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Medellín Air qUality Initiative



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Outline

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Why MAuI

Model Predictive Control

Measurement

Models

Uncertainty reduction

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for life

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Introduction



Marzo 6 2018 9:52 am

Marzo 11 2018 9:53 am

Why MAul?



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WORKSHOP **Atmospheric Pollution and its Impacts**

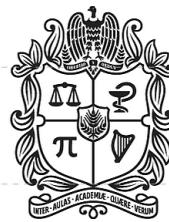


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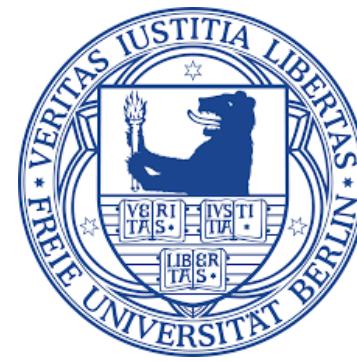
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de MAR DEL PLATA



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VU

VRIJE
UNIVERSITEIT
AMSTERDAM



DRI
Desert Research Institute

Particle Vision
Die Partikelspezialisten

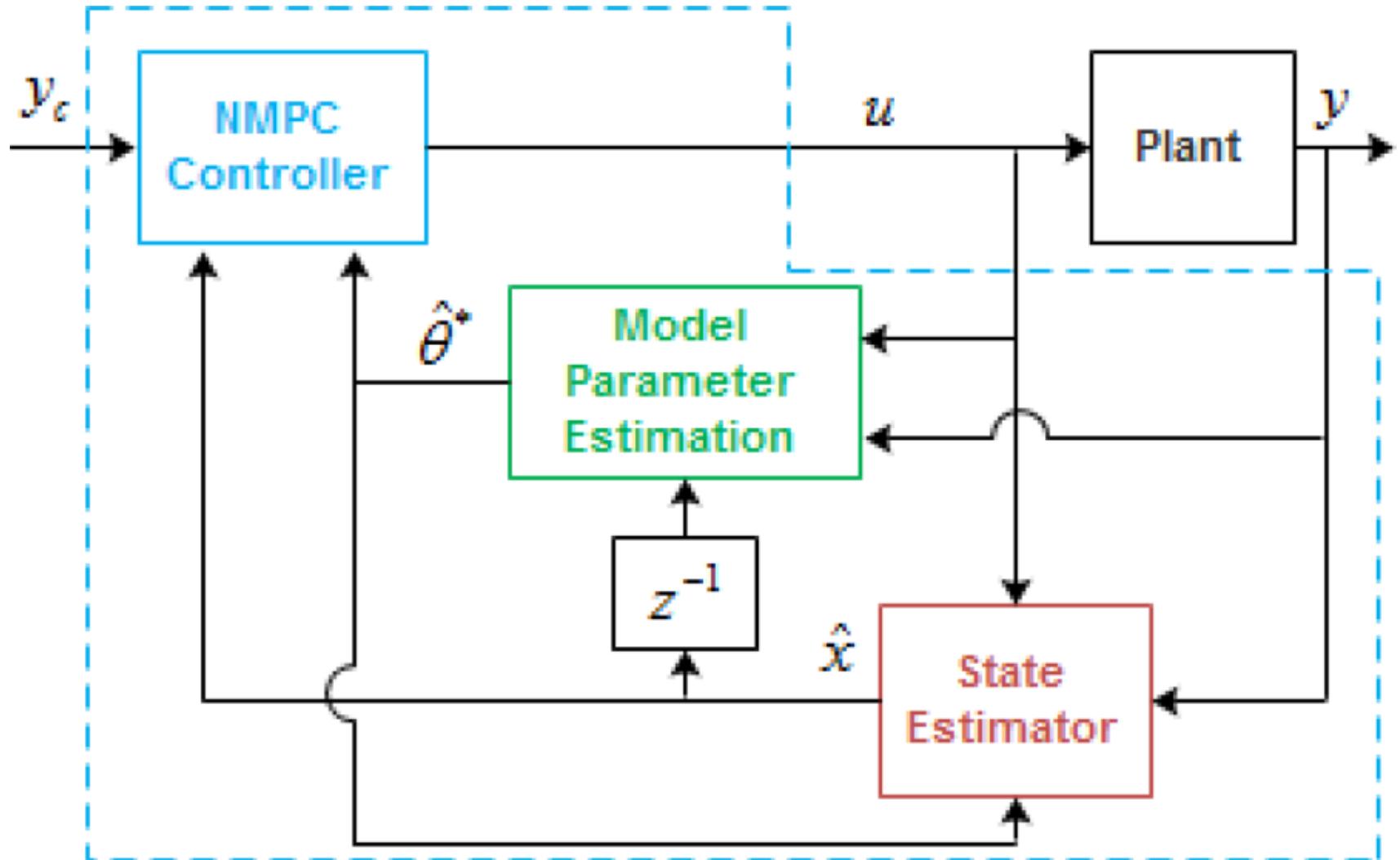
LOUIS BOLK
INSTITUUT

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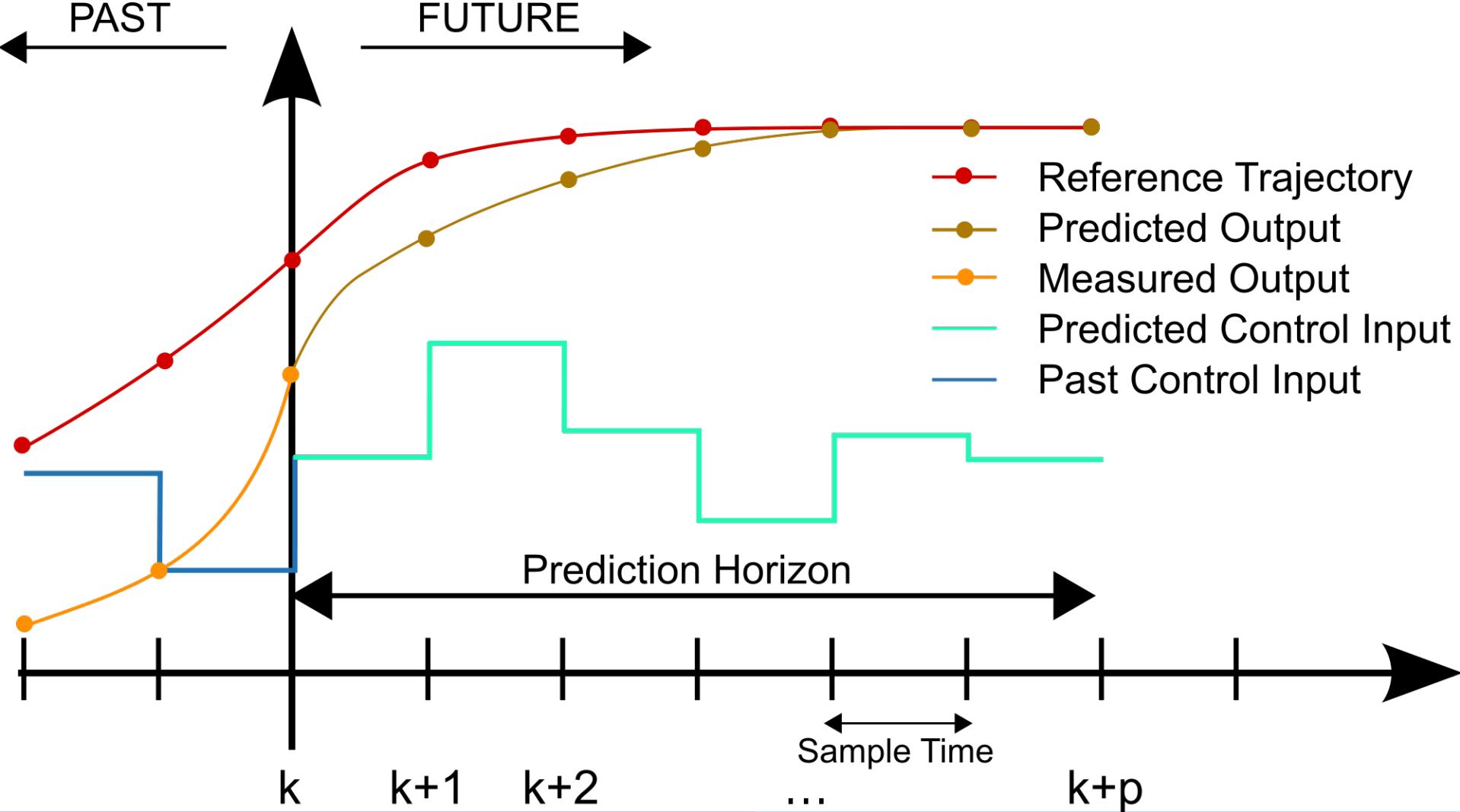
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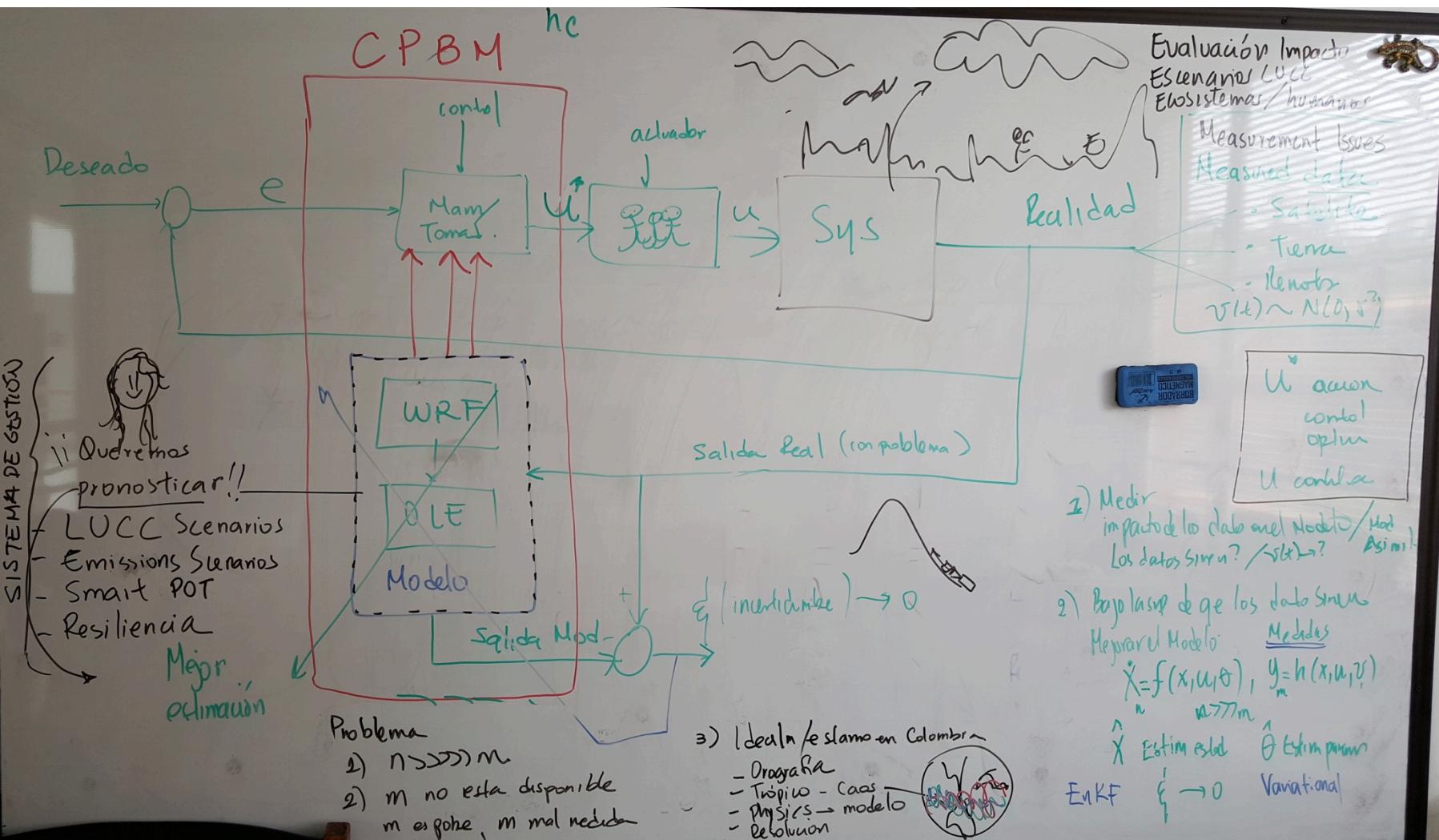
Model Predictive Control



