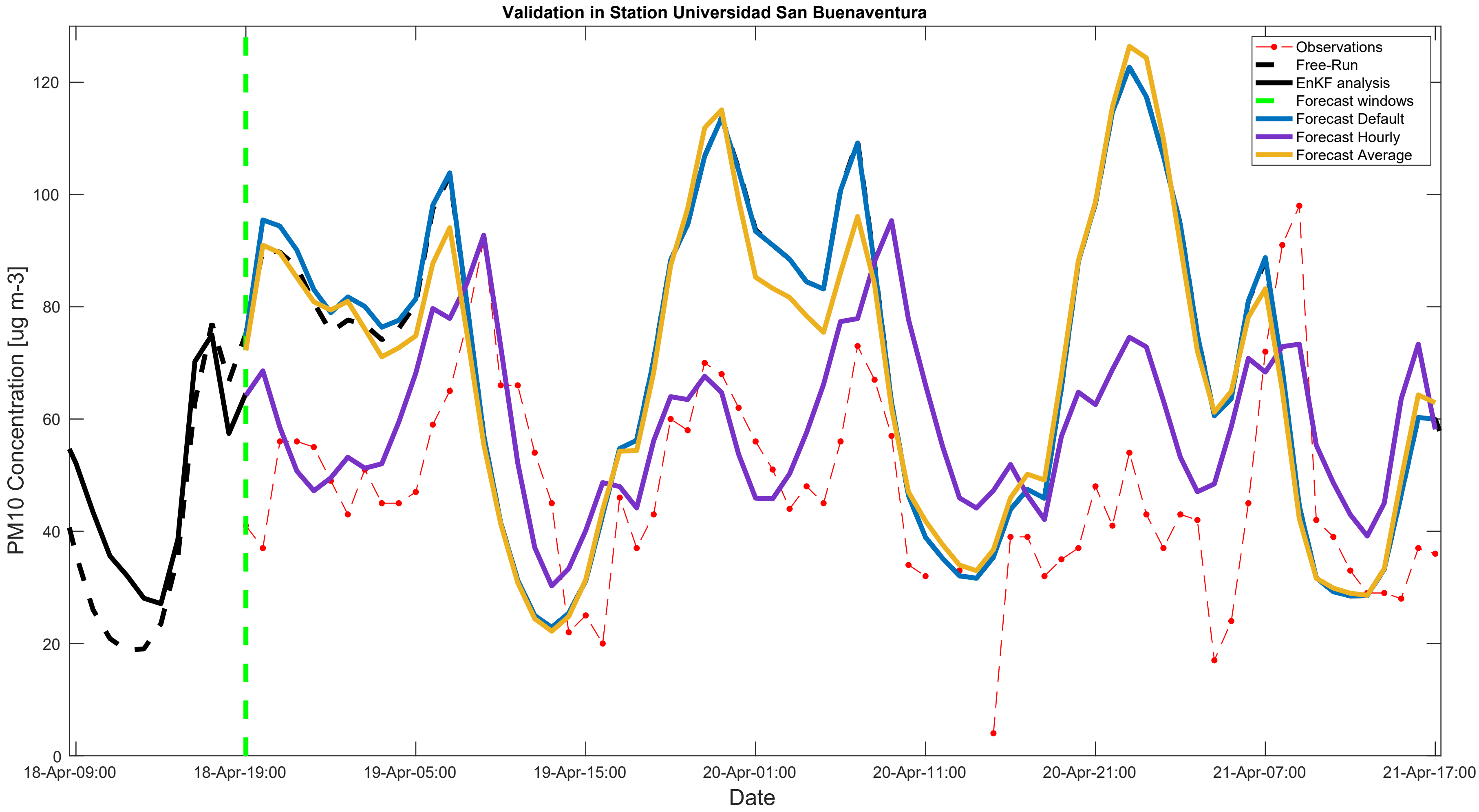
Preliminary Results

Second period PM2.5



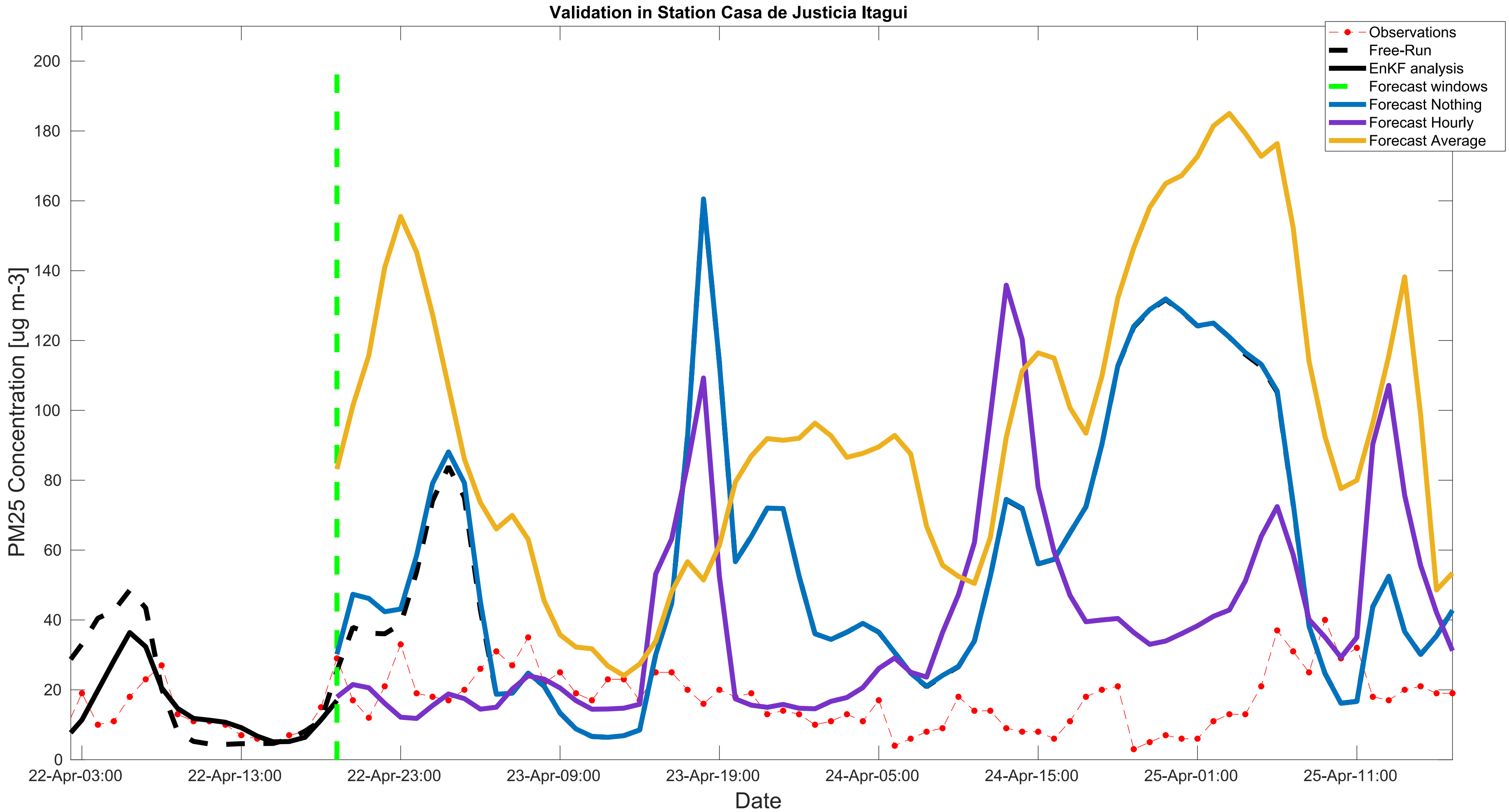
Preliminary Results

Second period PM10



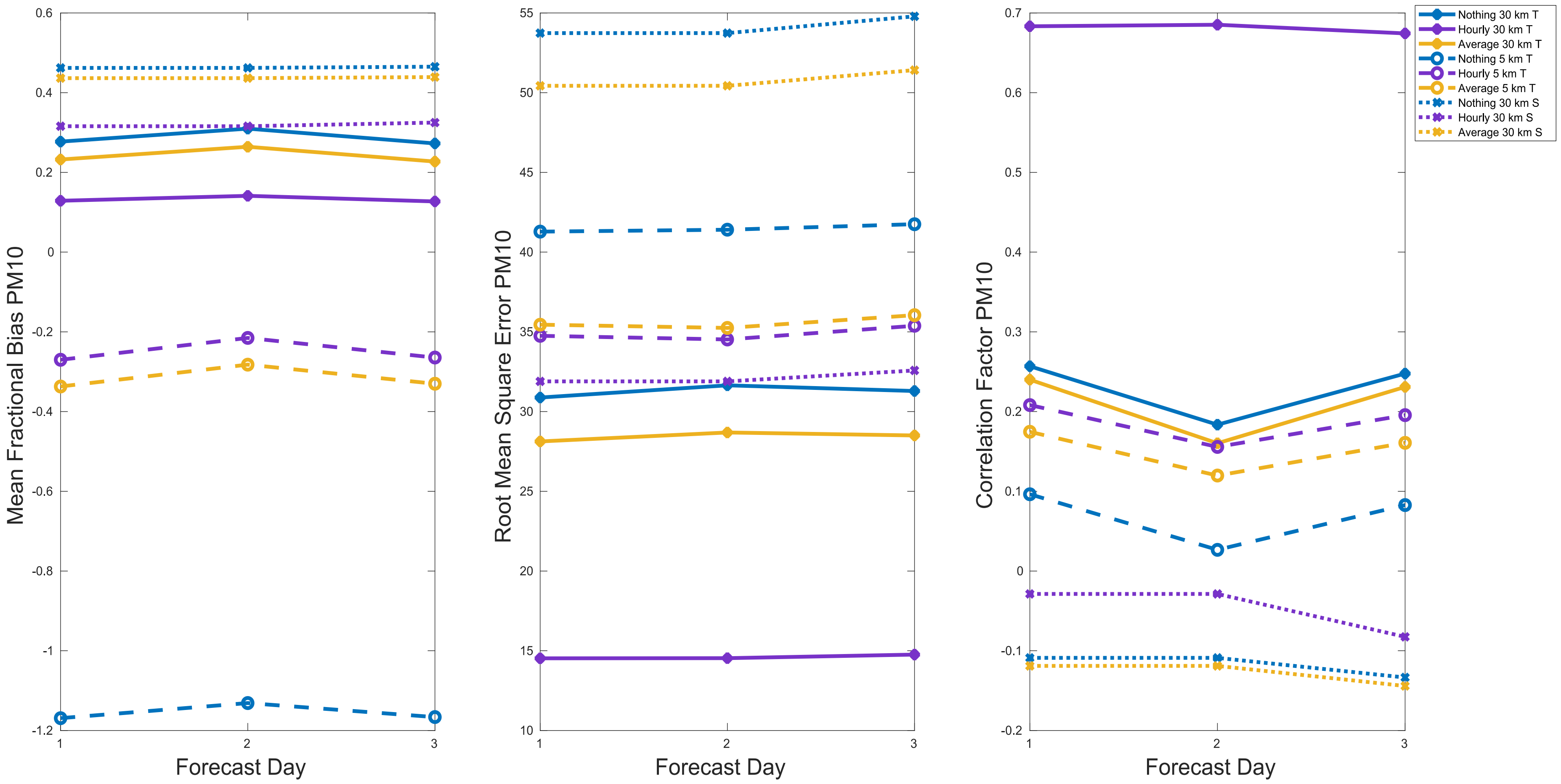
Preliminary Results

Second period PM2.5



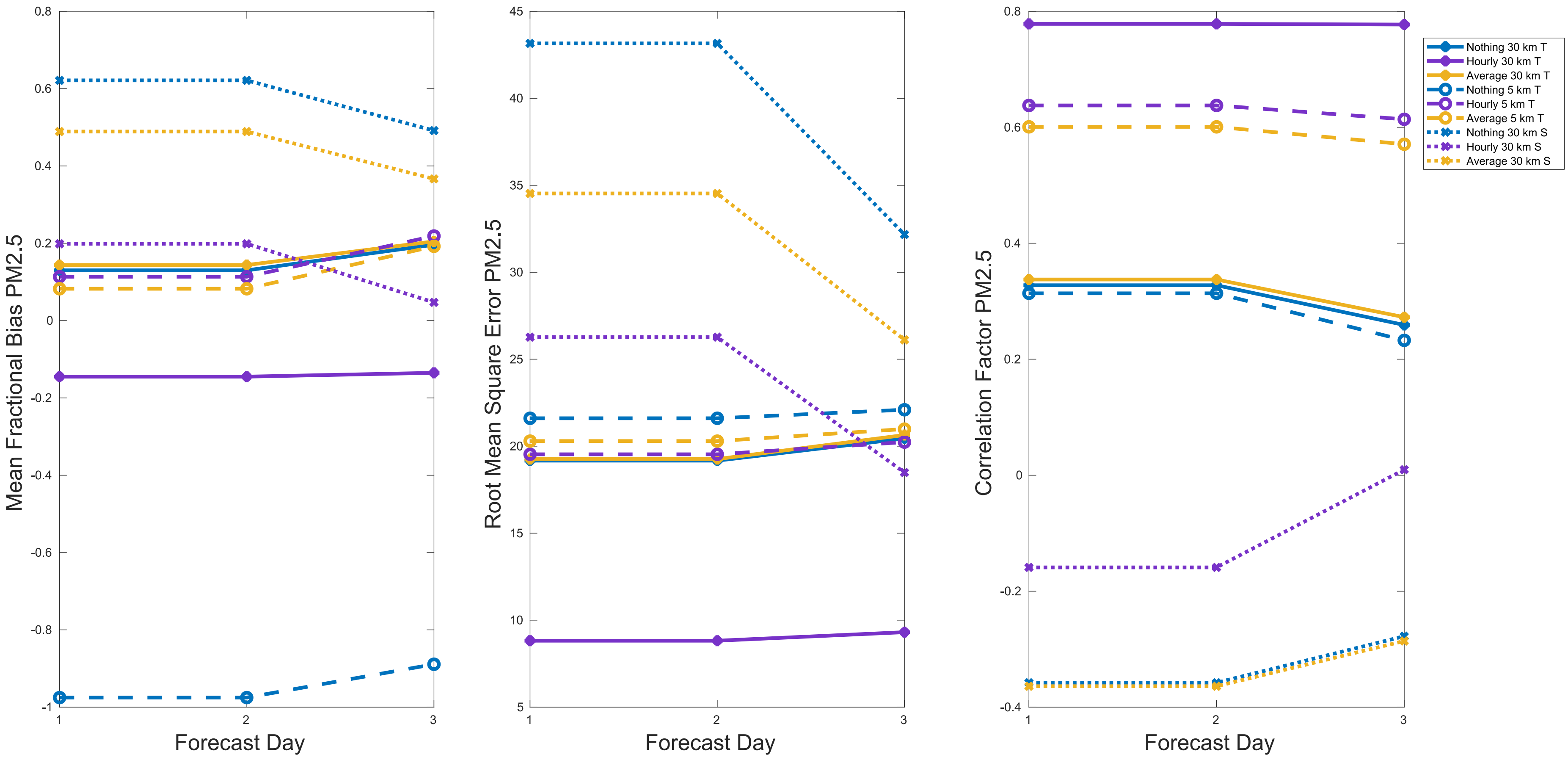
Preliminary Results

