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Data Assimilation Schemes in Colombian Geodynamics - Cooperative Research Plan for 2017 -2020 Between Universidad EAFIT and TUDelft

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Outline

- Introduction & Research relevance
  - Environmental Emergency (Contingency) 2016
  - Air Quality & Pollution
  - Air Quality Monitoring & Modeling (Valle de Aburrá)
- Theoretical framework
- Research Proposal

Environmental Emergency (a.k.a. Contingency)

Medellin, Mar-Apr 2016

Environmental Emergency (a.k.a. Contingency)

Medellin - Mar 18-Apr 19, 2016

- $PM_{2.5}$ > 125 µg/m^3
  (WHO guidelines max. 25 µg/m^3)
- Days without car & motorcycles
- Restricted truck (*volquetas*) movement
- Cease of outdoor activities
- Regional rush hour traffic restrictions (*pico y placa*)
- Free Metro

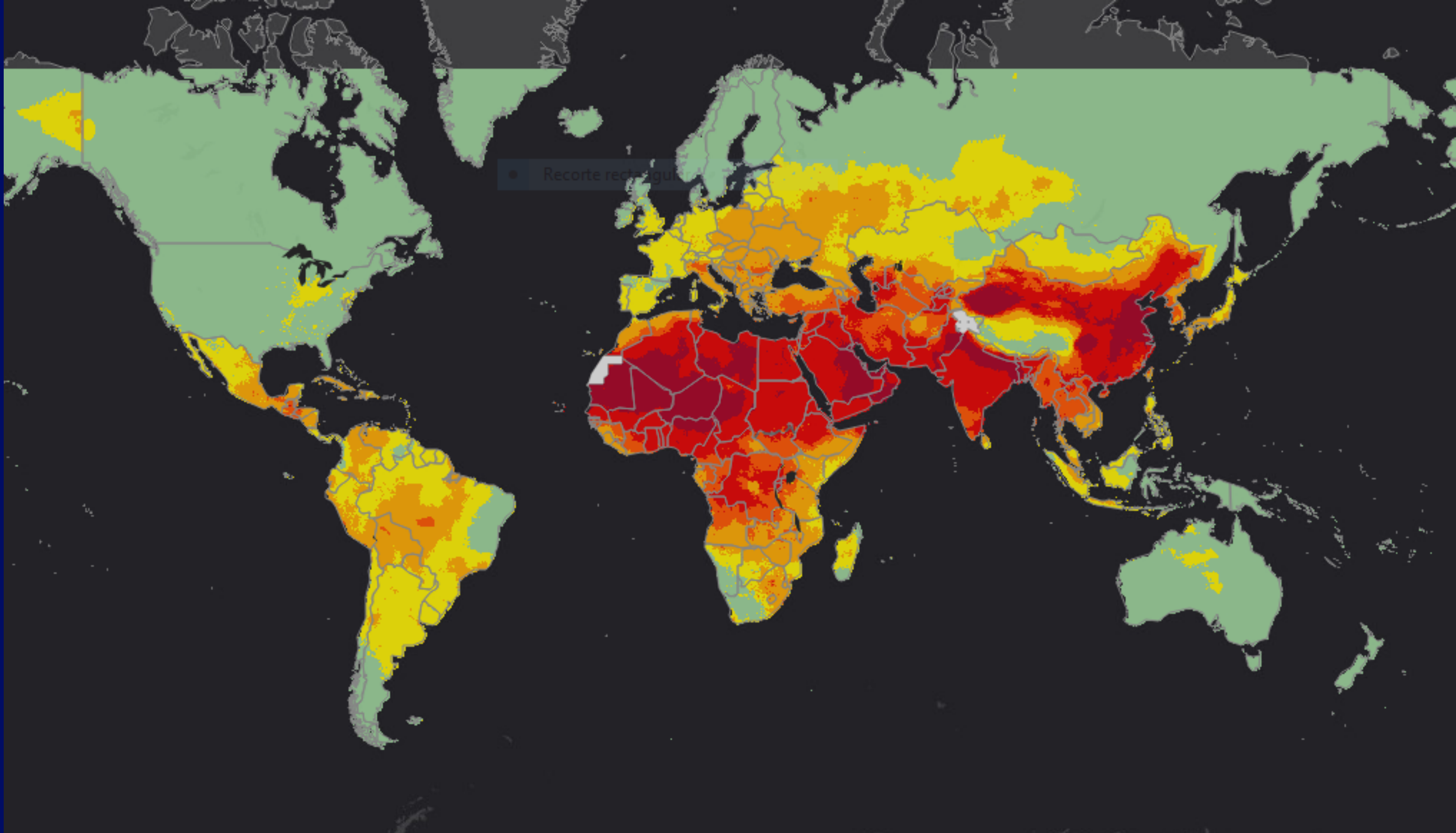
Source: El Colombiano, Medellín.

Health Impacts of Air Pollution

4^{th} among the global killers.

Medellín, Colombia, on April 8, 2016 (AFP Photo/Raul Arboleda)

- 6.5×10^6 deaths worldwide
- ~4000 deaths Medellin
- Associated with:
  - heart disease
  - obstructive lung disease
  - cancer
- >90% world population at risk



WHO – Air Pollution ($PM_{2.5,10}$) Interactive Map

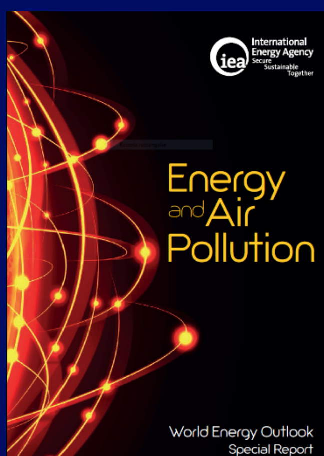
http://maps.who.int/airpollution/

Air Pollution

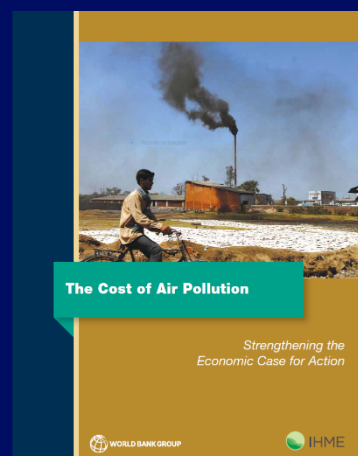
Issue of significant global concern

- Helsinki Protocol (1985) on the Reduction of Sulphur Emissions
- Oslo Protocol (1994) on Further Reduction of Sulphur Emissions
- 2015 World Health Assembly resolution to “address the adverse health effects of air pollution” (194 WHO member states)