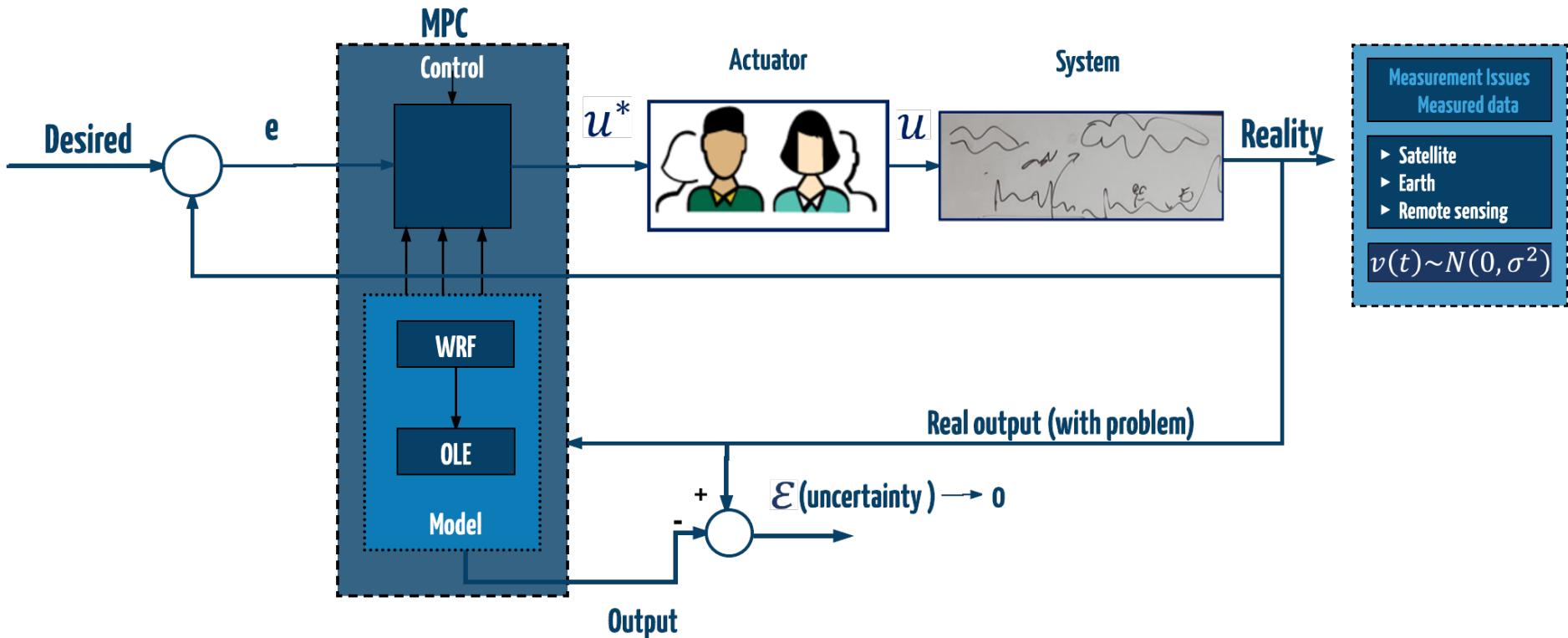
Model Predictive Control



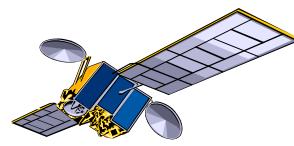
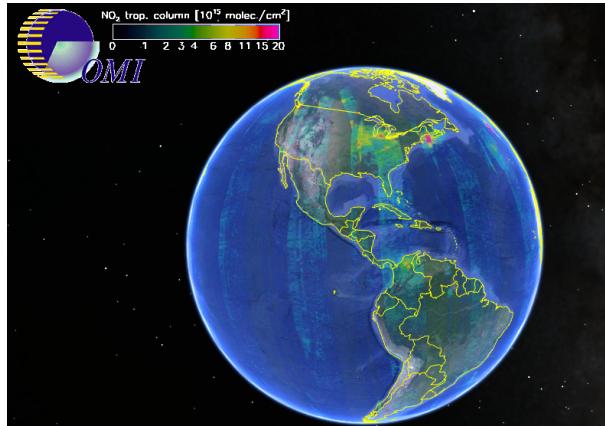
Model Based Predictive Control Scheme