PM10



Preliminary Results

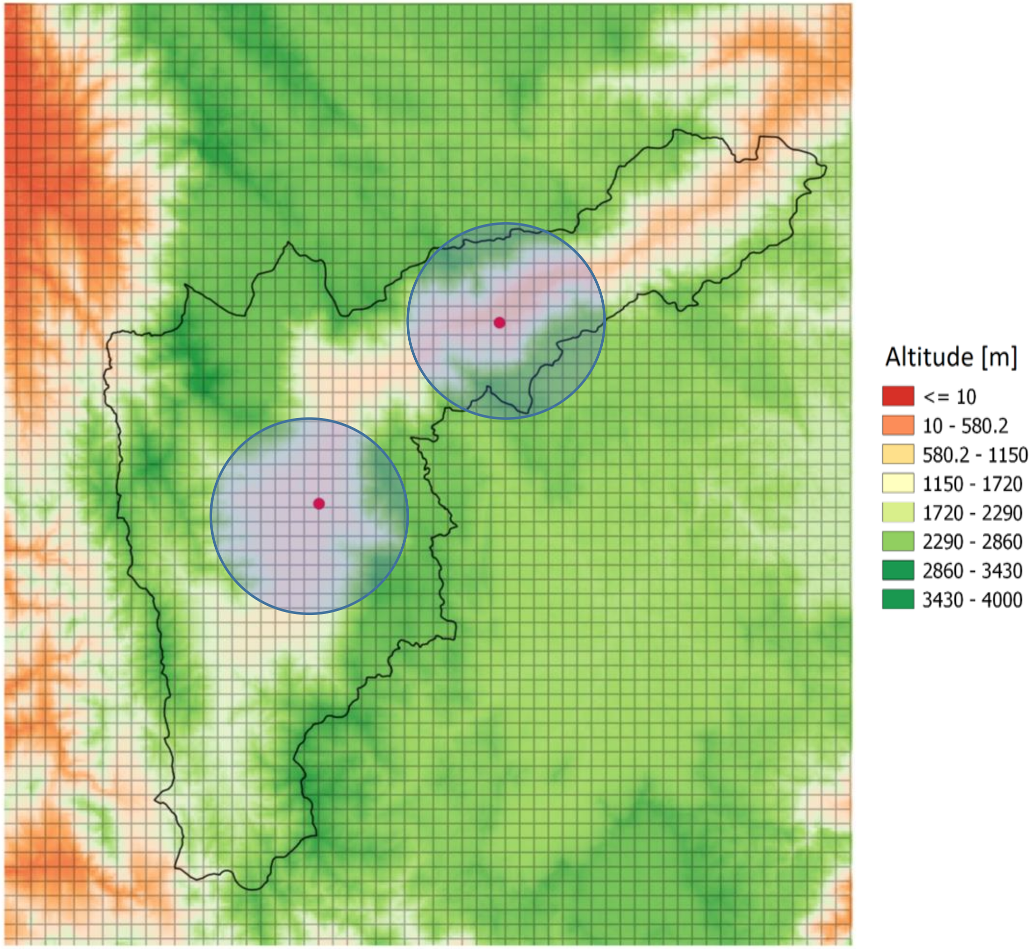
PM2.5



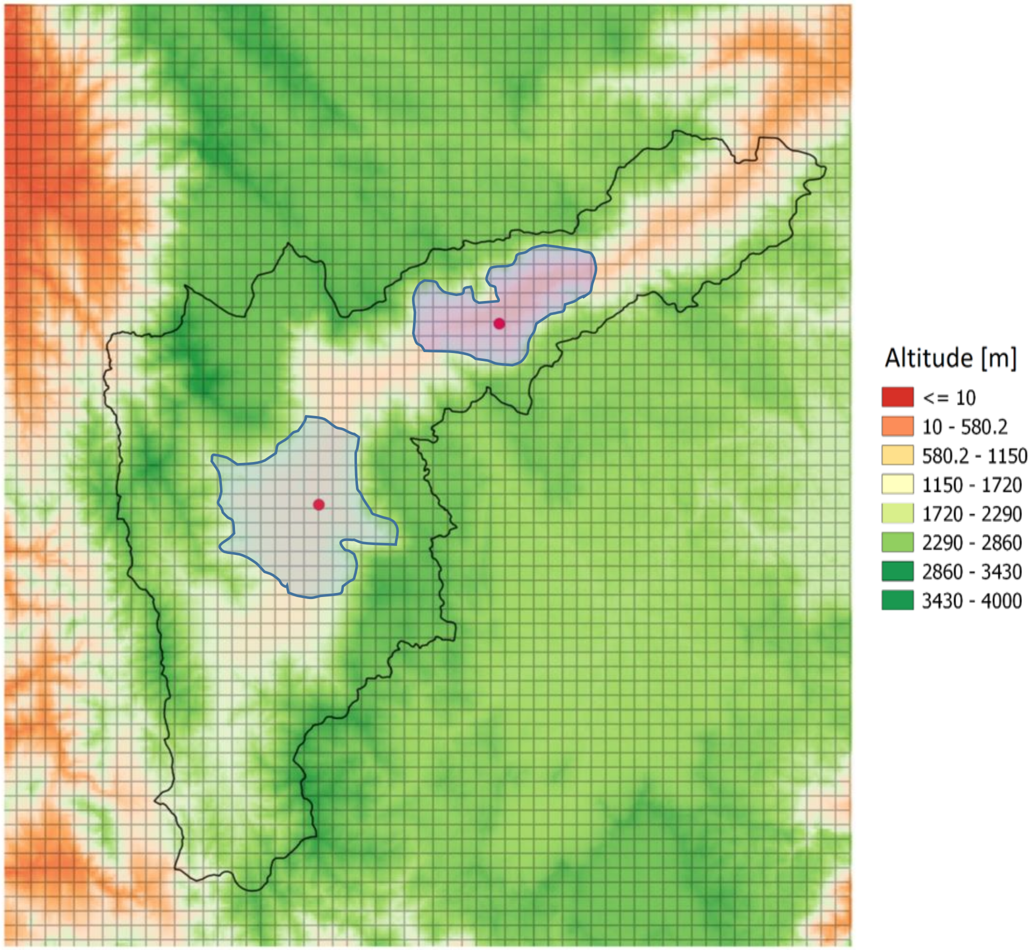
Covariance Estimation Using Knowledge About the System

The idea of the concept would be, how is it possible to incorporate previous information of the system in the covariance estimation?