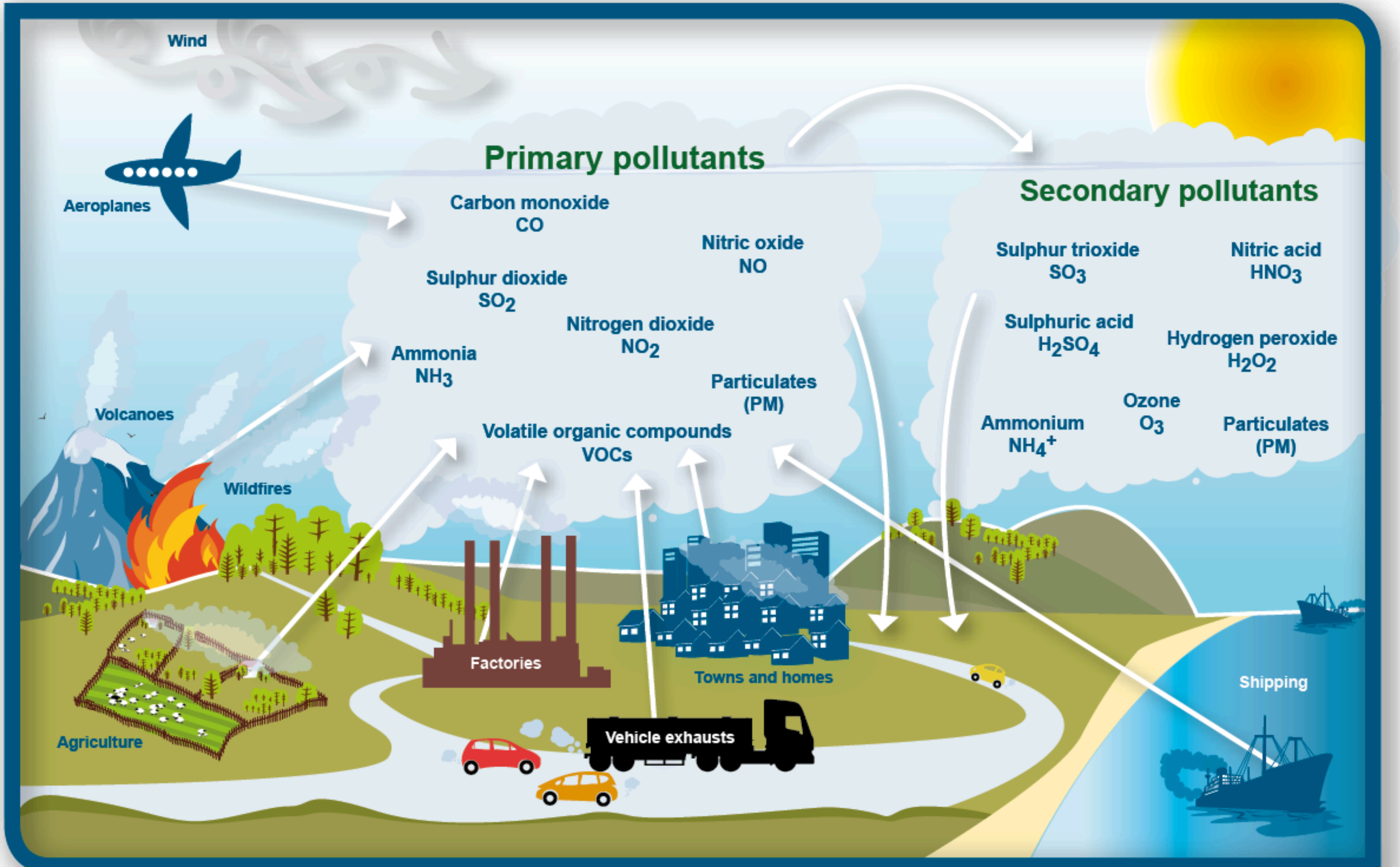
International Energy Agency
June, 2016



World Bank - IHME
September, 2016

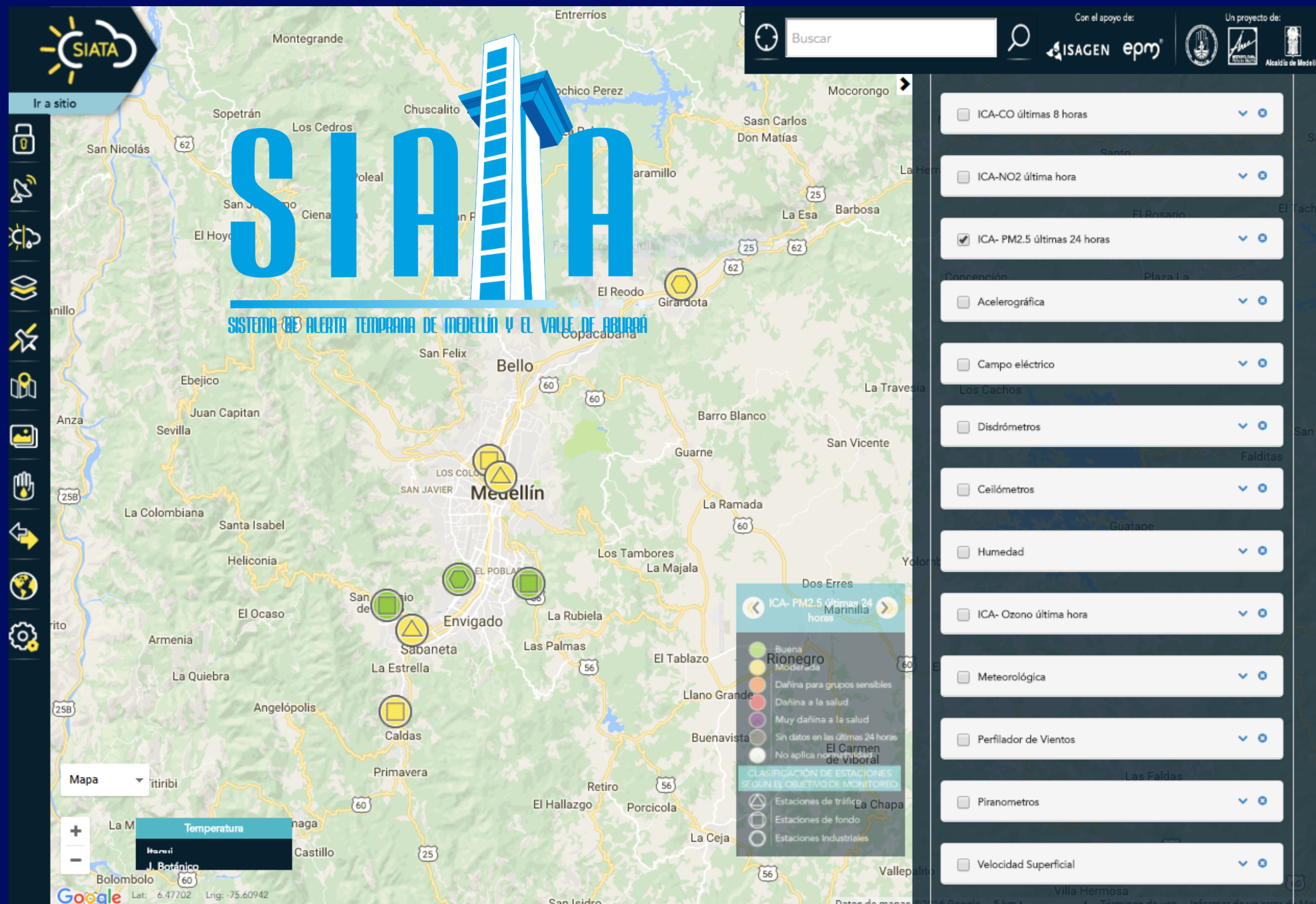


World Health Organization
September, 2016

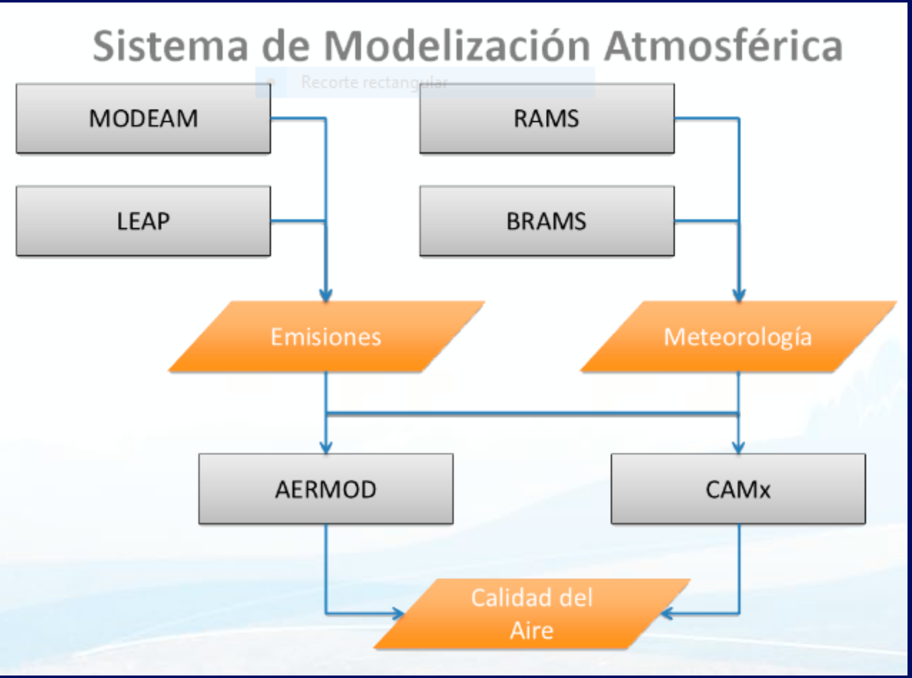


Source: Scotland's Environment, http://www.environment.scotland.gov.uk/media/26674/Sources-of-air-pollution_310314.png

Air Pollution Monitoring – Valle de Aburrá



Air Pollution Modeling – Valle de Aburrá



AERMOD
- Local Air Quality Model

CAMx
- Regional Air Quality Model

MODEAM, LEAP
- Emissions Models

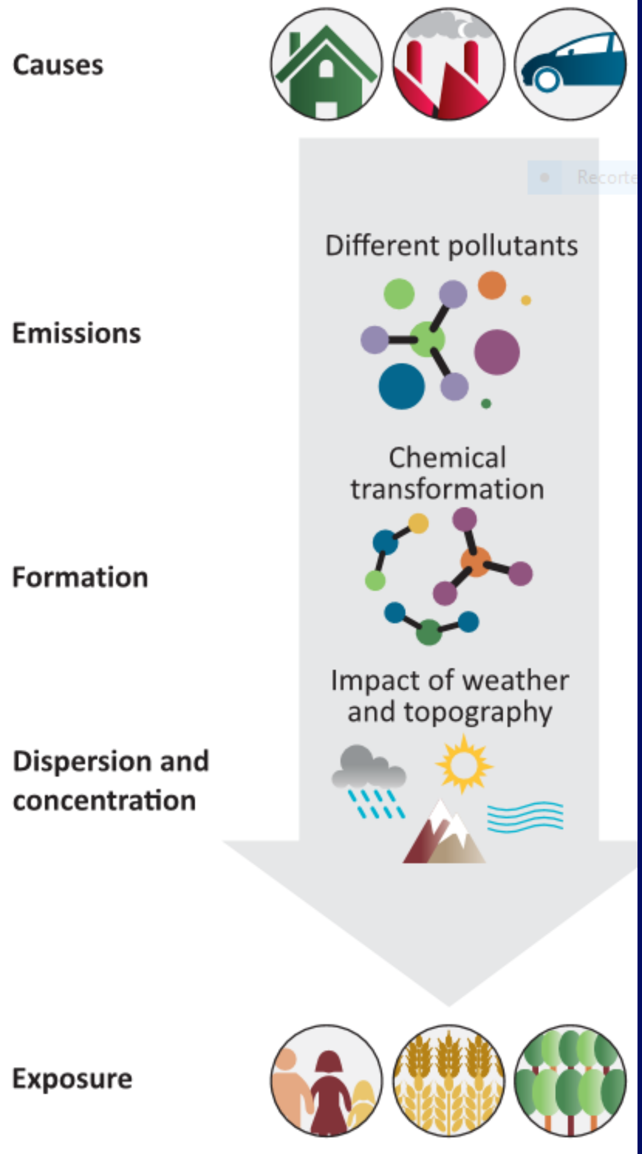
RAMS
- Regional Modeling System

BRAMS
- Regional Modeling System

Long-term goals:

To inform & motivate air quality-related public policy via...

Improved air quality models & **forecasts**



Source: IEA adapted from (EEA, 2016).

Human exposure to air pollution models (e.g., EXPAND, EXPOLIS, INDAIR)

Theoretical framework

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“The ensemble Kalman filter (EnKF) and its many variants have proven effective for data assimilation in large models, including those in atmospheric, oceanic, hydrologic, and petroleum reservoir systems. By bringing together technical experts, practitioners, researchers and students for presentations and informal exchange of information, we aim to share research results and suggest important challenges that have yet to be addressed”

...