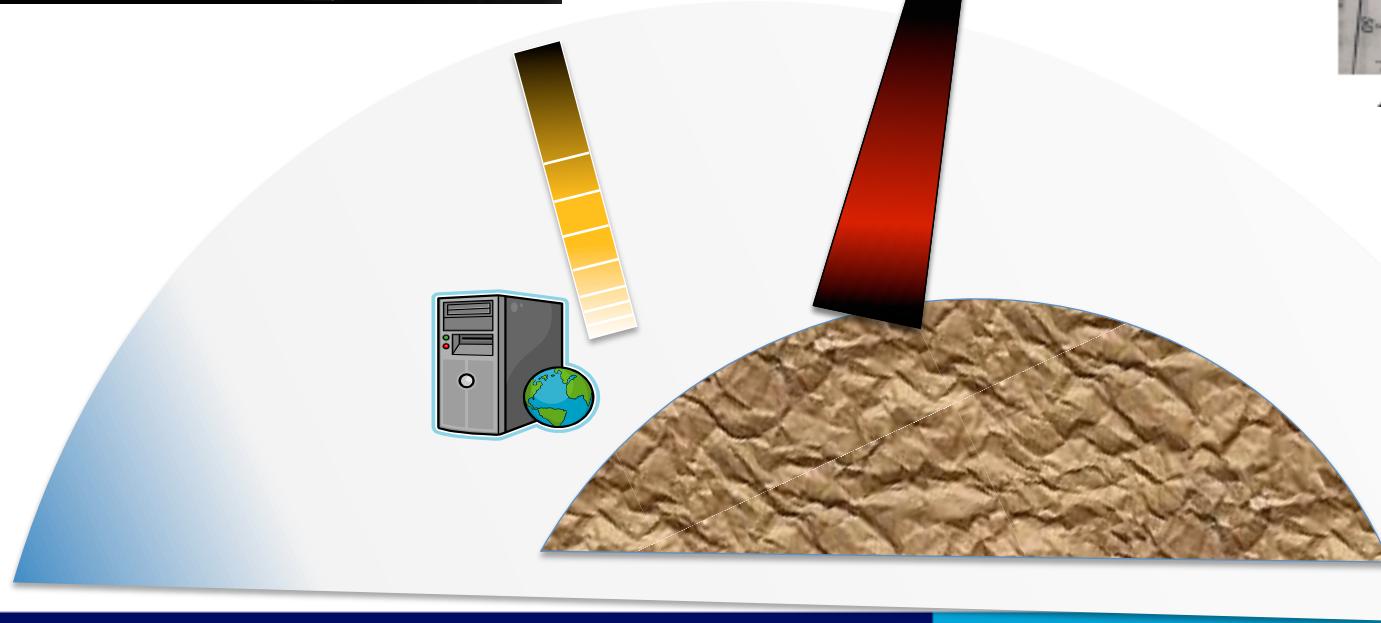
Model Based Predictive Control Scheme



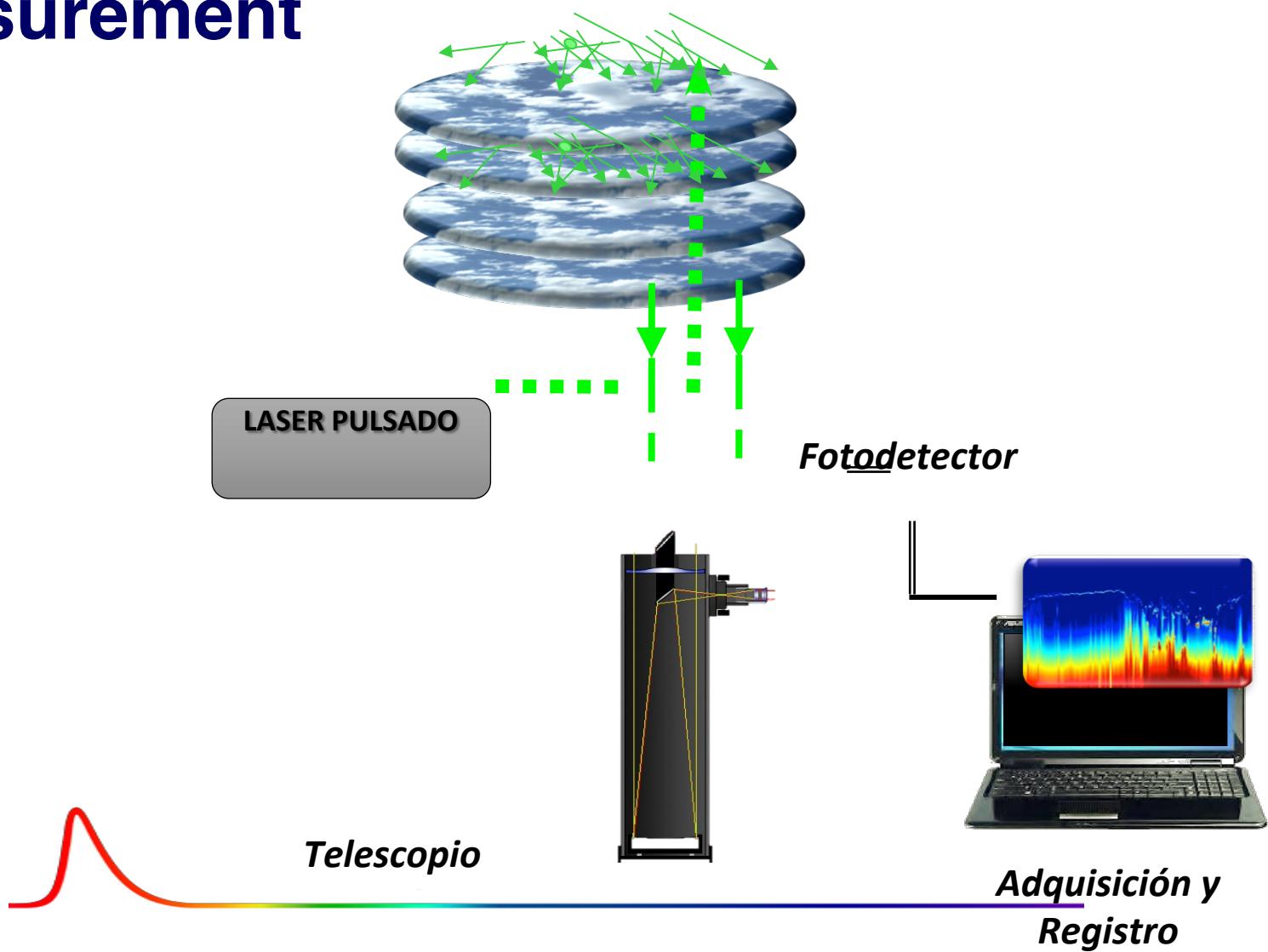
Measurement



Biomonitor
(*Tillandsia r.*)



Measurement



Models

Chemistry transport Model
LOTOS- EUROS

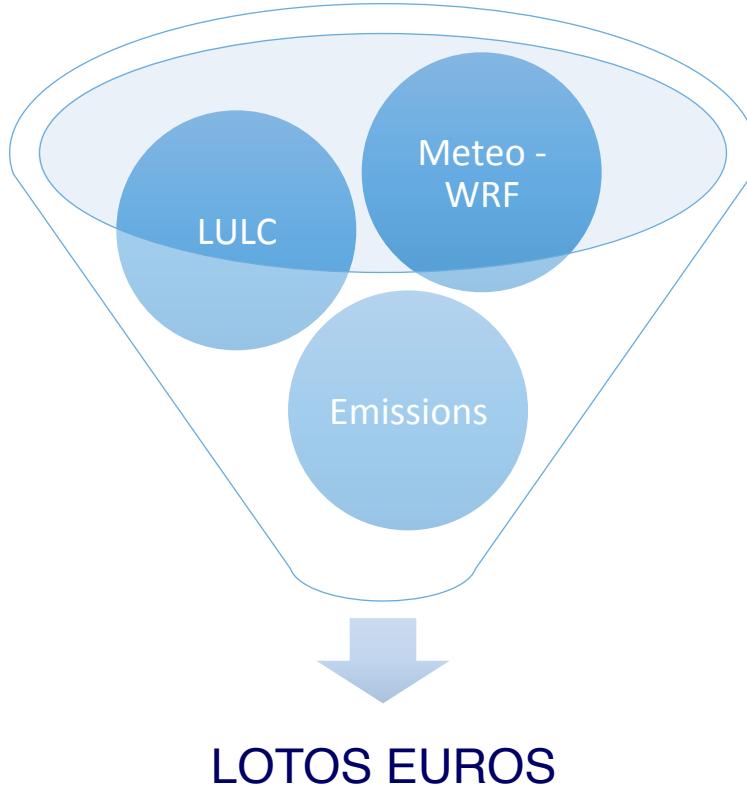
$$\frac{\partial C}{\partial t} + U \frac{\partial C}{\partial x} + V \frac{\partial C}{\partial y} + W \frac{\partial C}{\partial z} = \frac{\partial}{\partial t} \left(K_h \frac{\partial C}{\partial x} \right) + \frac{\partial}{\partial y} \left(K_h \frac{\partial C}{\partial y} \right) + \frac{\partial}{\partial z} \left(K_z \frac{\partial C}{\partial z} \right)$$