Covariance Estimation Using Knowledge About the System



Covariance Estimation Using Knowledge About the System



Covariance Estimation Using Knowledge About the System

According with the works (Nino-Ruiz & Sandu, 2015; Nino-Ruiz & Sandu, 2017), using a Shrinkage estimator:

$$\widehat{B} = \lambda \cdot \mu \cdot T + (1-\lambda) \cdot P^b \in R^{N \times N}$$

$$\mu = \frac{\sum_{i=1}^{N-1} \sigma_i^2}{n}$$

$$\lambda = min\left(\frac{\frac{N-2}{n} \cdot \sum_{i=1}^{N-1} \sigma_i^4 + \left[\sum_{i=1}^{N-1} \sigma_i^2\right]^2}{(N+2) \cdot \left[\sum_{i=1}^{N-1} \sigma_i^4 - \frac{\left[\sum_{i=1}^{N-1} \sigma_i^2\right]^2}{n}\right]}, 1 \right)$$

Covariance Estimation Using Knowledge About the System

Localization.
Local analyses methods can be used in the context of the Shrinkage estimator.

Covariance Inflation
It can be seen that inflating each deviation by a factor of ρ has the following effect on

$$\widehat{B} = \lambda \cdot \mu \cdot T + [(1-\lambda) \cdot \rho^2] \cdot P^b \in R^{N \times N}$$

Thank you very much for your attention

Tusen takk for din oppmerksomhet

Heel erg bedankt voor je aandacht

Muchas gracias por su atención

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