[http://www.iris.no/enkf/enkf-homepage]

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

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

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

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

$\mathcal{M}_{k,k-1}\colon \mathbb{R}^{m_x} \to \mathbb{R}^{m_x}$ $\mathcal{H}_k\colon \mathbb{R}^{m_x} \to \mathbb{R}^{m_y}$

[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 ans covariance as the analysis state and error covariance matrix with the ensemble *n* typically much smaller than the dimension m_x in large scale applications.

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

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

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

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

$$\mathbf{x}^a_{k,i} = \mathbf{x}^f_{k,i} + \mathbf{K}_k[\mathbf{y}^s_{k,i} - \mathcal{H}_k(\mathbf{x}^f_{k,i})], \quad \text{for} \quad i = 1, 2, \ldots, n,$$

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

$$\hat{\mathbf{S}}^f_k = \frac{1}{\sqrt{n-1}}[\mathbf{x}^f_{k,1} - \hat{\mathbf{x}}^f_k, \ldots, \mathbf{x}^f_{k,n} - \hat{\mathbf{x}}^f_k],$$

$$\hat{\mathbf{S}}^{yy}_k = \frac{1}{\sqrt{n-1}}[\mathbf{y}^f_{k,1} - \hat{\mathbf{y}}^f_k, \ldots, \mathbf{y}^f_{k,n} - \hat{\mathbf{y}}^f_k],$$

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

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

- Variational methods for the parameter estimation

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

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

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

[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]

Measuring the impact of observations (data) over the performance of a Data Assimilation Scheme in the enhancement of a model.

$$\begin{aligned}\Delta J(k,m) \approx\ & [(\mathbf{y}(k+m) - H\hat{\mathbf{x}}(k+m|k)) + (\mathbf{y}(k+m) - H\hat{\mathbf{x}}(k+m|k-1))]' \\ & \mathbf{R}(k+m)^{-1}\mathbf{D}(k+m|k-1)\mathbf{D}(k|k-1)' \\ & \left(\mathbf{D}(k|k-1)\mathbf{D}(k|k-1)' + \mathbf{R}(k)\right)^{-1}(\mathbf{y}(k) - H\hat{\mathbf{x}}(k|k-1))\end{aligned}$$

[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]

During the last 3 years, the MahPhys group has been developing and improving the Data Assimilation schemes from at least three points of view, regarding the two types of data assimilation techniques: the variational methods, and sequential methods.

1. The reduced adjoint approach theoretical and idealized test cases (Altaf et al, 2013)
2. The quantification of the impact of data in reservoir modeling through observation sensitivity matrixes (Krymskaya, 2013)
3. Ensemble spurious correlations in Ensemble Kalman Filter (Fu et al, 2015- 2016) (Evans, 2009)
4. Observational spurious correlations solution in 4-d variational Data assimilation(Lu et al, 2015-2016)(Beney, 1982) (Jackson, 1991)
5. Conservation of mass and Preservation of possivity in physical meaning variables for Enseble-Type kalman Filter Algorithms (Tijana et al, 2014) and The observation impact analysis methods for Storm Surge - TSBOI- MM algorithm (Verlaan and Sumihar, 2016)

Theoretical Questions

To analyze and/or quantify the impact of the proper selection of a data subset

Based in previous work of observation sensitivity matrix (Krymskaya et al, 2010) and its properties such as

- Structure: symmetry, scaling, positive (semi)definiteness
- Matrix norm
- Uncertainty measurement
- Evaluation with SVD and trace analysis

for the quantification of the impact in modeling.

Videos

To answer the question: is it possible, under lineality and stationarity assumptions, to use the observation impact analysis methods developed by Verlaan and Sumihar, 2016 to improve the Data Assimilation Schemes over LOTOS-EUROS model forecasting?.

This will be held by studying the impact of the observations at the most recent analysis update under Ensemble based schemes in LOTOS EUROS model for volcanic ash.

$$\tilde{\mathbf{x}}(k|k-1) = \begin{bmatrix} \hat{\mathbf{x}}(k+m|k-1) \\ \hat{\mathbf{x}}(k|k-1) \end{bmatrix}$$

$$\tilde{H}_a = [\mathbf{0} \;\; H]$$
$$\tilde{H}_v = [H \;\; \mathbf{0}]$$

$$\tilde{\mathbf{x}}(k|k) = \tilde{\mathbf{x}}(k|k-1) + \tilde{\mathbf{K}}_c \left(\mathbf{y}(k) - \tilde{H}_a \tilde{\mathbf{x}}(k|k-1)\right)$$

$$H\hat{\mathbf{x}}(k+m|k) = \tilde{H}_v \tilde{\mathbf{x}}(k|k-1) + \tilde{H}_v \tilde{\mathbf{K}}_c \left(\mathbf{y}(k) - \tilde{H}_a \tilde{\mathbf{x}}(k|k-1)\right)$$

The extension of the trj-4DVar (Lu et al, 2015) to bigger systems and mathematically feasible solutions to solve the modified cost function in a new or improved approach adjoint free. We find feasible to try a hybrid scheme for the ill conditioned problem in order to deal with reduced observational noise.

The use of a formal sensitivity analysis for the perturbation of the inputs to the two experience based modifications in cost function in the trj-4DVar (Lu et al, 2016 under review), specifically in the penalty term in order to develop a generalized method and probe the stability of the solution.