$$| + E + R + Q - D - W$$



Models

Chemistry transport Model
LOTOS- EUROS

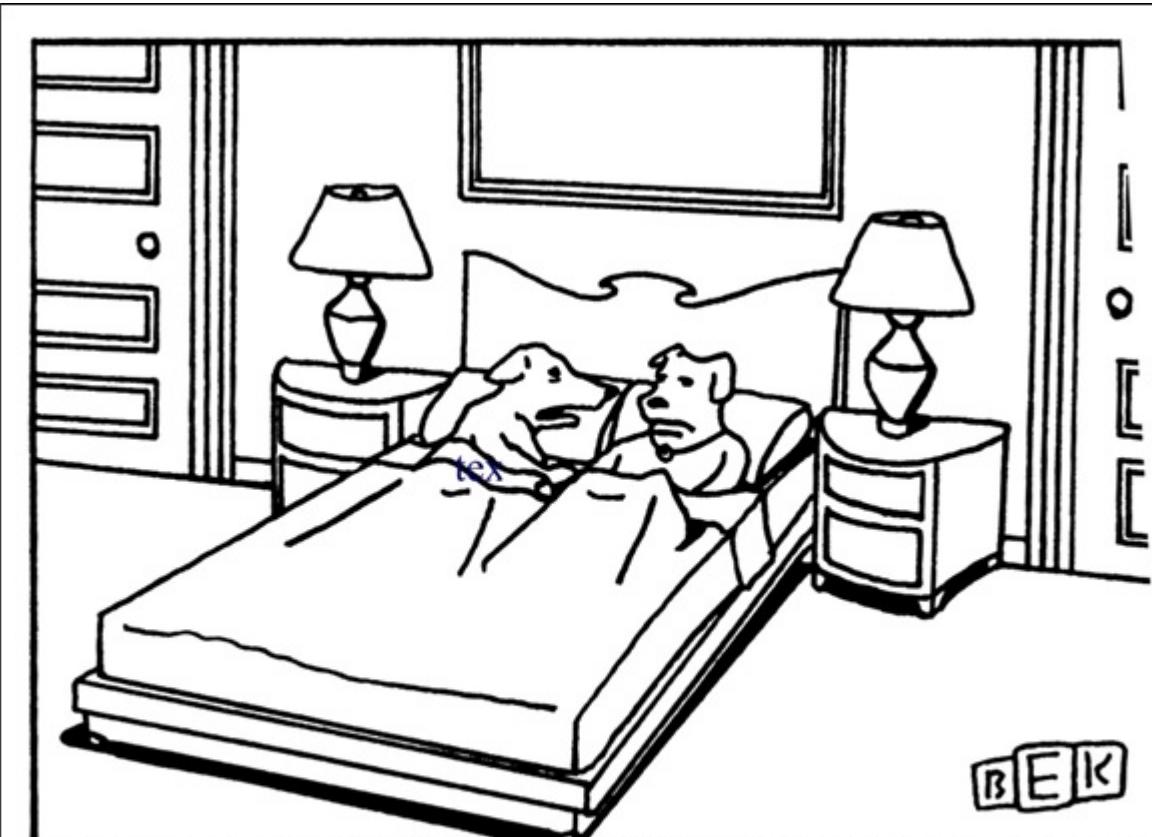


Models

Weather research Forecast WRF

$$\begin{aligned} \partial_t U + m_x [\partial_x(Uu) + \partial_y(Vu)] + \partial_\eta(\Omega u) \\ + (m_x/m_y)(\alpha/\alpha_d) [\mu_d(\partial_x\phi' + \alpha_d\partial_x p' + \alpha'_d\partial_x \bar{p}) + \partial_x\phi(\partial_\eta p' - \mu'_d)] = F_U \\ \partial_t V + m_y [\partial_x(Uv) + \partial_y(Vv)] + (m_y/m_x)\partial_\eta(\Omega v) \\ + (m_x/m_y)(\alpha/\alpha_d) [\mu_d(\partial_x\phi' + \alpha_d\partial_x p' + \alpha'_d\partial_x \bar{p}) + \partial_x\phi(\partial_\eta p' - \mu'_d)] = F_U \\ \partial_t W + (m_x m_y/m_y) [\partial_x(Uw) + \partial_y(Vw)] + \partial_\eta(\Omega w) \\ - m_y^{-1} g(\alpha/\alpha_d) [\partial_\eta p' - \bar{\mu}_d(q_v + q_c + q_r)] + m_y^{-1} \mu'_d g = F_W, \\ \partial_t \mu'_d + m_x m_y [\partial_x U + \partial_y V] + m_y \partial_\eta \Omega = 0 \\ \partial_t \phi' + \mu_d^{-1} [m_x m_y (U \partial_x \phi + V \partial_y \phi) + m_y \Omega \partial_\eta \phi - m_y g W] = 0. \\ \partial_t \Theta + m_x m_y [\partial_x(U\theta) + \partial_y(V\theta)] + m_y \partial_\eta(\Omega\theta) = F_\Theta \\ \partial_t Q_m + m_x m_y [\partial_x(Uq_m) + \partial_y(Vq_m)] + m_y \partial_\eta(\Omega q_m) = F_{Q_m}. \\ \partial_\eta \phi' = -\bar{\mu}_d \alpha'_d - \alpha_d \mu'_d. \end{aligned}$$

Uncertainty Reduction

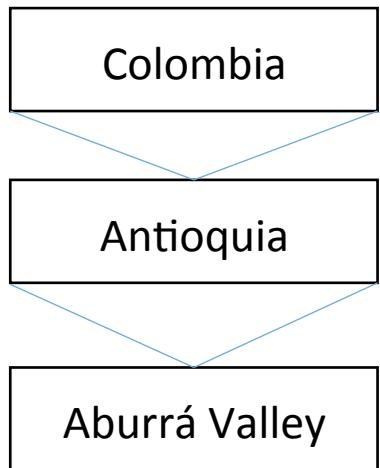


"Since we're both being honest, I should tell you I have fleas."

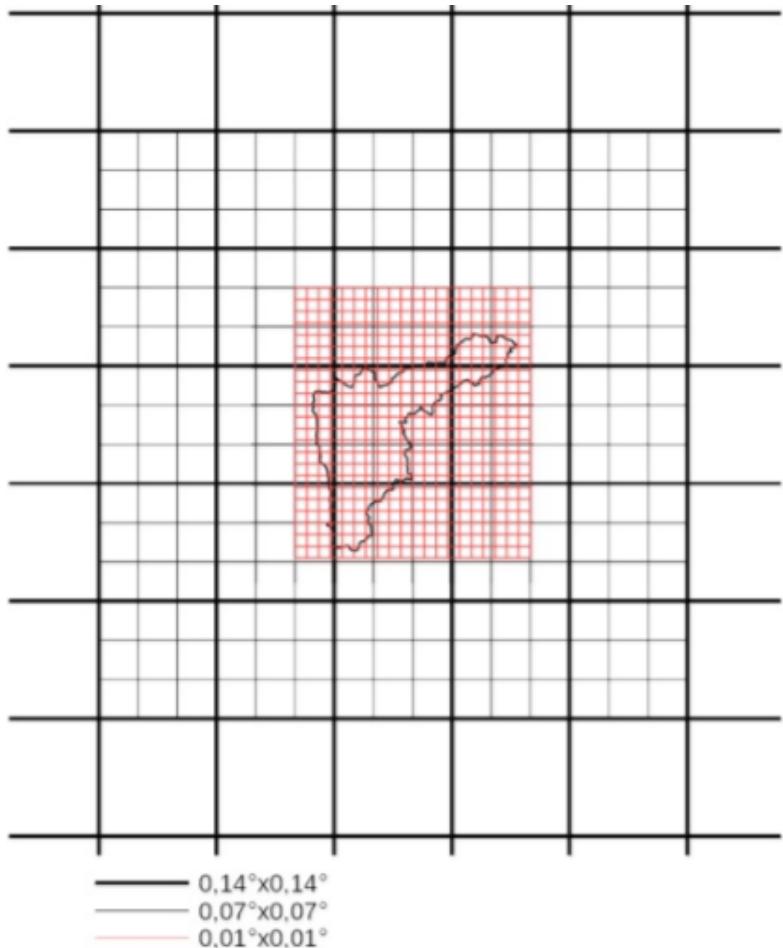
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Modeling and Simulation

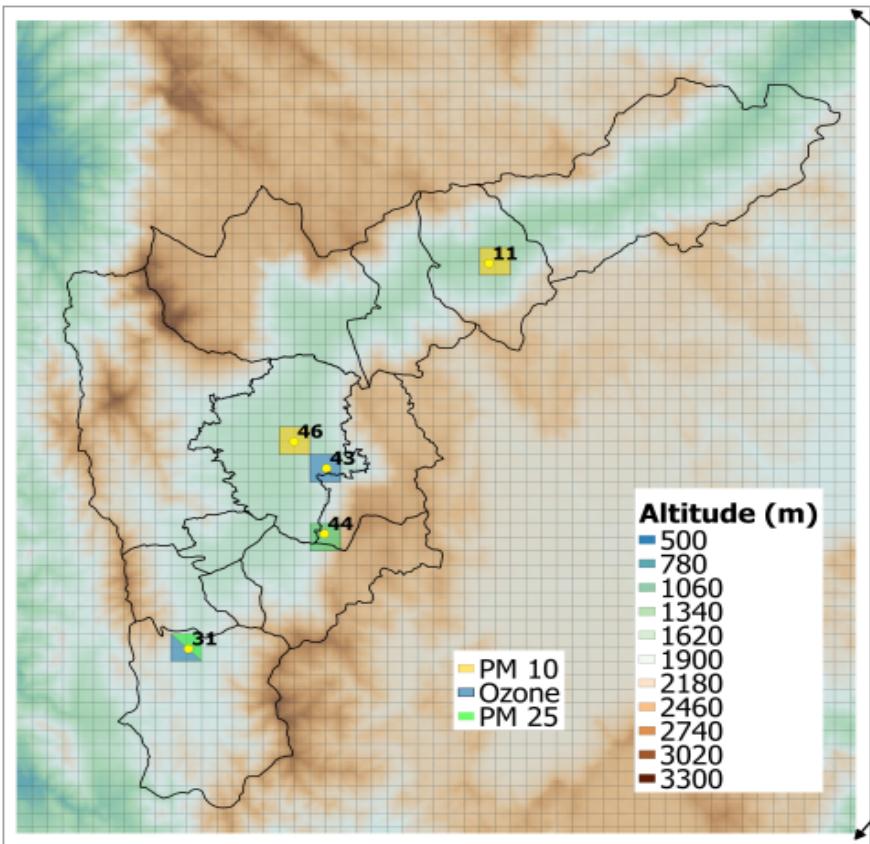
Nested domains



0.7 Degrees 77.86 Km Long x 77,71 Km Lat
0.14 Degrees 15.6 Km Long x 15,4 Km Lat
0.07 Degrees 7.8 Km Long x 7,7 Km Lat
0.01 Degrees 1.11 Km Long x 1,1 Km Lat

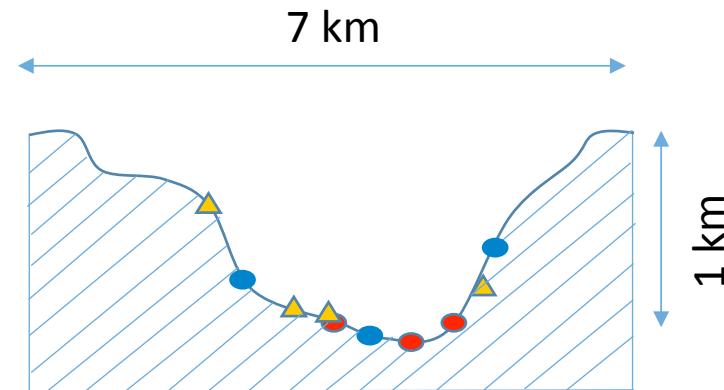


Model assimilation for Medellín



Topographical map of the region under study, showing the political boundaries of the Aburrá Valley cities.

