Applications of linearized physics

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Thanks to: P. Lopez, S. Lang, C. Cardinali

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Linearized models in NWP

- **different applications:**
  - **variational data assimilation** ⟵ *like incremental 4D-Var*
  - **singular vector computations** ⟵ *initial perturbations for EPS*
  - **sensitivity analysis** ⟵ *forecast errors*

- **first applications with adiabatic linearized model**

- **nowadays, the physical processes included in the linearized model**

Linearized model with physical processes

Including physical processes can:

- **in variational data assimilation:**
  - reduce spin-up
  - provide a better agreement between the model and data
  - produce an initial atmospheric state more consistent with physical processes
  - allow the use of new observations *(rain, clouds, soil moisture, …)*

- **in singular vector computations:**
  - help to represent some atmospheric features

    (processes in PBL, tropical instabilities, development of baroclinic instabilities, …)

- **in sensitivity analysis:**
  - allow a reduction of forecast error

- **adjoint of physical processes can also be used for:**
  - model parameter estimation
  - sensitivity of the parametrization scheme to input parameters

Why physical parametrizations in data assimilation?

- In current operational systems, most used observations are directly or indirectly related to temperature, wind, surface pressure and humidity outside cloudy and precipitation areas (~ 10 million observations assimilated in ECMWF 4D-Var every 12 hours).

- Physical parametrizations are used during the assimilation to link the model's prognostic variables (typically: T, u, v, q_v and P_s) to the observed quantities (e.g. radiances, reflectivities,…).

- Observations related to clouds and precipitation also started to be routinely assimilated *(presentation of A. Geer)*,

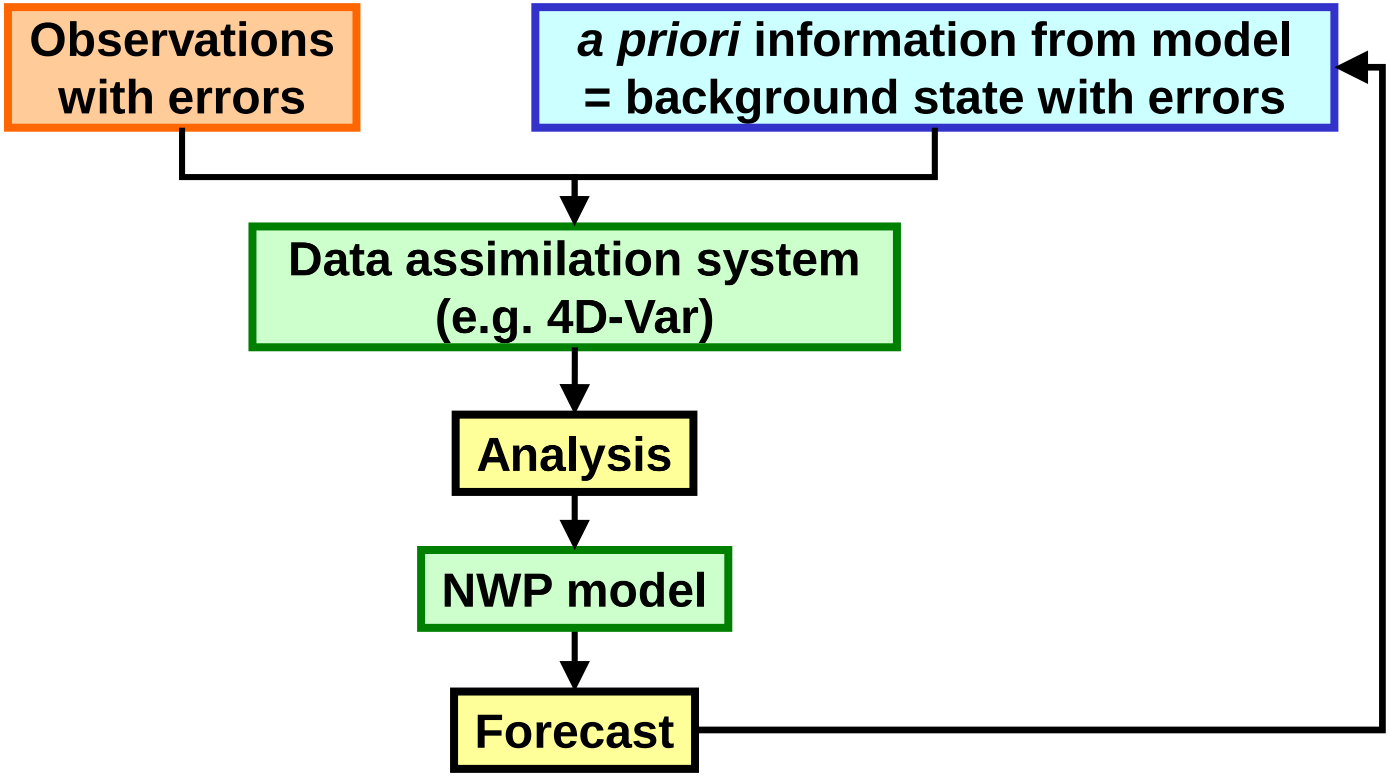
  → but how to convert such information into proper corrections of the model's initial state (prognostic variables T, u, v, q_v, P_s) is not so straightforward.

  For instance, problems in the assimilation can arise from the discontinuous or non-linear nature of physical processes *(presentation of P. Lopez)*.

Physical parametrizations are needed in data assimilation:

- to link the model variables to the observed quantities,
- to evolve the model state in time during the assimilation (e.g. 4D-Var).

Simplistic description of data assimilation and forecasting system



Example: Physics (full & simplified) in incremental 4D-Var system

4D-Var →

$$\min J(\boldsymbol{\delta}\mathbf{x}_0) = \frac{1}{2}\boldsymbol{\delta}\mathbf{x}_0^T\mathbf{B}^{-1}\boldsymbol{\delta}\mathbf{x}_0 + \frac{1}{2}\sum_{i=0}^{n}(\mathbf{H}_i(\boldsymbol{\delta}\mathbf{x}_i) - \mathbf{d}_i)^T\mathbf{R}_i^{-1}(\mathbf{H}_i(\boldsymbol{\delta}\mathbf{x}_i) - \mathbf{d}_i)$$

$$\Leftrightarrow \nabla_{\delta\mathbf{x}_0} J = \mathbf{B}^{-1}\boldsymbol{\delta}\mathbf{x}_0 + \frac{1}{2}\sum_{i=0}^{n}\mathbf{M}^T(t_i,t_0)\mathbf{H}_i^T\mathbf{R}_i^{-1}(\mathbf{H}(\delta\mathbf{x}_i) - \mathbf{d}_i) = 0$$