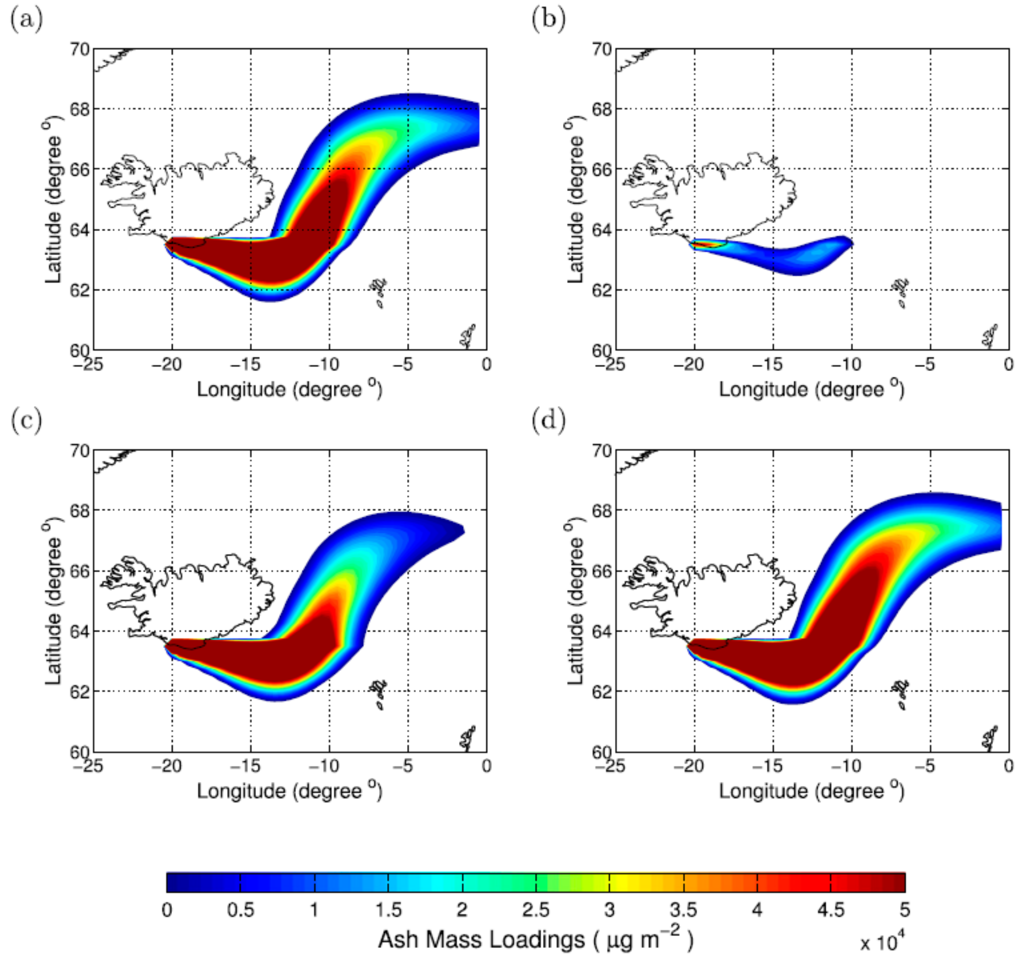

FIG. 5. Forecast of ash columns generated with emission rates of (a) the truth, (b) the background, (c) estimated through the standard 4D-Var method, and (d) estimated through the Trj4Dvar method at 1900 UTC 14 Apr 2010.

To develop further evidence and formalize the postulate of accuracy of the method for a physical-related window of assimilation, regarding the demonstrated accuracy in assimilation windows that does not compromise the constant concentration of particles in atmosphere (Lu et

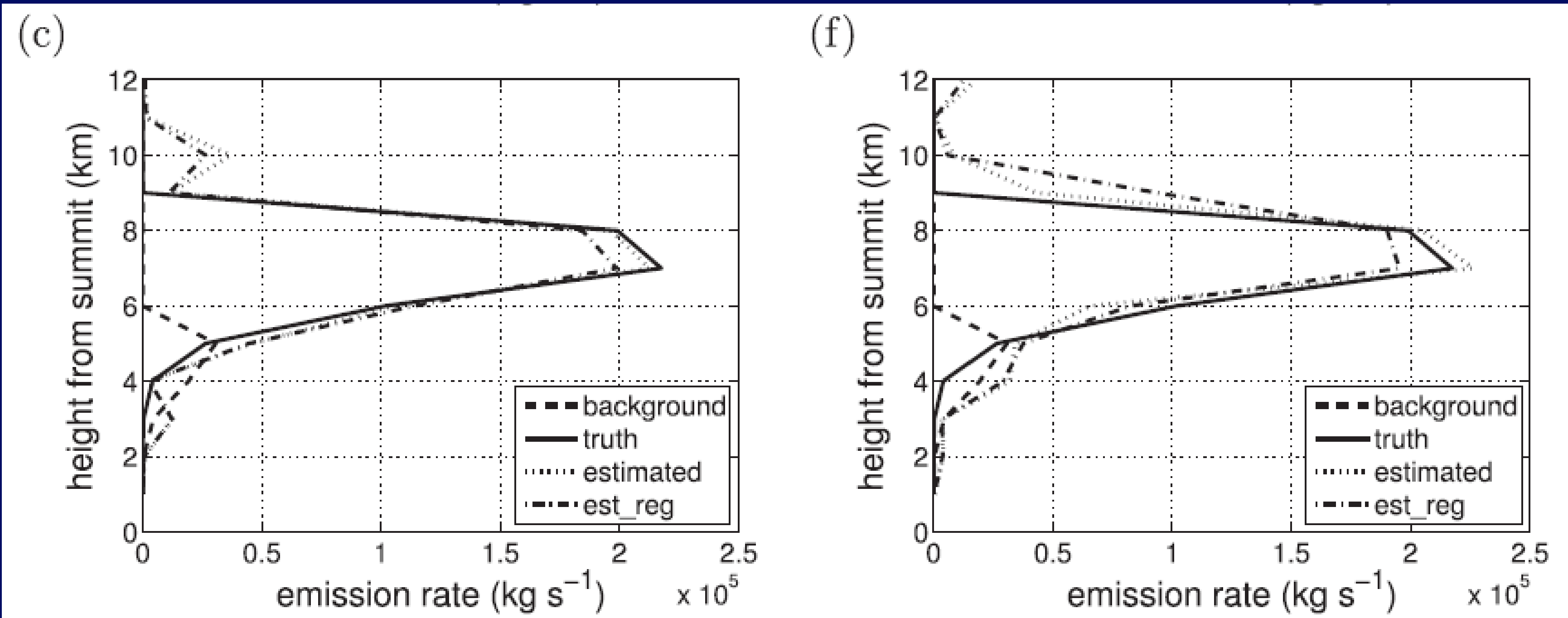

FIG. 9. Trj4DVar results of twin experiments with (a)–(c) 10% and (d)–(f) 50% observation noise and assimilation window of (a),(d) 1; (b),(e) 3; and (c),(f) 6 h.