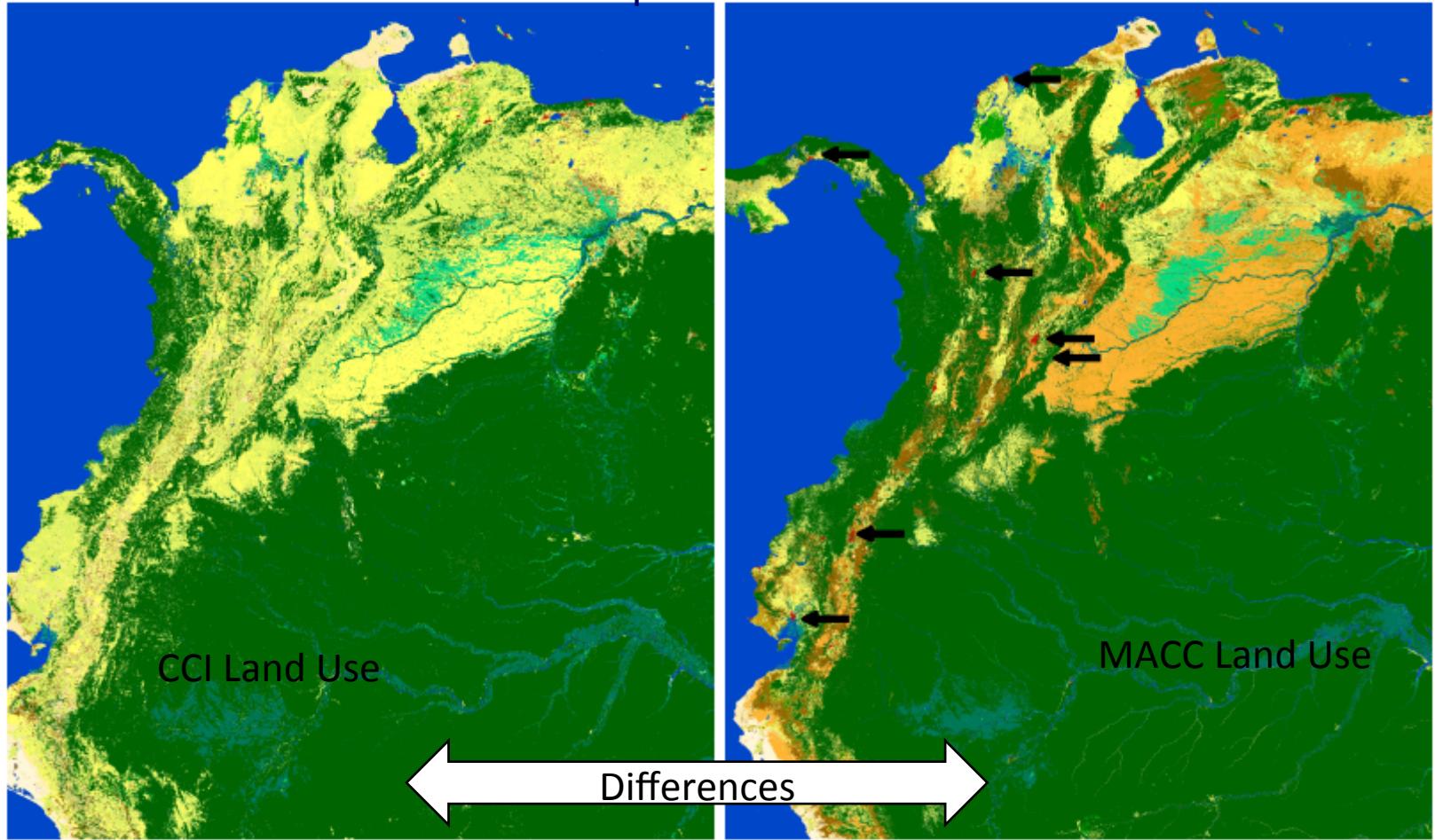
Topographical characteristic of Aburrá deep-seated mountain valley



- ▲ Citizens
- Ground based measurements
- Roads

Sources of uncertainty of L.E in Colombia

Inputs Land Use/ Land Cover to be updated



Data assimilation relies on the use of an extension for high dimensional systems of the classical approach for filtering called the Kalman Filter

$$\mathbf{x}_k = \mathcal{M}_{k,k-1}(\mathbf{x}_{k-1}) + \mathbf{u}_k,$$

$$\mathbf{y}_k = \mathcal{H}_k(\mathbf{x}_k) + \mathbf{v}_k.$$

$$\mathbf{x}_k \in \mathbb{R}^{m_x} \quad \mathbf{y}_k \in \mathbb{R}^{m_y} \quad \mathbf{u}_k \in \mathbb{R}^{m_x} \quad \mathbf{v}_k \in \mathbb{R}^{m_y}$$

$$\mathcal{M}_{k,k-1}: \mathbb{R}^{m_x} \rightarrow \mathbb{R}^{m_x} \quad \mathcal{H}_k: \mathbb{R}^{m_x} \rightarrow \mathbb{R}^{m_y}$$

[Evensen, 2009] \mathbf{u}_k and \mathbf{v}_k are independent white noise

The EnKF is a modification that uses Monte Carlo approach to estimate the minimum variance solution to the state estimation problem.

At the analysis step in the EnKF, an ensemble of the system state, is generated with sample mean and covariance as the analysis state and error covariance matrix with the ensemble n typically much smaller than the dimension mx in large scale applications.

$$\mathbf{X}_{k-1}^a = \{\mathbf{x}_{k-1,i}^a : i = 1, 2, \dots, n\}$$

By propagating the analysis ensemble through the transition operator, we obtain forecast ensemble at the next data assimilation cycle.

$$\mathbf{X}_k^f = \{\mathbf{x}_{k,i}^f : \mathbf{x}_{k,i}^f = \mathcal{M}_{k-1,k}(\mathbf{x}_{k-1,i}^a) + \mathbf{u}_{k,i}, i = 1, 2, \dots, n\}$$

When a new observation is available, the analysis step is used to compute the analysis ensemble from its forecast counterpart based on the sample covariance matrix of the forecast ensemble.

Two types of data assimilation:

- Related to the Ensemble Kalman filter for state estimation

$$\mathbf{x}_{k,i}^a = \mathbf{x}_{k,i}^f + \mathbf{K}_k [\mathbf{y}_{k,i}^s - \mathcal{H}_k(\mathbf{x}_{k,i}^f)], \quad \text{for } i = 1, 2, \dots, n,$$

$$\mathbf{K}_k = \hat{\mathbf{P}}_k^{xy} (\hat{\mathbf{P}}_k^{yy} + \mathbf{R}_k)^{-1},$$

$$\hat{\mathbf{S}}_k^f = \frac{1}{\sqrt{n-1}} [\mathbf{x}_{k,1}^f - \hat{\mathbf{x}}_k^f, \dots, \mathbf{x}_{k,n}^f - \hat{\mathbf{x}}_k^f],$$

$$\hat{\mathbf{S}}_k^{yy} = \frac{1}{\sqrt{n-1}} [\mathbf{y}_{k,1}^f - \hat{\mathbf{y}}_k^f, \dots, \mathbf{y}_{k,n}^f - \hat{\mathbf{y}}_k^f],$$

$$\mathbf{x}_{k,i}^a = \hat{\mathbf{x}}_k^a + \sqrt{n} (\mathbf{L}_k \mathbf{C}_k \boldsymbol{\Xi}_k)_i, \quad \text{for } i = 1, \dots, n$$

$$(\delta \mathbf{x}_{k,i})_j = (\hat{p}_{xy,k}^j / \hat{p}_{yy,k}^f) \delta y_{k,i}, \quad j = 1, \dots, m_x,$$

- Variational methods for the parameter estimation

$$X(t_{i+1}) = M_i X(t_i), \quad i = 1, \dots, m-1, \quad X(t_{i+1}) \in \Re^n$$

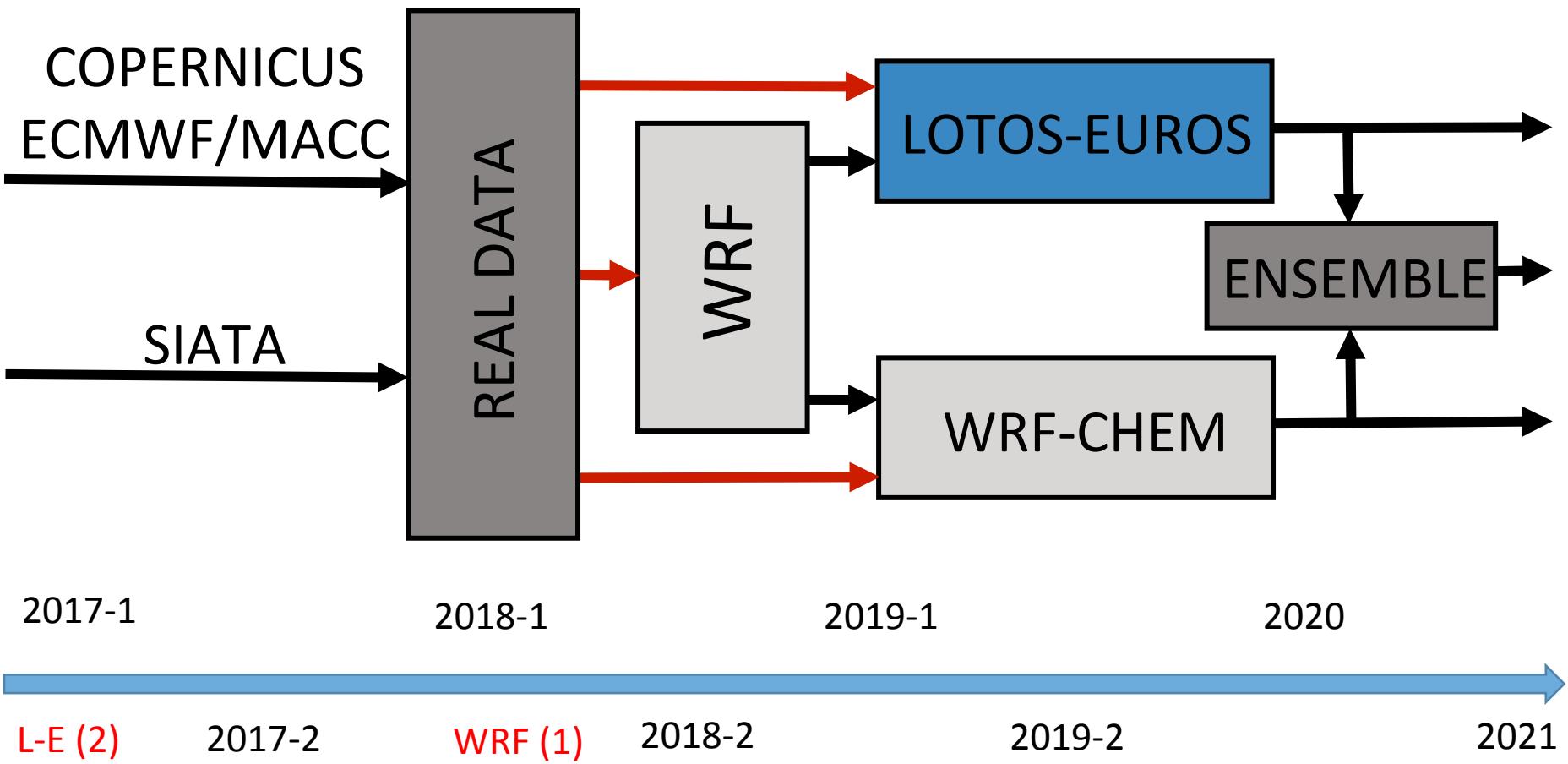
$$Y(t_i) = H(X(t_i)) + \eta(t_i), \quad H : \Re^n \rightarrow \Re^q$$

$$\begin{aligned} J(X_0) = & \frac{1}{2} (X^b - X_0)^T B_0^{-1} (X^b - X_0) + \frac{1}{2} \sum_i (Y(t_i) \\ & - H(X(t_i)))^T R_i^{-1} (Y(t_i) - H(X(t_i))), \end{aligned}$$