$\mathbf{d}_i = y_i^o - H_i(\mathbf{x}_i^b)$ - innovation vector

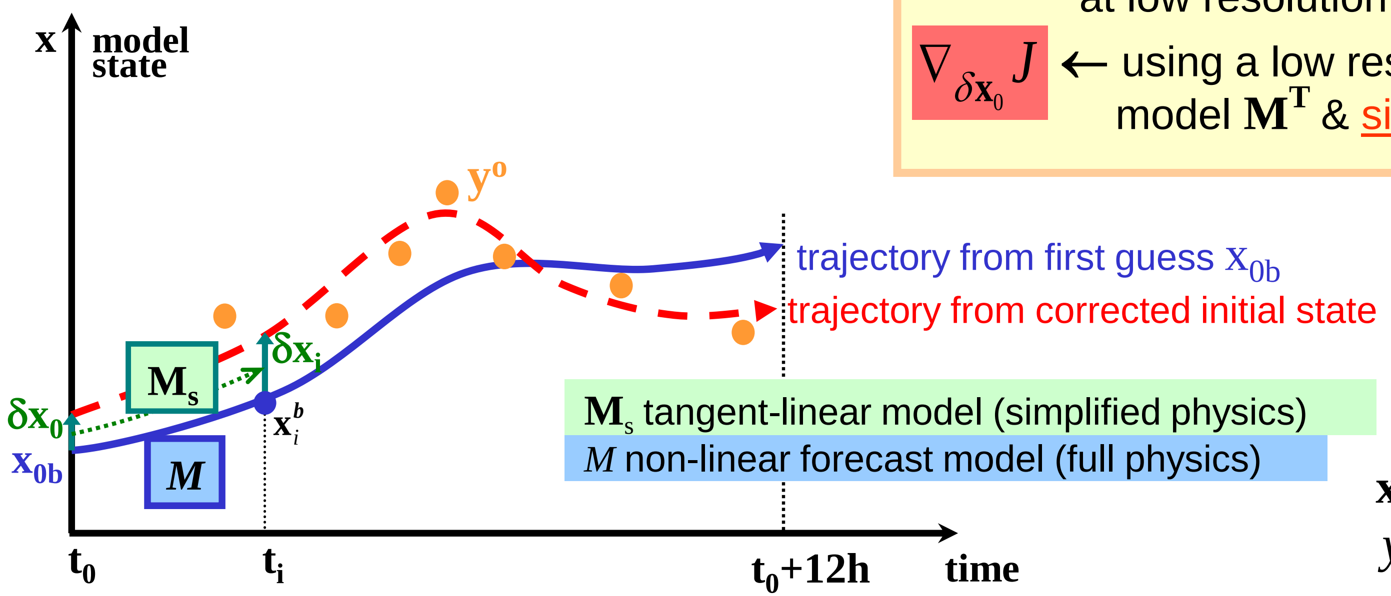
H_i non-linear observation operator

$\mathbf{H}_i$ tangent-linear observation operator

$\mathbf{d}_i$ ← using non-linear model M at high resolution & full physics

$\delta\mathbf{x}_i$ ← using tangent-linear model $\mathbf{M}$ at low resolution & simplified physics

$\nabla_{\delta\mathbf{x}_0} J$ ← using a low resolution adjoint model $\mathbf{M}^\mathbf{T}$ & simplified physics

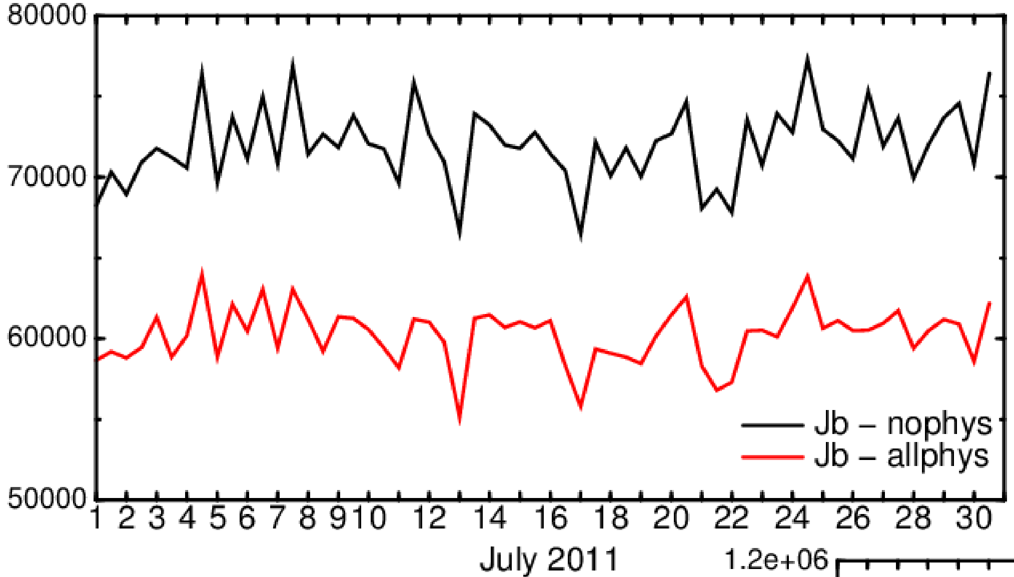


$\mathbf{x}_i$ – model state at t_i

y_i^o – observations at t_i

Impact of linearized physics on analysis

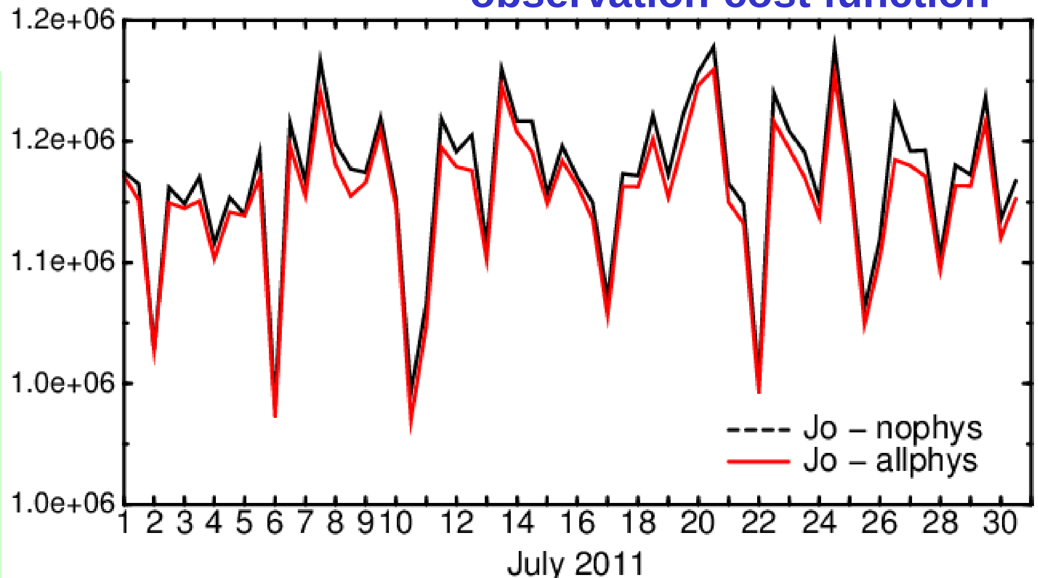
Coming just from including the ECMWF linearized physics in 4D-Var *(Janisková & Lopez, 2013)*