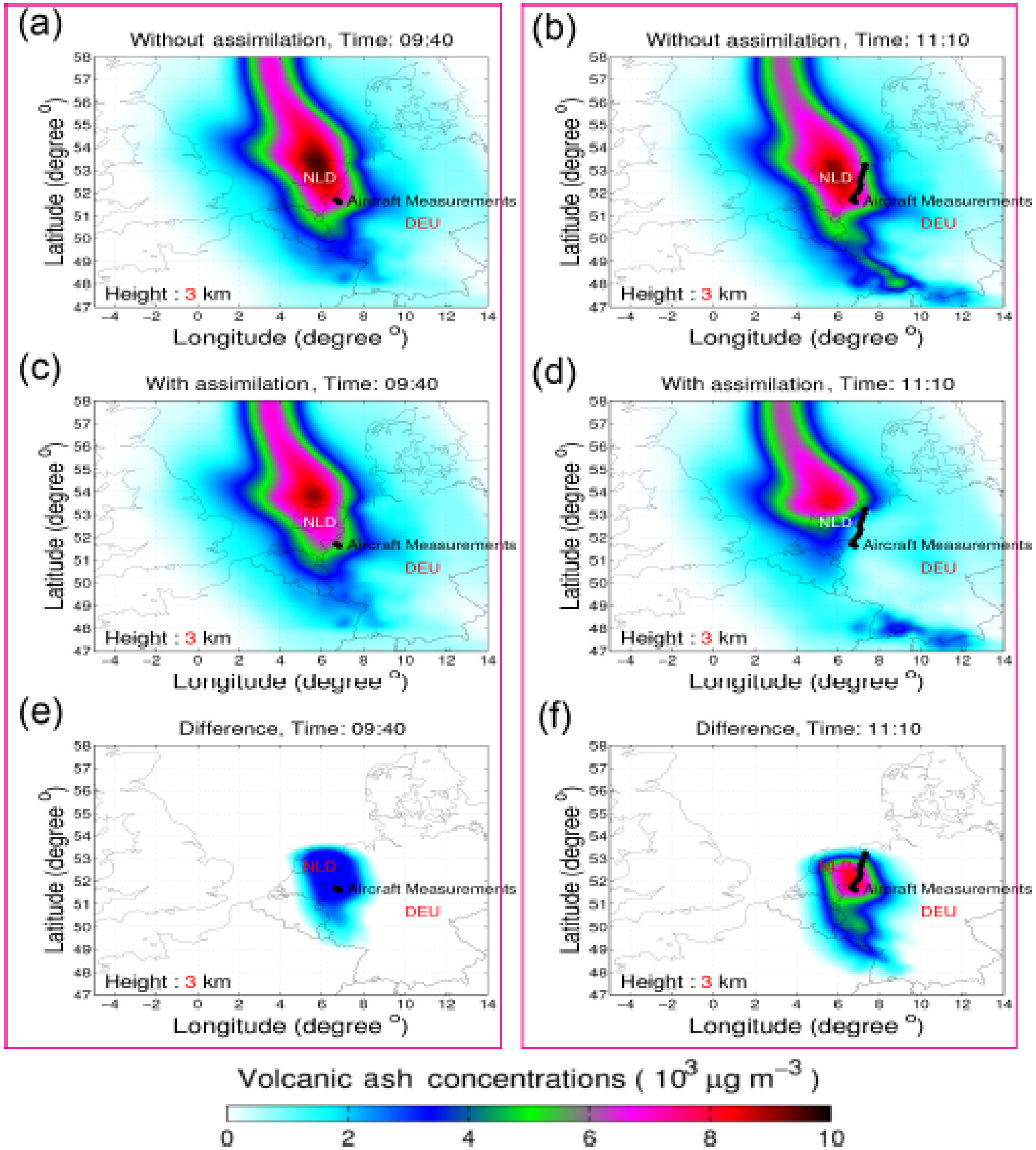

Figure 3. Comparison with and without assimilating aircraft in situ measurements on 18 May 2010. **(a, b)** Simulation results without assimilation at 09:40 and 11:10 UTC. **(c, d)**, Simulation results with assimilation at 09:40 and 11:10 UTC. **(e)** Differences of **(a, c)**. **(f)** Differences of **(b, d)**. The differences are in absolute values which are obtained by numerically subtracting the values between **(a, c)**, or **(b, d)**. Panels **(e, f)** represent the areas where the assimilation has effect.

To merge both “spurious” approaches for “multiple observations” problems (variable localization).

Research Proposal

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General Objective

“To start a research collaboration between both Mathematical Sciences Department at Universidad EAFIT and Applied Mathematical Department at TU Delft in order to develop and improve the Data Assimilation Schemes regarding the rigurosity and relevance of the theoretical and practical issues on the field, over complex dynamics such as environmental modeling.

This allows for the merging of the PhD programs and improves the capability of our departments to provide solutions to modeling issues worldwide.”

Specific Objectives

1. To start a joint research program for the development of Data Assimilation schemes.

2. To strengthen the research capabilities of the Systems and Control research line of the Mathematical Modeling research group through the formation of Doctoral students in Mathematical Engineering and Applied Mathematics programmes.

3. To improve the sequential methods for data assimilation.

4. To improve the variational methods for data assimilation.

5. To perform properly the mathematical analysis of the algorithms developed, related to insigth, understanding, conditioning, deep performance and so on.

6. To contribute satisfactorily to the field of data assimilation through de development of new schemes from the solution of the particular problem related to air quality in Colombia.

Specific Objectives

7. To provide interdisciplinary work between the research groups of the School of Sciences at Universidad EAFIT.

8. To develop an approach for the Modelling of the Air Quality in Colombia through LOTOS-EUROS Model and learn on how the model behaves in different regions of the world.

9. To contribute to forecasting systems of Air Quality in Colombia using LOTOS-EUROS Model through Data Assimilation taking into account the need for more data provided by govermental agencies such as Area Metropolitana.

10. To analyze and evaluate the dynamics underlying the atmospheric behavior in Area Metropolitana, as the initial step in the development of a city-scale, pollution exposure risk model to explore the ecological and human health impact from the Biological Sciences framework.

Specific Objectives

11. To train two doctoral students under a joint scheme between the PhD in Mathematical Engineering (EAFIT) and Applied Mathematics (TUDELFT) programmes

12. To impact the programme of master in Applied Mathematics at Universidad EAFIT with research in Data Asimilation with applications to History matching.

13. To contribute to the international mobility of faculty and students for research

References

Schaap, M., van Loon, M., ten Brink, H. M., Dentener, F. J., and Builtjes, P. J. H.: Secondary inorganic aerosol simulations for Europe with special attention to nitrate, Atmos. Chem. Phys., 4, 857-874, doi:10.5194/acp-4-857-2004, 2004.

E. C. Monahan, D. E. Spiel, K. L. Davidson A Model of Marine Aerosol Generation Via Whitecaps and Wave Disruption Chapter Oceanic Whitecaps Volume 2 of the series Oceanographic Sciences Library pp 167-174

Soares, J., Kousa, A., Kukkonen, J., Matilainen, L., Kangas, L., Kauhaniemi, M., Riikonen, K., Jalkanen, J.-P., Rasila, T., Hanninen, O., Koskentalo, T., Aarnio, M., Hendriks, C., and Karppinen, A.: Refinement of a model for eval- uating the population exposure in an urban area, Geosci. Model Dev., 7, 1855- 1872, doi: 10.5194/gmd-7-1855-2014, 2014

References

Flemming, J., Inness, A., Flentje, H., Huijnen, V., Moinat, P., Schultz, M. G., and Stein, O.: Coupling global chemistry transport models to ECMWF's integrated forecast system, Geosci. Model Dev., 2, 253-265, doi:10.5194/gmd- 2-253-2009, 2009.