[Barbu 2010, Krymskaya, 2013, Sebacher, 2014, Altaf 2015, Fu et al, 2015, Lu et al, 2015, Krymskaya, 2013, Tijana et al, 2014 Verlaan and Sumihar, 2016]

Ensemble-Based twin experiments

Localization and impact quantification strategies



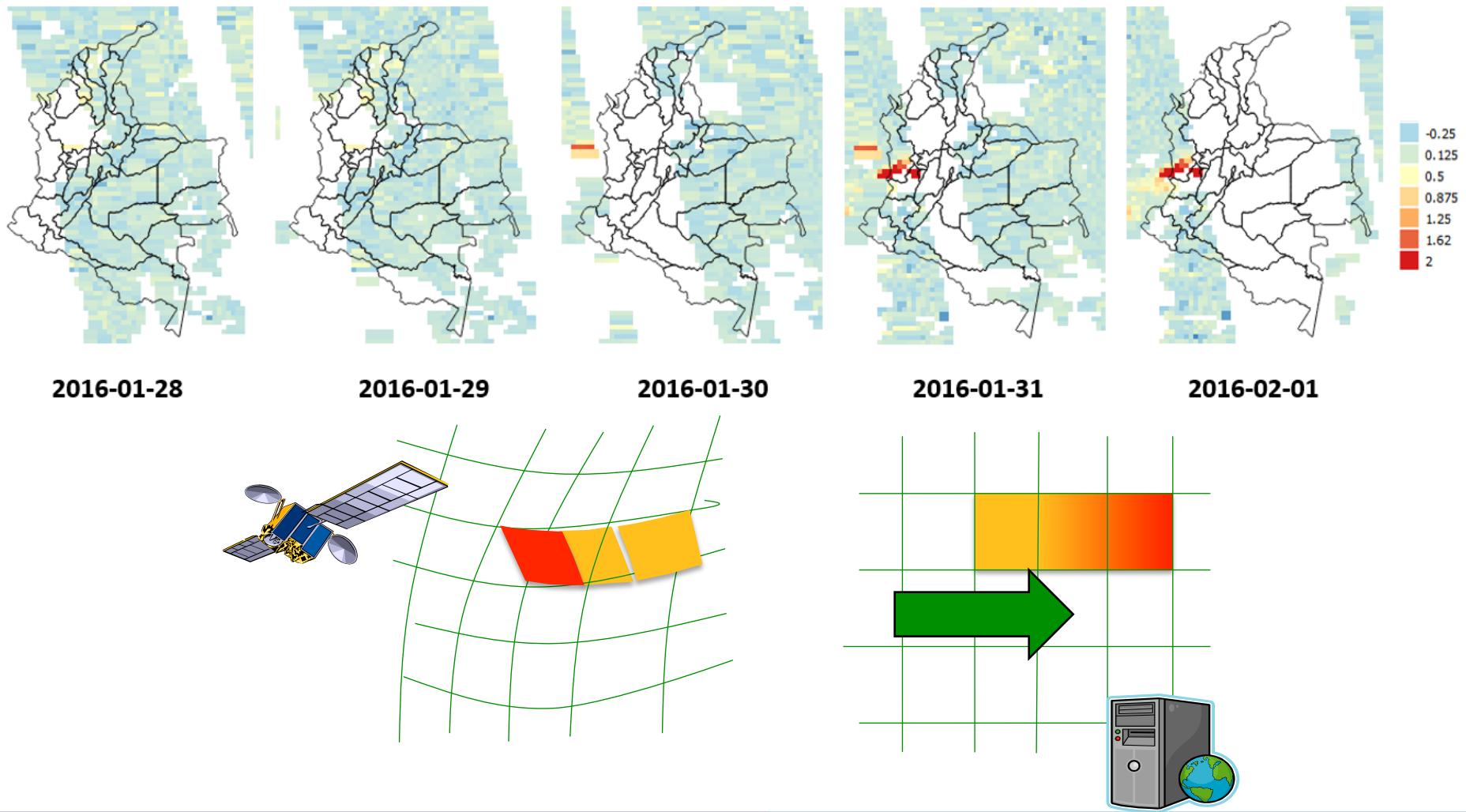
Challenges



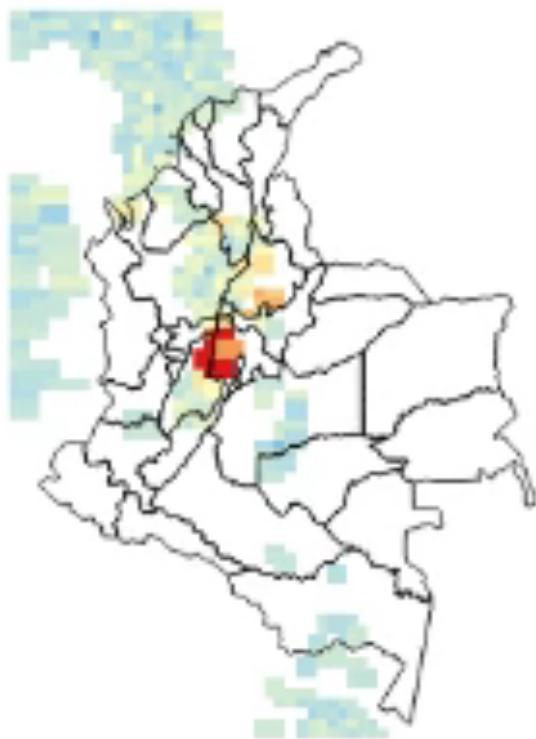
Spatial resolution: $\sim 25 \text{ km} \times 25 \text{ km}$

Temporal resolution: 1 image per day of the same point,
sun-synchronous orbit, 1:40 pm nadir capture over Colombia