background cost function

$$J = J_o + J_b$$

observation cost function



4D-Var experiment – July-Sept.2011

nophys = only very simple vertical diffusion and surf.drag of *Buizza (1994)*

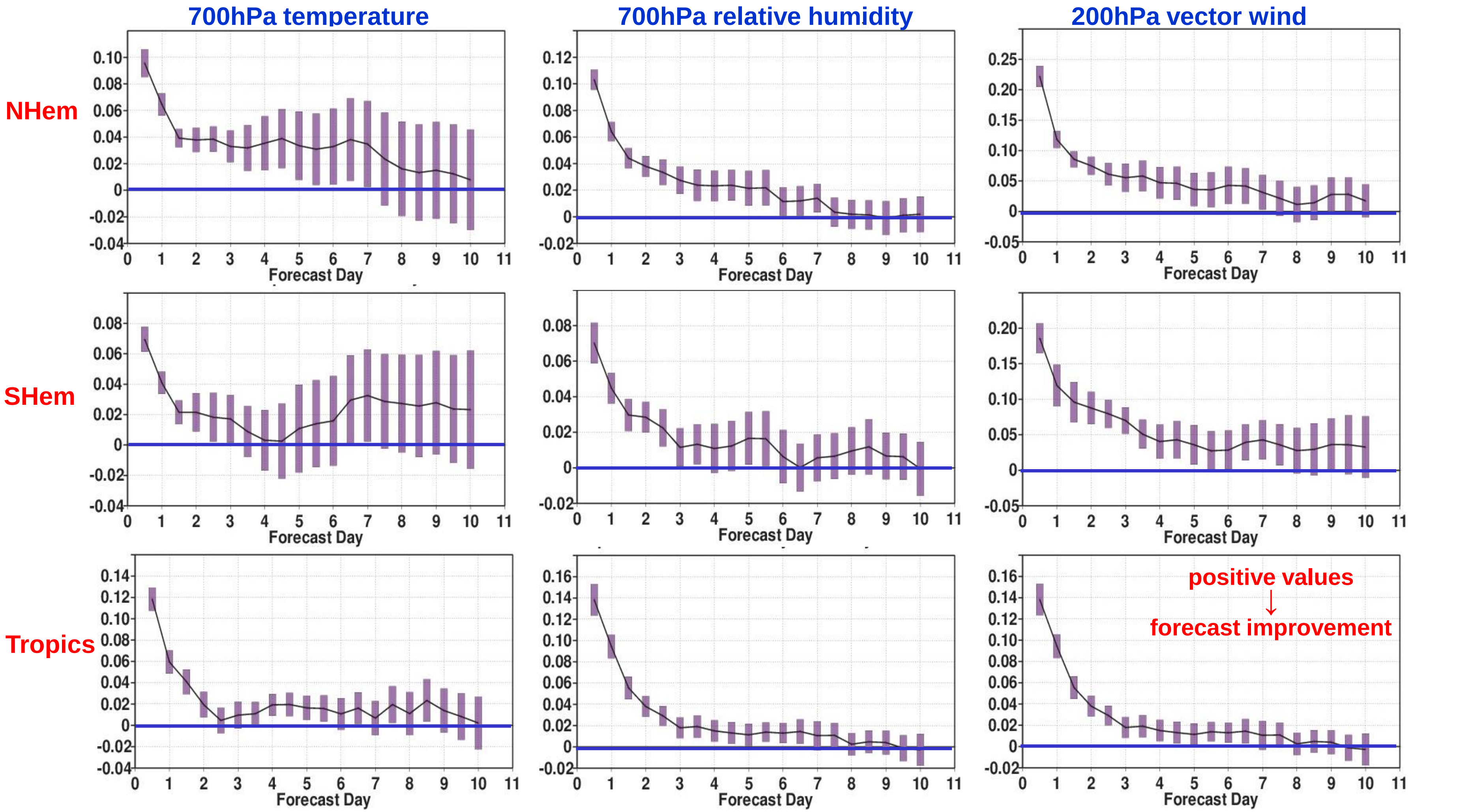
allphys = all linear. phys.parametrization:

dry
- *vertical diffusion*
- *gravity wave drag*
- *radiation*
- *nonorog. gravity wave drag*

moist
- *large scale cond. & precip.*
- *convection*

Direct relative improvement of forecast scores from linearized physics (1)

Coming just from including the ECMWF linearized physics in 4D-Var *(Janisková& Lopez, 2013)*

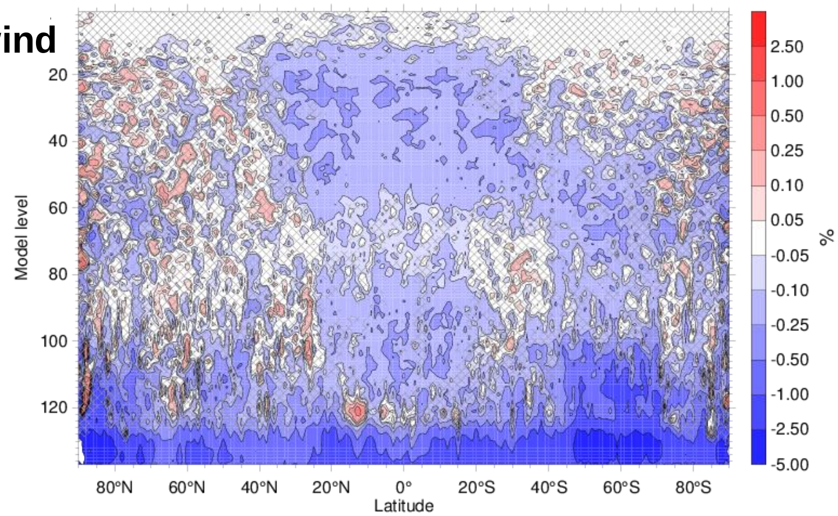


Anomaly correlation – July-Sept. 2011: bars indicate significance at 95% confidence level

T511L91 FC run: Forecast scores against operational analysis

Direct relative improvement of forecast scores from linearized physics (2)

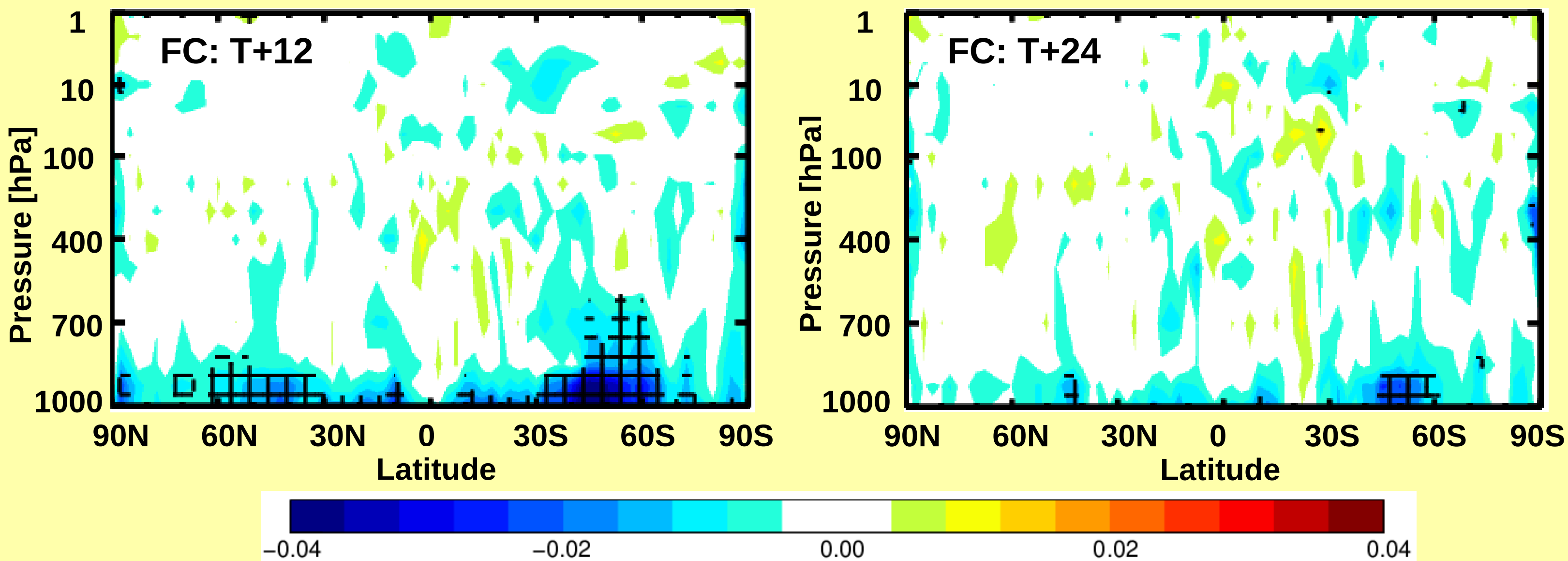
u-wind



Relative impact [%] of the surface related modifications in the tangent-linear model (TL) on TL approximation:

12-hour evolution of zonal wind increments

Negative values (blue)
↓
improvement



Forecast: Wind vector

Difference in RMS error normalized by RMS error of control: wind vector – February-March 2014

Examples of rain & cloud related observations and their assimilation

In global models :

- Operational assimilation of:
  - satellite infrared radiances in overcast conditions at ECMWF *(McNally 2009)*
  - microwave radiances in all sky conditions *(Bauer et al. 2010, Geer et al. 2010)*
  - direct 4D-Var of NCEP Stage IV radar & gauge hourly precipitation data *(Lopez 2011)*

- Experimental assimilation of :
  - 1D+4D-Var of SSMI/TMI rainfall rates *(Mahfouf et al. 2003)*
  - cloud-affected infrared radiances from AIRS in 4D-Var *(Chevallier et al. 2004)*
  - cloud optical depth from MODIS in 4D-Var *(Benedetti and Janisková 2008)*
  - 4D-Var assimilation of SYNOP rain gauge data *(Lopez 2012)*
  - 1D+4D-Var of cloud information from satellite cloud radar & lidar *(Janisková 2015)*

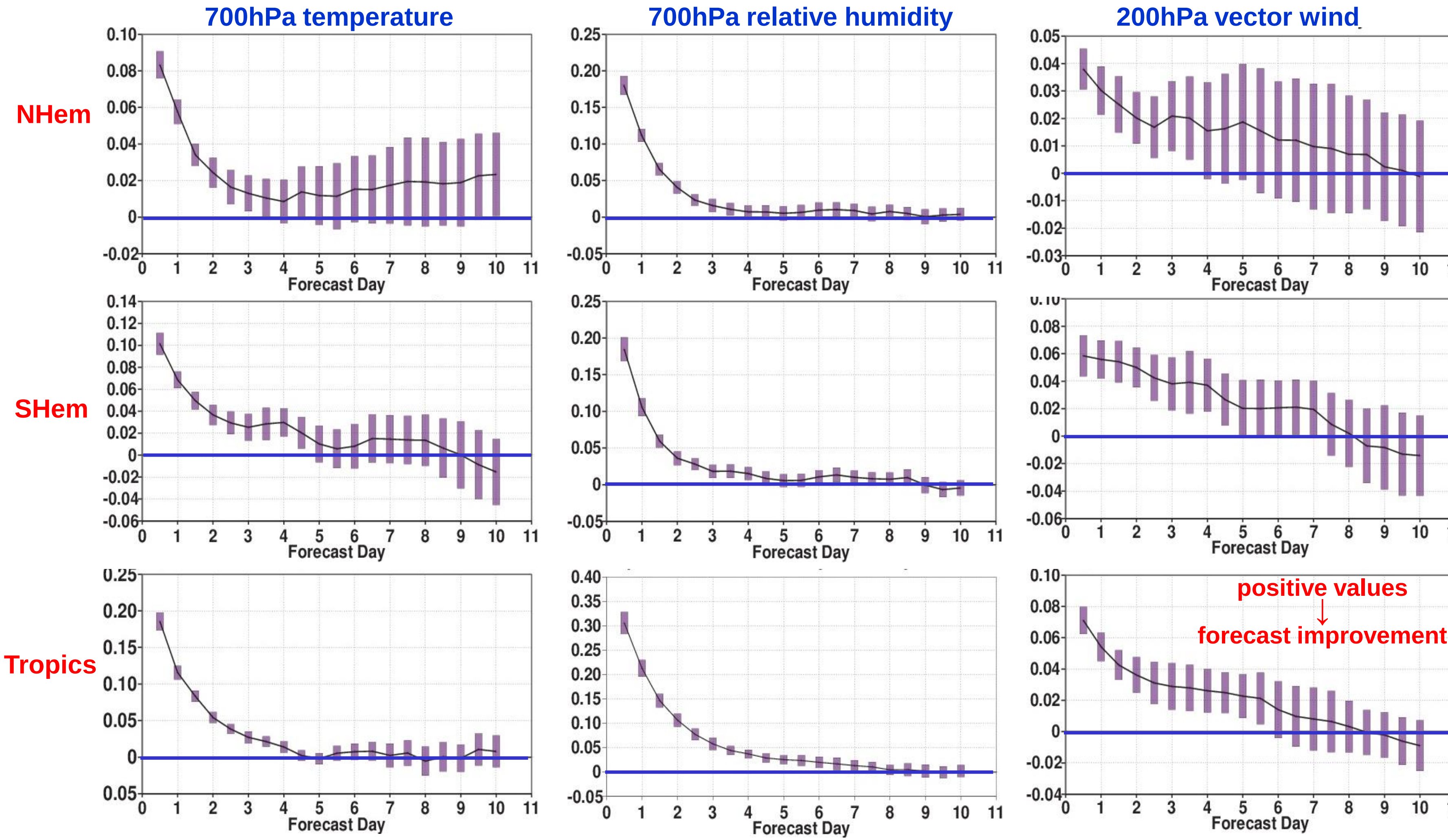
In mesoscale models :

- Cloud analyses based on nudging technique *(Macpherson et al. 1996, Lipton & Modica 1999, Bayer et al. 2000)*
- Ground-based precipitation radar assimilation in 4D-Var *(Tsuyuki et al. 2002)*
- Testing visible & infrared cloudy satellite radiances in 4D-Var *(Vukicevic et al. 2004)*

1D-Var – One-Dimensional Variational assimilation
MODIS – Moderate Resolution Imaging Spectroradiometer
AIRS – Advanced Infrared Sounder
SSM/I – Special Infrared Sounder

Indirect relative improvement of forecast scores from ECMWF linearized physics

Using observations directly related to the physical processes *(e.g. rain, clouds,…)*



Anomaly correlation – June-Aug. 2014: bars indicate significance at 95% confidence level