Kaiser, J. W., Heil, A., Andreae, M. O., Benedetti, A., Chubarova, N., Jones, L., Morcrette, J.-J., Razinger, M., Schultz, M. G., Suttie, M., and van derWerf, G. R.: Biomass burning emissions estimated with a global fire assimi- lation system based on observed fire radiative power, Biogeosciences, 9, 527 554, 24 doi:10.5194/ bg-9-527-2012, 2012.

Martijn Schaap, Renske M.A. Timmermans, Michiel Roemer, G.A.C. Boersen, Peter J.H. Builtjes, Ferd J. Sauter, Guus J.M. Velders, Jeanette P. Beck The LOTOS EUROS model: description, validation and latest developments Inter- national Journal of Environment and Pollution (IJEP), Vol. 32, No. 2, 2008 Fountoukis, C. and Nenes, A.: ISORROPIA II: a computationally efficient thermodynamic equilibrium model for aerosols, Atmos. Chem. Phys., 7, 4639- 4659, doi:10.5194/acp-7-4639-2007, 2007.

References

G. Fu, H.X. Lin, A.W. Heemink, A.J. Segers, S. Lu., T. Palsson c Assimilat- ing aircraft-based measurements to improve forecast accuracy of volcanic ash transport. Atmospheric Environment 115 (2015) 170e184

G. Fu. A. W. Heemink, S. Lu. A.J. Segers, K. Weber, and H.X. Lin. Under review in ACP. Model-based aviation advice on distal volcanic ash clouds by assimilating aircraft insitu measurements.

G. Fu, H.X. Lin, A.W. Heemink, S. Lu and A.J. Segers. Under review Mon Wea Rev 2016. A backtracking-localized Ensemble kalman filters for assimilat- ing aircraft in-situ volcanic ash measurements. S.

S. Lu, H.X. Lin, A.W. Heemink, G.Fu. A.J. Segers. Estimation of Volcanis Ash emissions using trajectory-based 4D-Var data Assimilation. (2015). Mon. Wea. Rev., doi:10.1175/mwr-d-14-0194.1

S. Lu, H.X. Lin, A.W. Heemink, A.J. Segers. And G.Fu. Under review in JGR Atmospheres. Estimation of volcanic ash emissions from satelite data combining ground based observations.

References

Bogdan Sebacher · Remus Hanea · Arnold Heemink. probabilistic parametrization for geological uncertainty estimation using the ensemble Kalman filter (EnKF) Comput Geosci (2013) 17:813–832 DOI 10.1007/s10596-013-9357-z

M.U. Altaf a, M. El Gharamti a, A.W. Heemink b, I. Hoteit. A reduced adjoint approach to variational data assimilation Comput. Methods Appl. Mech. Engrg. 254 (2013) 1–13 M.

M. U. Altaf,T. Butler, T. Mayo, X. Luo, C. Dawson, A. W. Heemink, AND I. Hoteit (2014) A Comparison of Ensemble Kalman Filters for Storm Surge As- similation. American meteorological society doi: 10.1175/MWR-d-13-00266.1

Krymskaya, M., Hanea, R., jansen, J., and A.W. Heemink. Observation sensitivity in computer-assisted history matching. In SPE/EUROPEC EAGE Annual Conference and Exhibition, barcelona, Spain.

Krymskaya, Mariya. Quantification of the impact of data in reservoir modeling. (2013) PhD Thesis in Applied Mathematics, DIAM TUDelft ISBN: 978-90-88-91-629-8

References

Krymskaya, M., Hanea, R., jansen, J., and A.W. Heemink. Observation sensitivity in computer-assisted history matching. In SPE/EUROPEC EAGE Annual Conference and Exhibition, barcelona, Spain.

Krymskaya, Mariya. Quantification of the impact of data in reservoir modeling. (2013) PhD Thesis in Applied Mathematics, DIAM TUDelft ISBN: 978-90-88-91-629-8

Jianbing Jin. Multiple Sources data Assimilation and HPC for Dust Forecasting System over China. Research proposal. April 29, 2016. MathPhys DIAM TuDelft.

J. Tijana, D. Mclaughlin, S. Cohn and M Verlaan. Conservation of mass and Preservation of Posivity with Ensemble-Type Kalman Filter Algorithms. Monthly Weather Review 142, N 2, pages 755-773 2014

M. Verlaan and J. Sumihar. Observation impact analysis methods for storm surge. Ocean Dynamics, vol 66 pages 221-241 (2016)

Altaf, M.U., Heemink, A.W., Verlaan, M.: Inverse shallow-water flow modeling using model reduction. Int. J. Multiscale Comp. Eng. 7(6), 577–594 (2009)

References

Malgorzata P. Kaleta, Remus G. Hanea, Arnold W. Heemink, Jan-Dirk Jansen. Model-reduced gradient-based history matching. January 2011, Vol- ume 15, Issue 1, pp 135–153 Computational Geosciences

R. Hanea. Assisted History Matching and Optimization. Statoil workshop. 2014

Remus Hanea, Olwijn Leeuwenburgh, Lies Peters and Frank Wilschut Cristian Maris, Gosia Kaleta, Wiktoria Lawniczak, Mariya Krymskaya. Applying the EnKF for a reservoir engineering application: Challenges and Solutions.2011

Slawomir Szklarz (TU-Delft University)—Remus Gabriel Hanea (TNO)—Elisabeth Peters (TNO) A Case Study of the History Matching Of A Sector Of The Norne Field Using the Ensemble Kalman Filter SPE EUROPEC/EAGE Annual Conference and Exhibition, 23-26 May, Vienna, Austria, 2011

S. Shah, A. W. heemink., U. Grawe, E. Deleersnijder. Adaptive time stepping algorithm for lagrangian transport models: theory and idealised test cases. Ocean Modelling, 68 (2013)9-21.

References

G. Evensen. Data Assimilation. The Ensemble Kalman filter. Springer 2009.

B. Kenney. Beware of Spurious self correlations! Water Resources Research, vol 18, N 4, pages 1040-1048, (1982)

D.A. Jackson ad K.M Somers. The spectre of spurious correlations. Oecologia (1991) 56:147-151

María E. Dillon, Yanina García Skabar, Juan Ruiz, Eugenia Kalnay, Estela A. Collini, Pablo Echevarría, Marcos Saucedo, Takemasa Miyoshi and Masaru Kunii. Application of the WRF-LETKF Data Assimilation System over South- ern South America: Sensitivity to Model Physics. Sixth WMO Data Assimila- tion Symposium Special Collection. DOI: http://dx.doi.org/10.1175/WAF-D- 14-00157.1 Received: 26 November 2014

Chengsi Liu. Ming Xue. Relationships among Four-Dimensional Hybrid Ensemble–Variational. Data Assimilation Algorithms with Full and Approximate Ensemble Covariance Localization. Sixth WMO Data Assimilation Symposium Special Collection.