Challenges



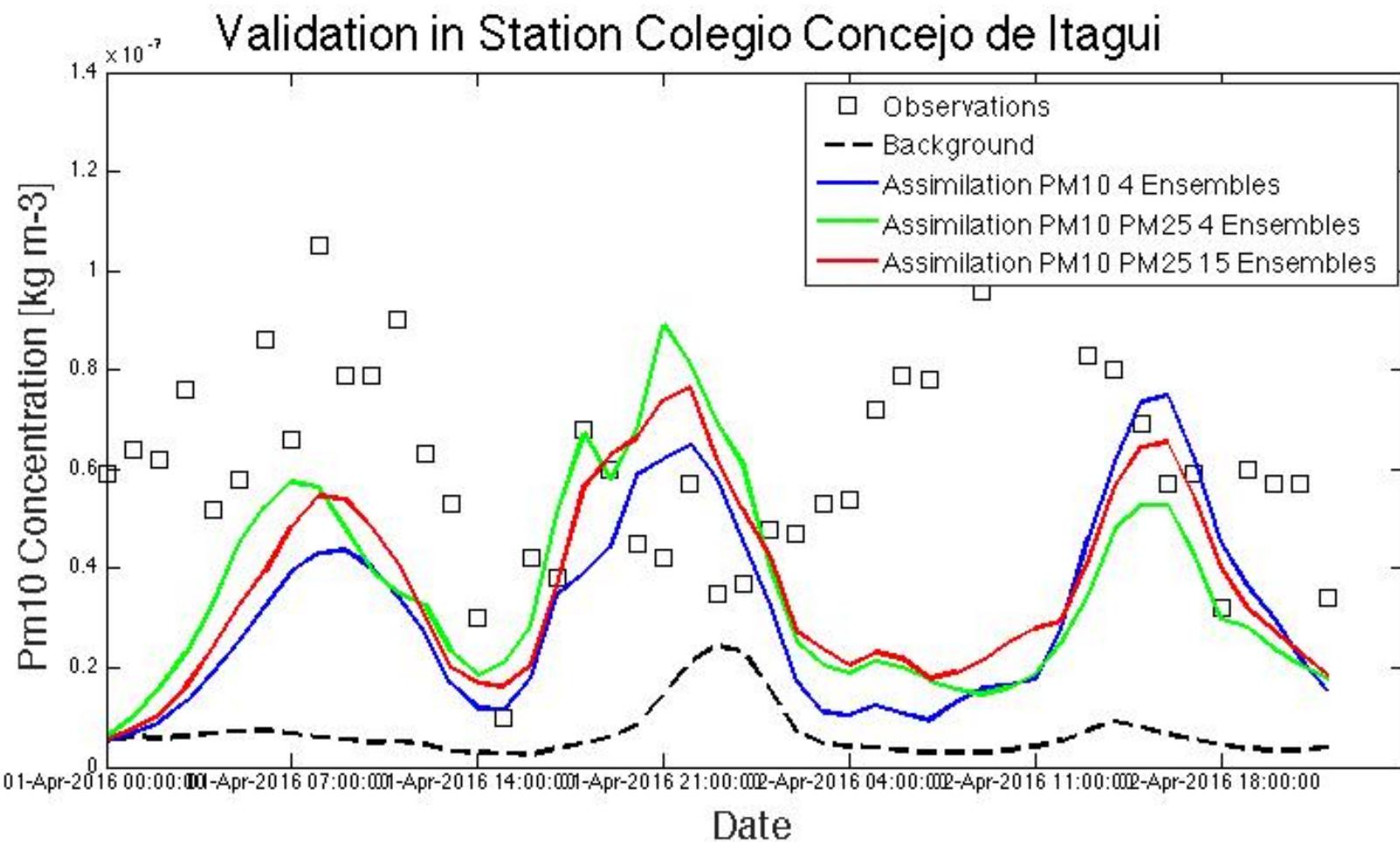
Challenges



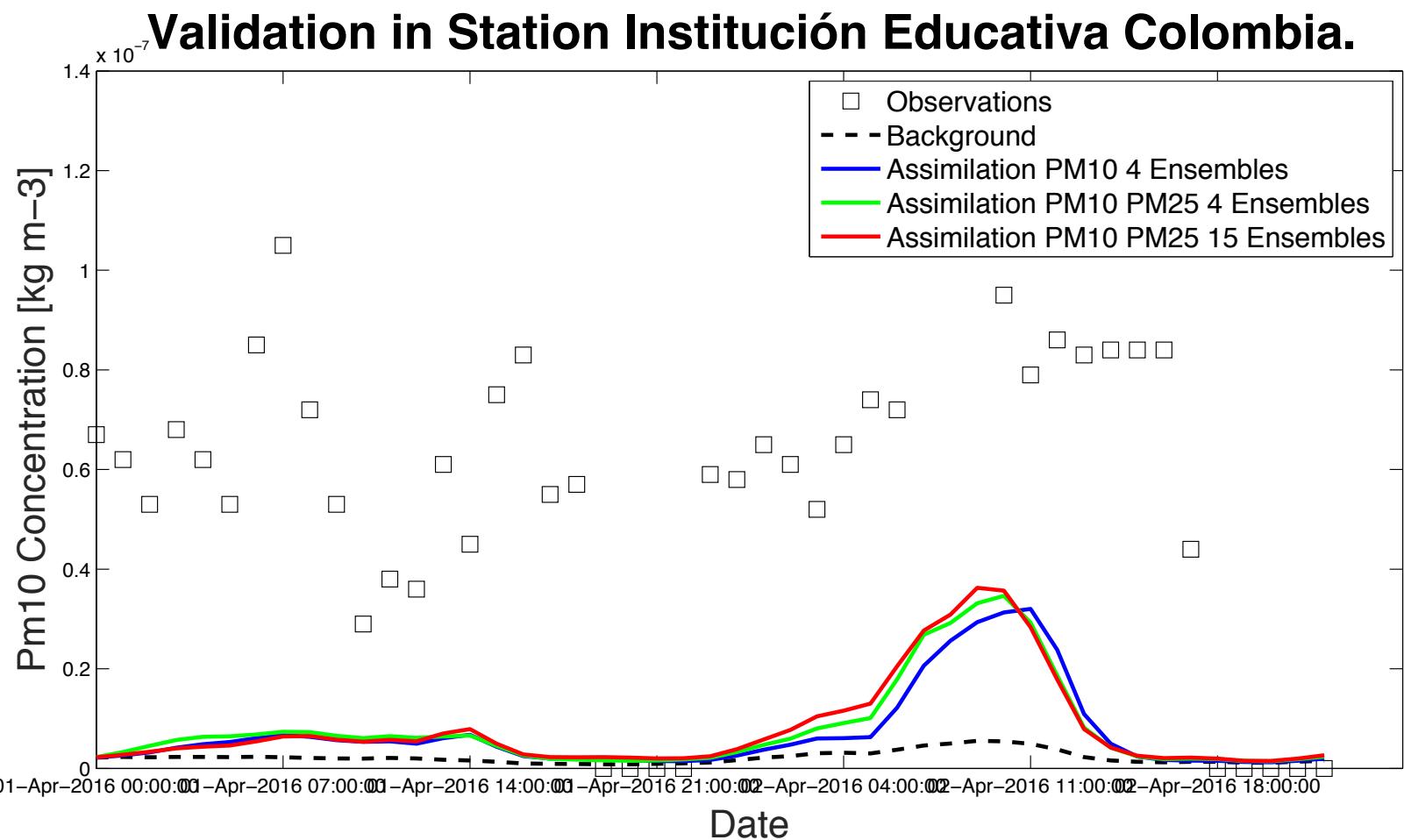
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SO₂ OMI data example