T799L137 FC run: Forecast scores against operational analysis

Own impact of combined ground-based radar & rain gauge observations

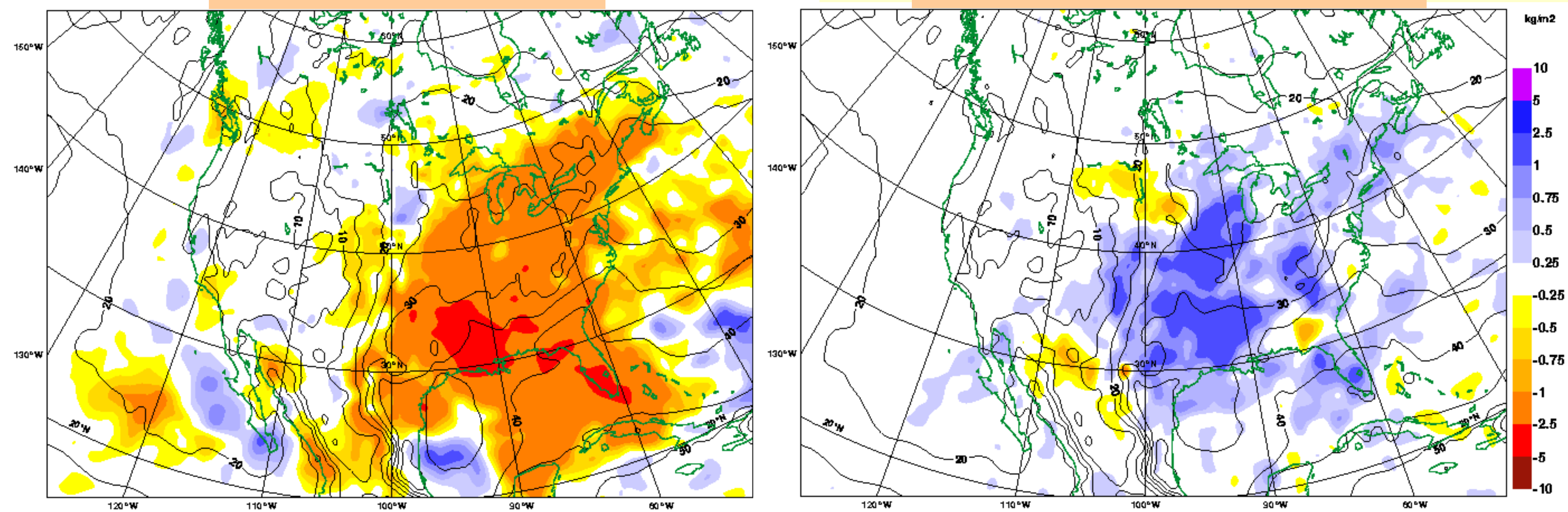
Three 4D-Var assimilation experiments (20 May - 15 June 2005):

CTRL = all standard observations.
CTRL_noqUS = all obs except <u>no moisture obs over US</u> (surface & satellite).
NEW_noqUS = CTRL_noqUS + <u>NEXRAD hourly rain rates over US</u> (“1D+4D-Var”).

Mean differences of TCWV analyses at 00UTC

CTRL_noqUS – CTRL

NEW_noqUS – CTRL_noqUS

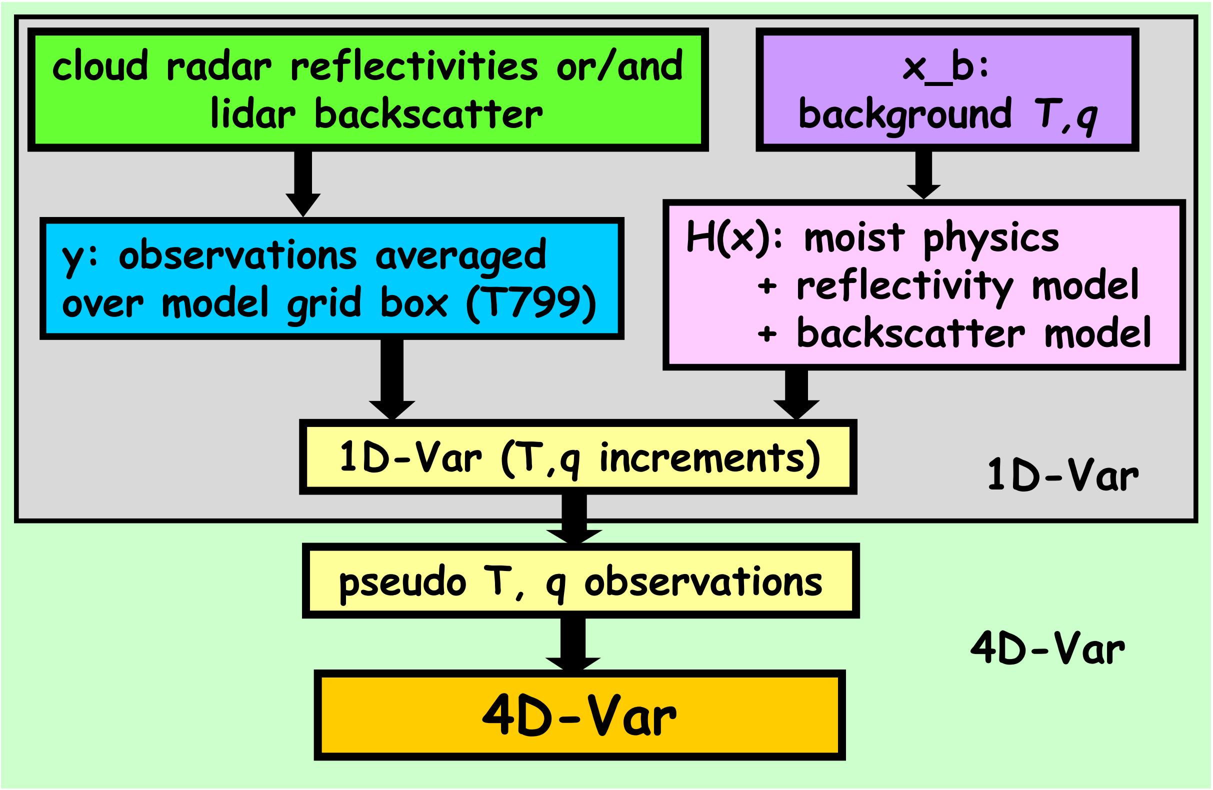


<u>*Lopez and Bauer (Monthly Weather Review, 2007)*</u>

Experimental assimilation of space-borne cloud radar & lidar obs. at ECMWF

- 1D-Var + 4D-Var approach built on experience of using such technique for formally operational assimilation of precipitation related observations *(Bauer et al. 2006 a, b):*
  - 1D-Var retrieval first run on the set of observations to produce pseudo-observations of temperature T and specific humidity q *(based on evaluation of T & q increments);*
  - modified *T* and *q* profiles then assimilated in the ECMWF 4D-Var system.