References

Omar V. Muller. Ernesto Berbery . Domingo Alcaraz-Segura. MICHAEL B. EK. Regional Model Simulations of the 2008 Drought in Southern South America Using a Consistent Set of Land Surface Properties. Journal of Climate. AMS DOI: 10.1175/JCLI-D-13-00463.1

Marie Minvielle AND Rene D. Garreaud.Projecting Rainfall Changes over the South American Altiplano. AMS(2011) DOI: 10.1175/JCLI-D-11-00051.1

Christopher l. Castro and Hsin-i chang. Francina Dominguez. Carlos Carrillo. Jae-kyung schemm. Hann-ming Henry Juang. Can a Regional Climate Model Improve the Ability to Forecast the North American Monsoon?. JOUR- NAL OF CLIMATE V OLUME 25. DOI: 10.1175/JCLI-D-11-00441.1 (2012)

Malgorzata P. Kaleta. Model-Reduced Gradient-based history matching. Master of Science in Applied mathematics geboren te Kalisz, Polen. Doctoral Thesis, TU Delft, 2011. ISBN: 978-90-8570-774-5.

Frankrijk geboren te Gaesti, Ensemble-based data assimilation schemes for atmospheric chemistry models. Alina Barbu. Diplome d estudes approfondies, Universite de Technologie Compiegne, Roemenie. Doctoral Thesis, TU Delft, 2010.

References

Bogdan marius Sebacher. Data Assimilation under Geological Constraint. Master of Science in Mathematics Romania. Doctoral Thesis TU Delft, 2014. ISBN: 978-94-6186-405-5.

Darya Spivakovska. Reverse time diffusion in enviromental models. Master of Science in mathematics, Ukrania. Doctoral Thesis, TU Delft, 2007. ISBN: 978-90-8559-587-8.

Eka Budiarto. Modeling Geometrical uncertainties for radiotherapy plan optimization without margins. Master of Sciences in Industrial Mathematics, Doctoral Thesis, TU Delft. ISBN: 978-946-1087-898.

Shah Muhammad. Dynamic Positioning of Ships: A nonlinear control design study.Master of Sciences in mathematics. Doctoral Thesis TU Delft, 2012. ISBN: 978-94-6186-026-2

Adriana Natacha Amicarellia*, Olga Lucía Quintero Montoya+, Fernando di Sciascioa A review of State Estimation and Control in the Fermentation Process of Zymomonas mobilis.. Bioprocesos, Vol 3, 2015. Amicarelli,

References

Amicarelli, A, Quintero, OL, di Sciascio, F Behavior Comparison for Biomass Observers in Batch Processes. Asia-Pacific Journal of Chemical Engineering, 2013

Adriana Amicarelli, Fernando di Sciascio, Olga L. Quintero and Oscar Ortiz. On-line Biomass Estimation in a Batch Bio-technological Process: Bacillus thuringiensis delta - endotoxins production. Biomass, Biomass, Book edited by: Maggie Momba and Faizal Bux, ISBN 978-953-307-113-8, pp. 202, September 2010, Sciyo. Chapter 4, pp 79 -112

Scaglia, G.;Rosales, A. ;Quintero Montoya, O. ;Mut, Valinear-interpolation-based controller design for trajectory tracking of mobile robots..Department of Mathematics, Florida Institute of Technology, USA . Control Engineering Prac- tice, 18 (2010) 318–329.

Scaglia, G. ;Mut, V. ;Jordán, M.;Calvo, C. ;Quintero Montoya, O Mobile Robot Control Based on Robust Control Techniques. 2009. Journal of En- gineering Mathematics Volume 63 Number 1, DOI 10.1007/s10665-008-9252-0, Enero, page 17-32.

References

Quintero Montoya, O. ;Amicarelli, A. ;Scaglia, G. ;di Sciascio, F. Control based on numerical methods and recursive Bayesian estimation in a continuous alcoholic fermentation process. 2009. BioResources. 4(4), 1372-1395.

G. Scaglia, O. Quintero, V. Mut, F. di Sciascio. Numerical Methods Based Controller Design for Mobile Robots. Robotica, Published online by Cambridge University Press 23 Jun 2008.

O. Quintero, A. Amicarelli, F di Sciascio, and G Scaglia. State Estimation in Alcoholic continuous fermentation of Zymomonas Mobilis using recursive bayesian Filtering: A Simulation approach. Bioresources issue 3 (2) May 2008

O. Lucia. Quintero, Adriana Amicareli. Fernando di Sciascio.Biomass Estimation in Batch Process through Particle Filters. XV Congreso latinoamericano de Control Automatico CLCA 2012 octubre 23-26 Lima, Peru.

Monica Hernández Lordui, Adalberto G Díaz T, Olga Lucia Quintero.Modelo Matemático de un Motor de Combustión Interna para uso en Control. XV Congreso latinoamericano de Control Automatico CLCA 2012 octubre 23-26 Lima, Peru

References

O. Quintero, A. Amicarelli, F. di Sciascio, Recursive Bayesian Filtering for States Estimation: An Application Case in Biotechnological Processes, en 3th joint international Meeting of Institute of matematical Statistics (IMS) – In- ternational Society for Bayesian Anlysist (ISBA), Markov Chain Monte Carlo Theory and Practice MCMSKi in Bornio Italy, Jan 8-11, 2008.

O. Quintero, G.Scaglia, A. Amicarelli, F. di Sciascio. Bioprocess control strategy based on numerical methods and linear algebra: Second Approach, en IASTED International Conference in Modelling Identification and Control MIC 2008 conference en Insbruck Austria, Febrero 11-13 de 2008.

G. Scaglia, O. Quintero, V. Mut, F. di Sciascio. Numerical Methods based controller design for mobile robots. Case Study para el 17 IFACWorld congress in Seoul Korea 2007.

O. Quintero, G.Scaglia, F. di Sciascio, V. Mut. Numerical Methods Based Strategy and Particle Filter State Estimation For Bio Process Control, ICIT 2008 IEEE International Conference on industrial Technology, Chengdu china, April 24, 2008.

References

G. Scaglia,G., V. Mut, O Quintero et al, "Tracking Control of a Mobile Robot using LinearInterpolation. IMAACA, 2007 vol. 1, pp. 11-15, ISBN: 978-2-952071277.

G. Scaglia, O. Quintero, V Mut, F. di Sciascio Control de Trayectoria de Robots Moviles Usando Álgebra lineal., XII Congreso Latinoamericano de Control Automático CLCA 2006, Bahia, Brazil Martijn

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