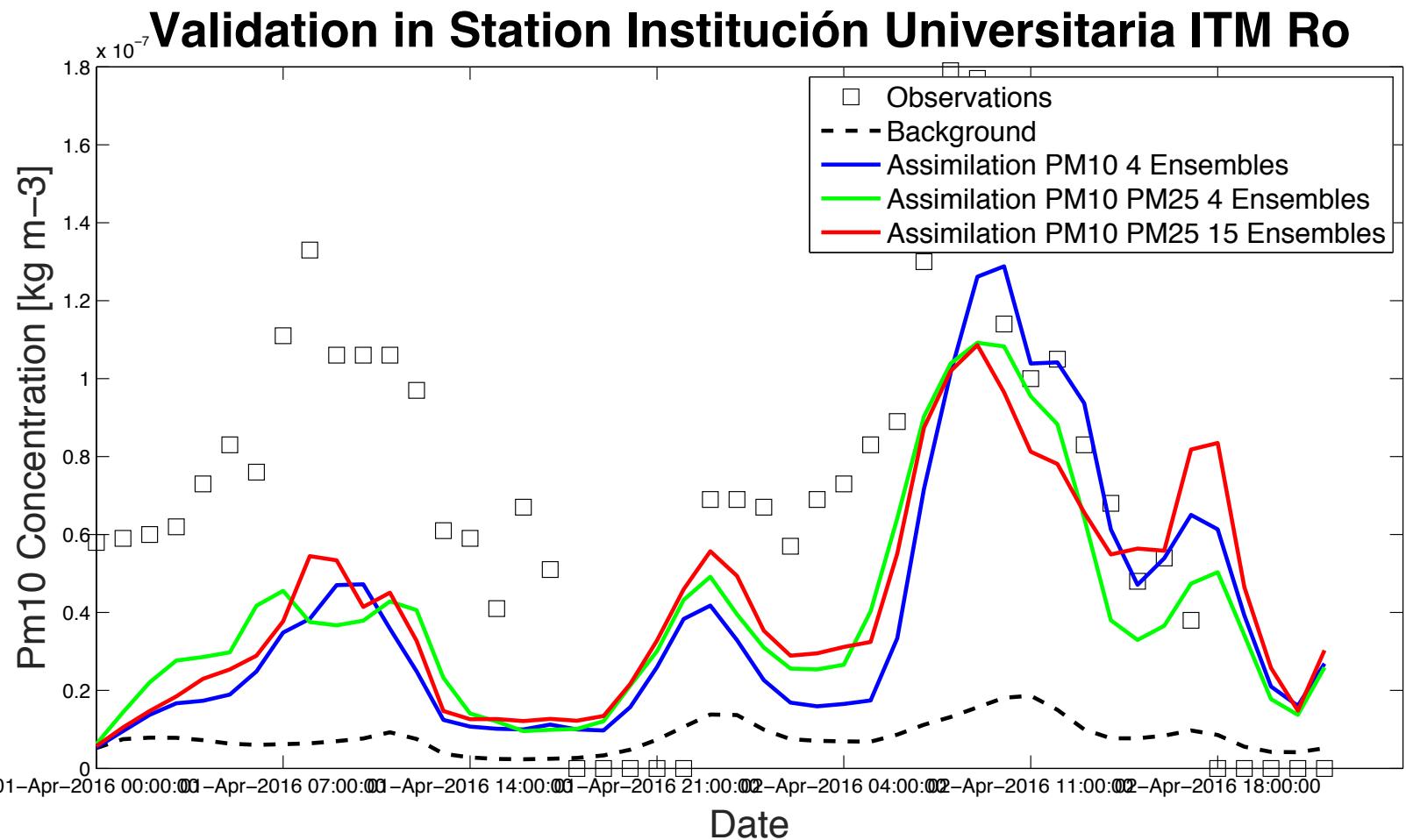
Conclusions



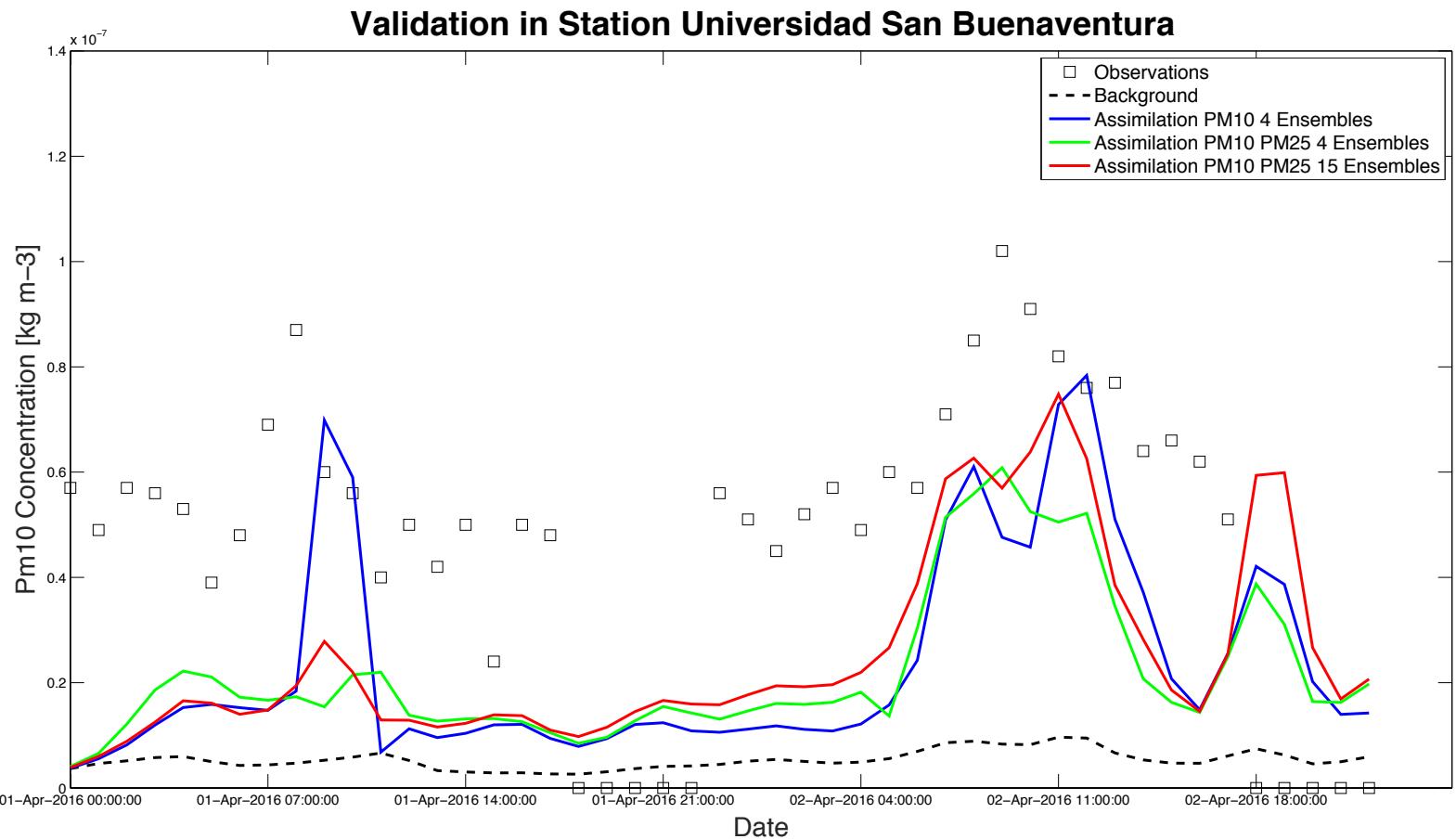
Conclusions



Conclusions



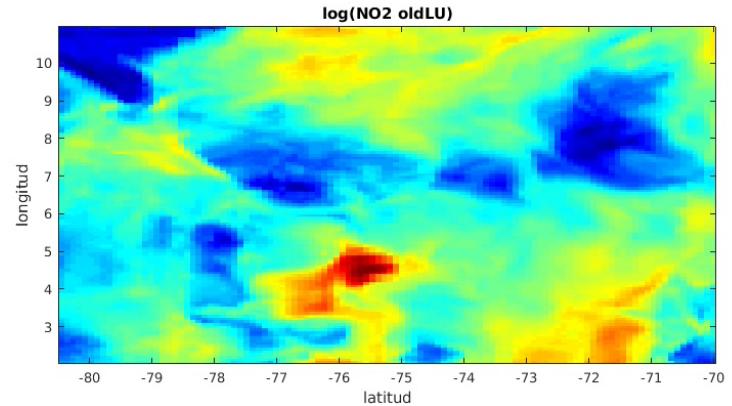
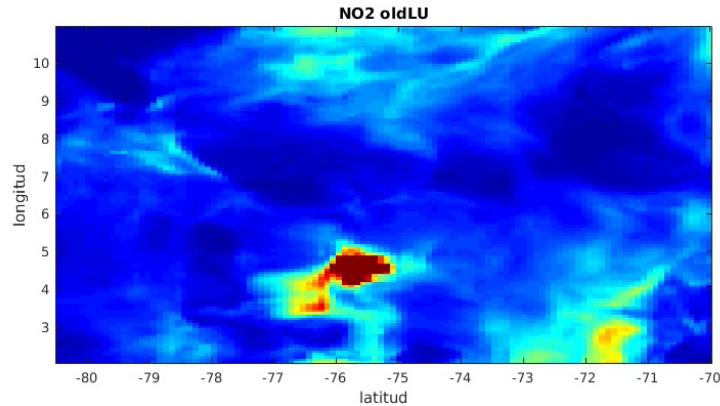
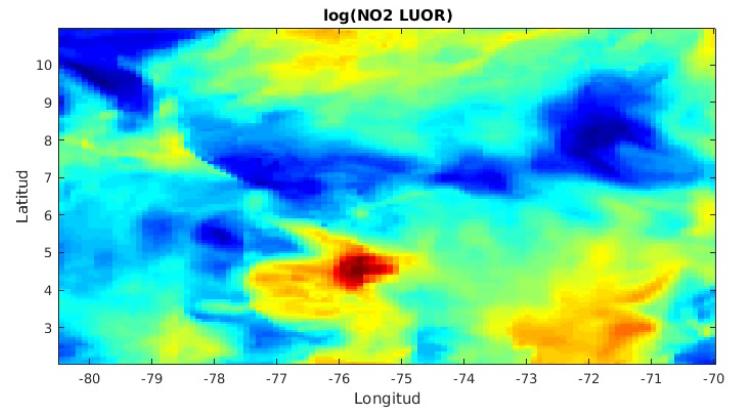
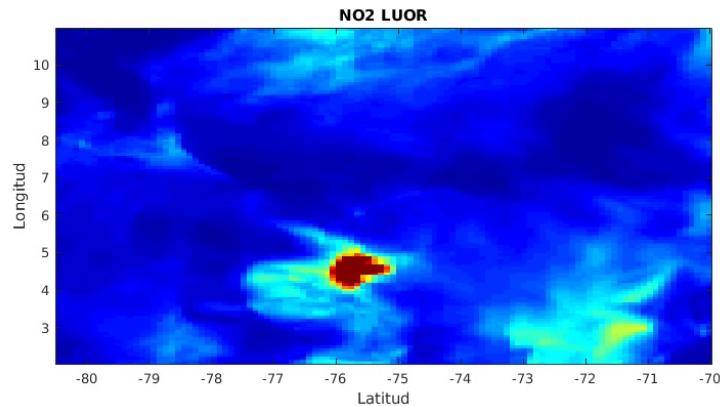
Conclusions



Conclusions

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File New Open Save All Save As Print Preview Exit

Figure 1



Conclusions

LOTOS-EUROS Coupling with a meteorological model like WRF. The WRF model is currently implemented in the region for the GIGA Research Group of the Universidad de Antioquia.

WRF is able to do a representation of the meteorology in a higher resolution than the databases available for the region.

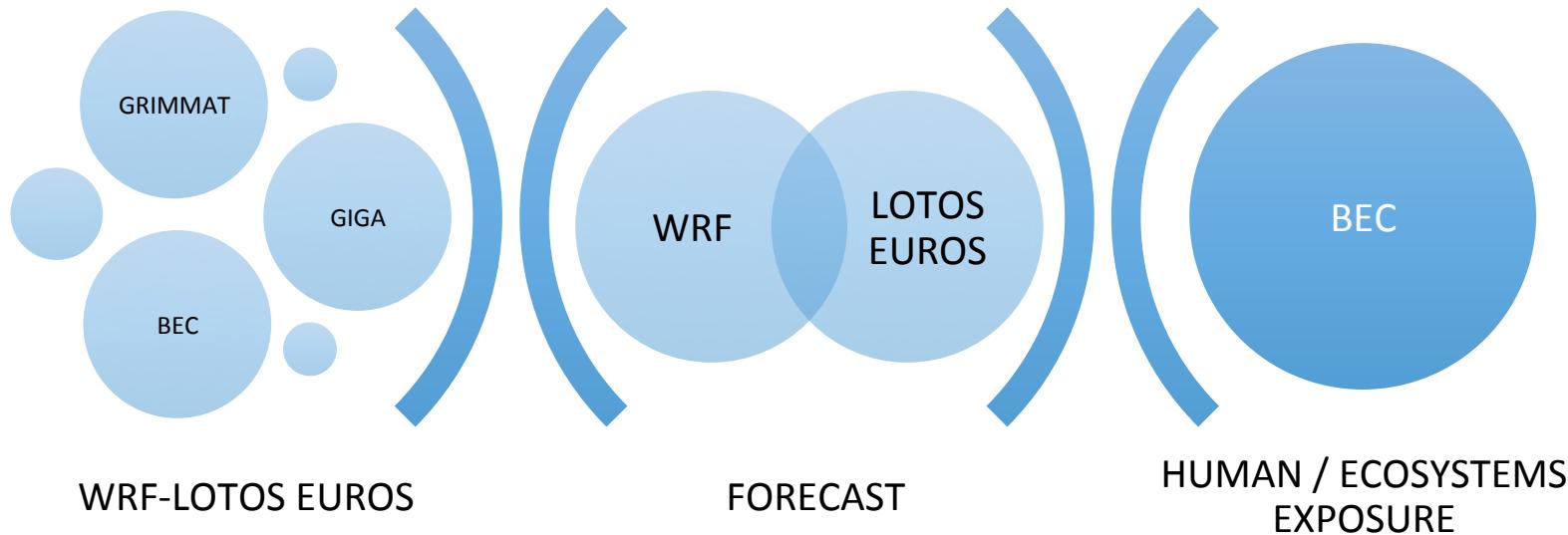
Data Assimilation and integration with Traffic models



Scale-FreeBack

Advanced Grant 2015

**Scale-Free Control for Complex
Physical Network Systems**



Thanks



Thanks

CENTRO DE COMPUTACIÓN CIENTÍFICA APOLO – Pineda,
Mateo y Andrés!

DIRECCIÓN DE INFORMÁTICA – Delio y Hugo!

Thank you all!