(Janisková et al. 2012, Janisková 2015)

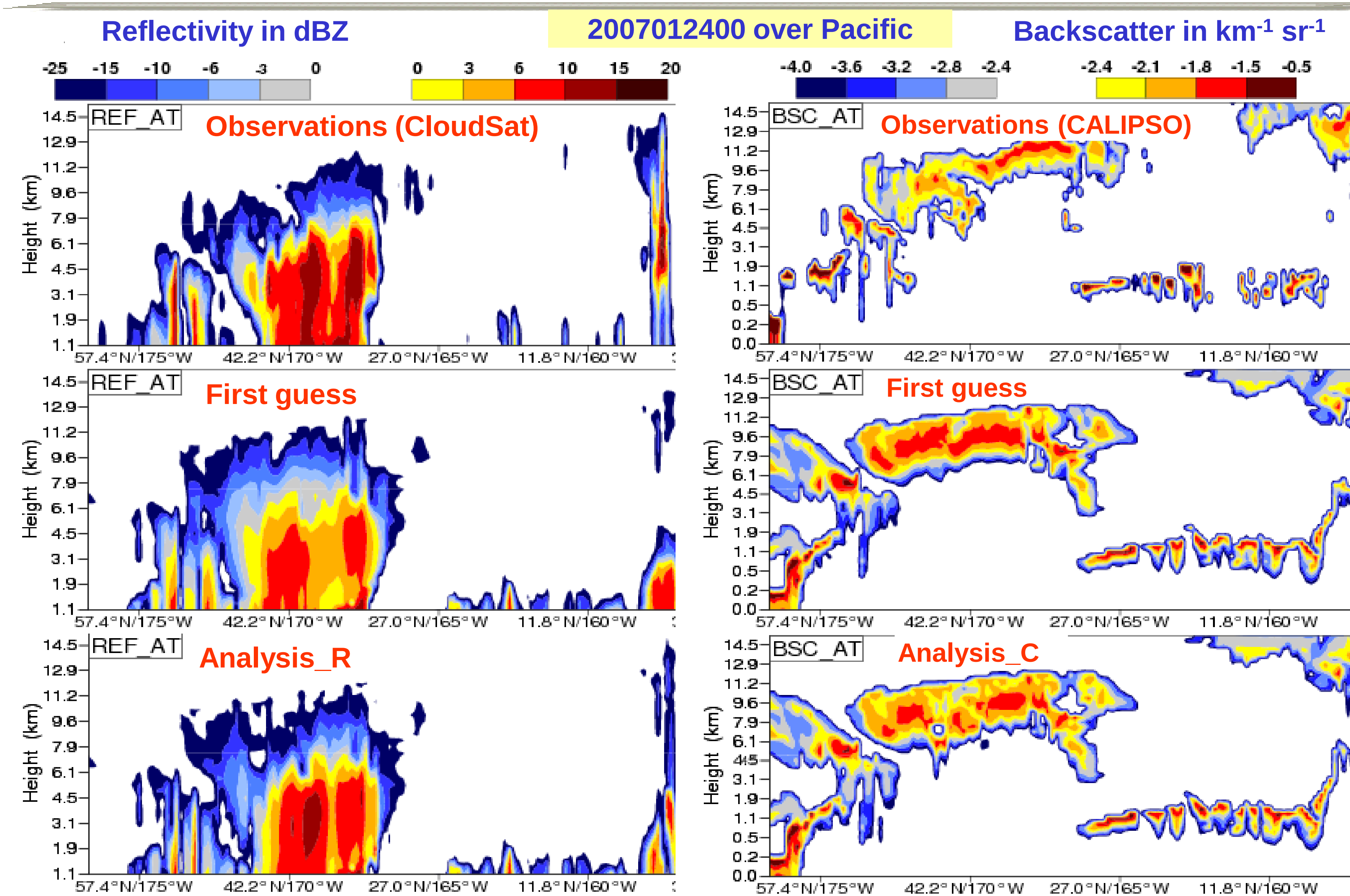


Observations:

- *cloud radar reflectivity: CloudSat at 94 GHz* ***(R)***
- *cloud lidar backscatter: CALIPSO at 532 nm* ***(L)***
- *combined* ***(C = R + L)***

1D-Var – One-Dimensional Variational assimilation
4D-Var – Four-Dimensional Variational assimilation

1D-Var of cloud radar reflectivity + lidar backscatter

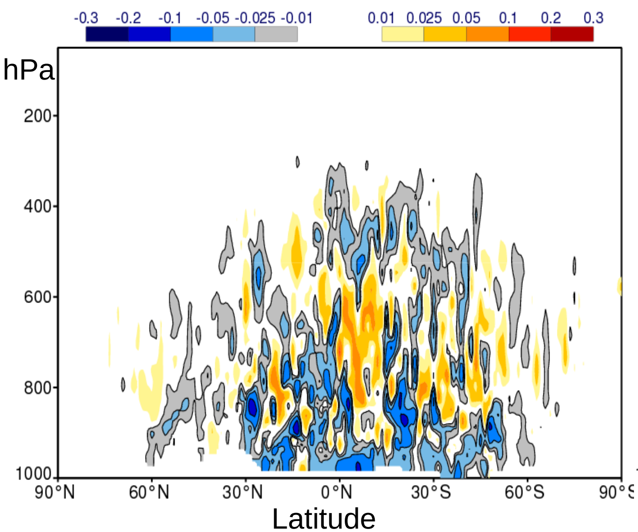


1D-Var analysis gets closer to assimilated and also independent observations:
impact of cloud radar reflectivity larger than of lidar backscatter

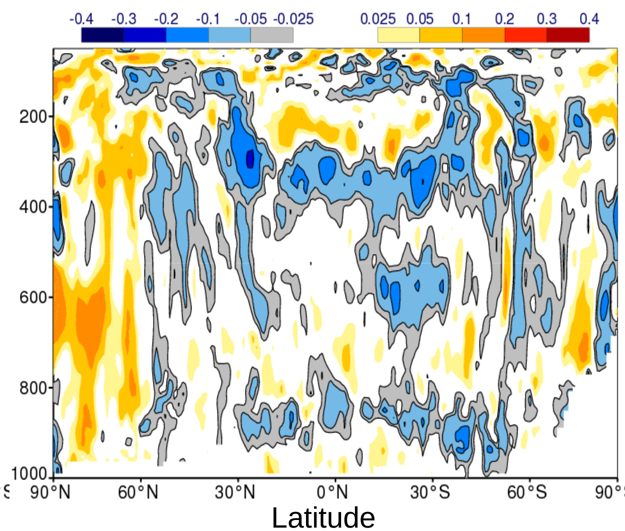
1D+4D-Var of satellite cloud radar & lidar – impact on subsequent forecast

- modified *T*, *q* profiles from 1D-Var of radar & lidar used as pseudo-obs in 4D-Var
- assimilation cycle of 12 hours, adding the new observations to the full system of regularly assimilated observations + 10-day forecast run from the analyses

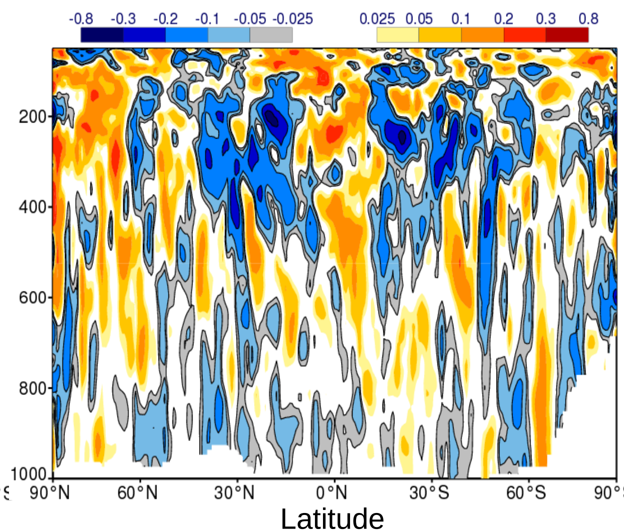
Specific humidity [g/kg] T+24



Temperature [K] T+24



Wind T+24



RMS (FCexp – AN) – RMS (FCref – AN)

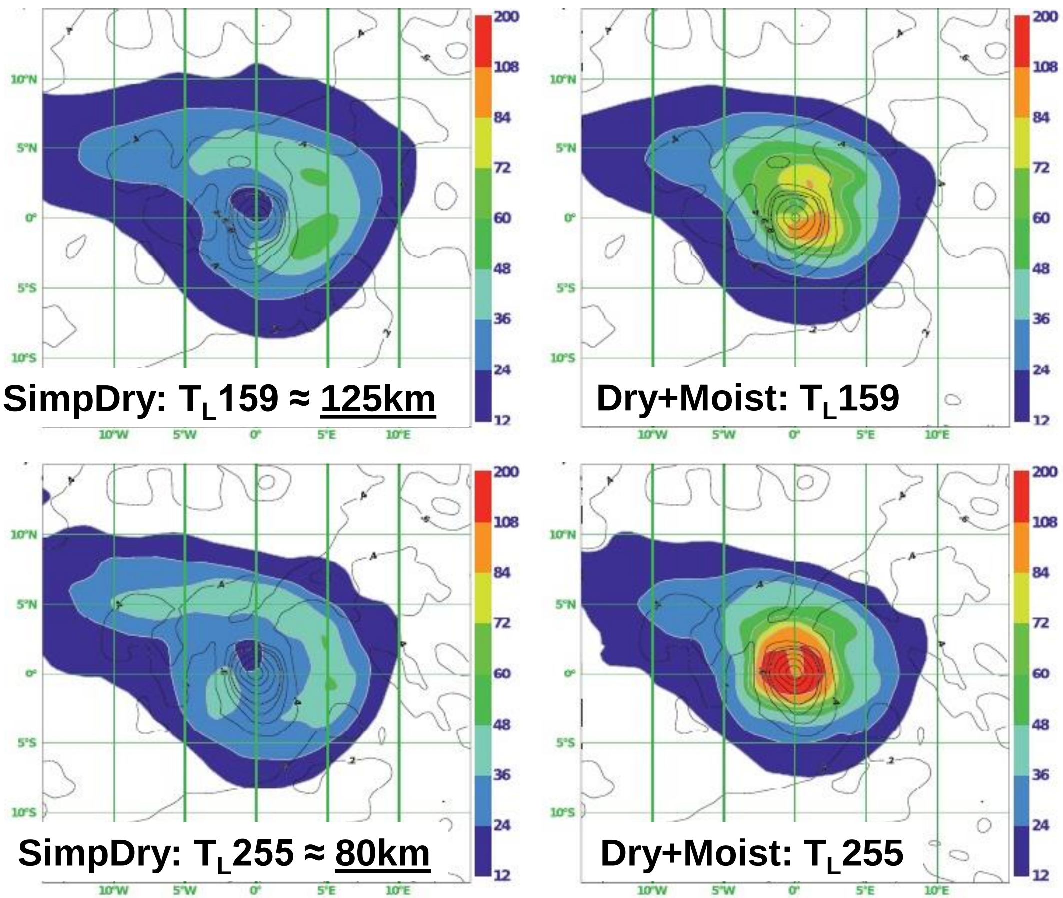
Negative values (blue colours): rms of EXP smaller than REF

Generally, a positive impact of the new observations on the subsequent forecast:

+ *even though it decreases in time, it is still noticeable up to 48-hour forecasts*
+ *small additional improvement when the radar and lidar observations combined*

Janisková, 2015

Using linearized physics in singular vector computation



- Singular vectors (SVs) used to generate perturbations to the initial conditions in the EPS of ECMWF.
- SVs = <u>the fastest-growing perturbations over a finite time interval</u>
  → sampling the dynamically most relevant structures to dominate the uncertainty sometime in future

<u>Composites of vertical integrated Total Energy of initial SVs 1-5</u>

Tropical cyclone (TC) Helene
(16 – 24 Sept. 2006)

- With increased resolution or including more diabatic processes in SV calculation:
  → *more SV structures associated directly with the TC than other flow features*
  → *baroclinic flow enhanced closer to the centre of TC when accounting for moist processes*
- If used to initialize EPS, higher resolution moist SVs → larger spread of wind speed, track and intensity of TC

SimpDry = only very simple vertical diffusion and surface drag of *Buizza (1994)*

Lang et al., 2012

Using adjoint model for sensitivity

• **adjoint models allow the computation of the gradient of one output parameter of a numerical model with respect to all its input parameters**

⇓

application in the study of sensitivity problems

Adjoint $\mathbf{F}^T$ of the linear operator $\mathbf{F}$ provides the gradient of an objective (cost) function J with respect to $\mathbf{x}$ *(input variables)* given the gradient of J with respect to $\mathbf{y}$ (*output variables*):

$$\frac{\partial J}{\partial \mathbf{x}} = \mathbf{F}^T \frac{\partial J}{\partial \mathbf{y}} \quad \text{or} \quad \nabla_{\mathbf{x}} J = \mathbf{F}^T \nabla_{\mathbf{y}} J$$

Adjoint sensitivity applications:

• For parametrization schemes – thorough evaluation of the relative importance of different variables *(i.e. identification to which variables the schemes are most sensitive)*

• Analysing sensitivity of a forecast error to initial conditions or any forecast aspect *(e.g. precipitation, cyclone, …)* to the model control variables

• In data assimilation systems – measuring sensitivity with respect to any parameter of importance:

(e.g., as a diagnostic tool to monitor the observation impact on short-range forecasts)

Adjoint sensitivity as a different tool for the validation of parametrization scheme

Sensitivity of one output variable to a number of input variables NVAR prescribed on several levels NLEV can be obtained in one run using adjoint technique instead of multiple runs required by traditional methods (usually ~ NVAR * NLEV)

- Example: sensitivity of the radiation scheme to input variables *(as such sensitivity is well known from previous studies of RT)*
- The gradient with respect to y of unity size (*i.e., perturbation of radiation fluxes with* $\pm 1\ W.m^{-2}$) is provided to the adjoint of radiation scheme

$$\nabla_{\mathbf{x}} J = \left(\frac{\partial F}{\partial \mathbf{x}}\right)^T$$

$(\partial F / \partial T)^T$	sensitivity to: temperature
$(\partial F / \partial q)^T$	specific humidity
$(\partial F / \partial a)^T$	cloud cover
$(\partial F / \partial q_{lw})^T$	cloud lwc
$(\partial F / \partial q_{iw})^T$	cloud iwc

$$\nabla_{\mathbf{x}} J = \mathbf{F}^T \nabla_{\mathbf{y}} J = \left(\frac{\partial F}{\partial \mathbf{x}}\right)^T \frac{\partial J}{\partial \mathbf{y}}, \text{ with } \nabla_{\mathbf{y}} J = 1 \longrightarrow \nabla_{\mathbf{x}} J = \mathbf{F}^T \text{ or } \nabla_{\mathbf{x}} J = \left(\frac{\partial F}{\partial \mathbf{x}}\right)^T$$

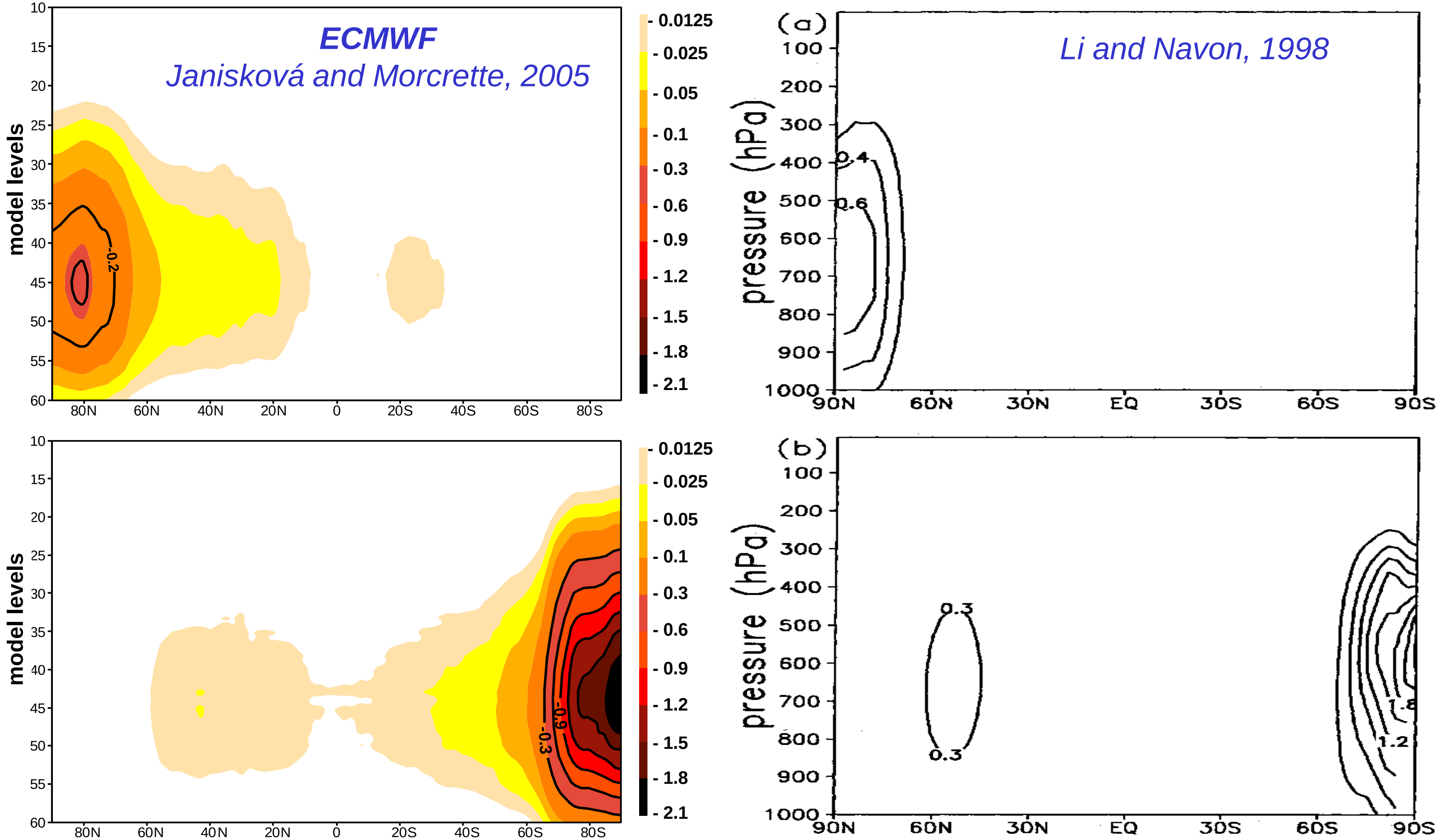
where $\mathbf{F}^T$ is the adjoint of the linear operator $\mathbf{F}=\partial F/\partial x$ and F is the nonlinear operator

Examples of adjoint sensitivity for physical parametrization (1)

Comparison with previous studies

summer

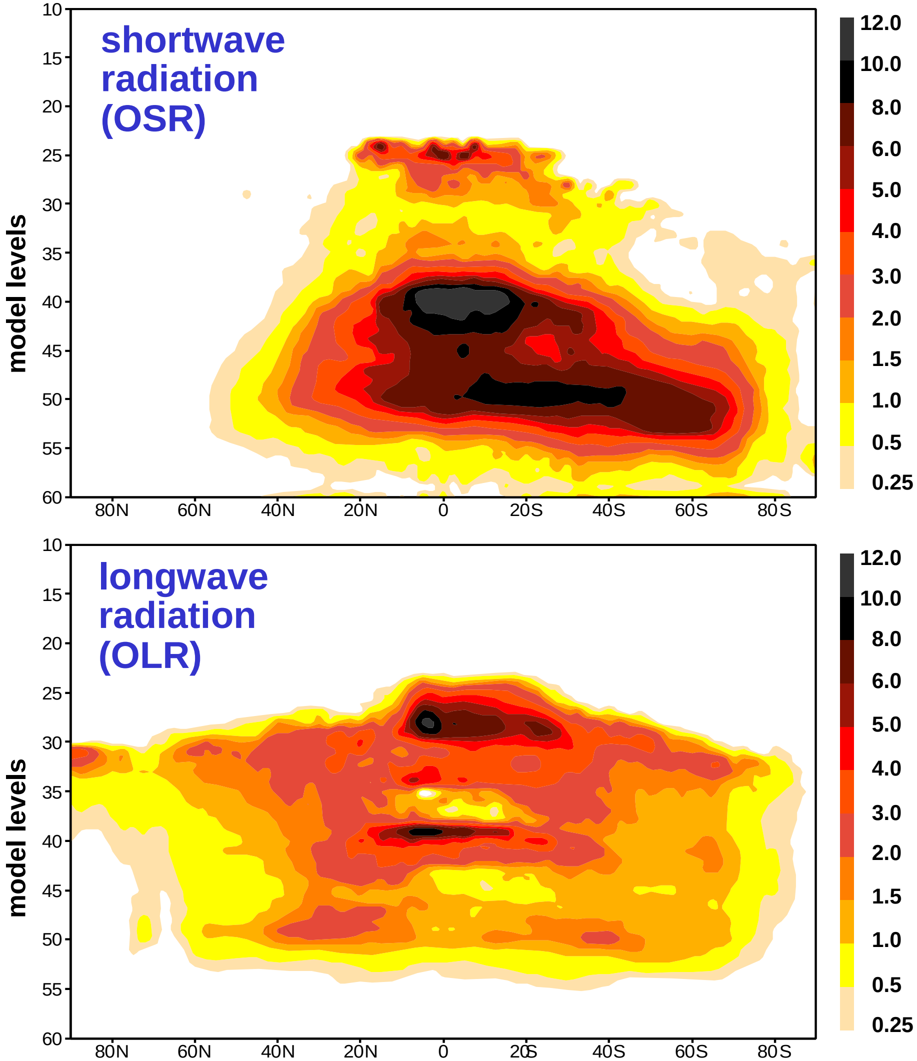
winter



Sensitivity of the shortwave upward radiation flux at the TOA w.r.t. specific humidity [$W.m^{-2}/g.kg^{-1}$]
CLEAR SKY

Examples of adjoint sensitivity for physical parametrization (2)

Sensitivity of the shortwave/longwave upward radiation flux at the TOA (OSR/OLR) w.r.t. <u>cloud fraction</u> [W.m^{-2}/cloudfr] **WINTER**



Within the range of validity of the TL approximation for adjoint of the radiation schemes:

- in high-sensitivity regions, a cloud fraction perturbation of 0.1 leads to an absolute increase of ~1 W m^{-2} in OSR or OLR

<u>Janisková and Morcrette, 2005</u>

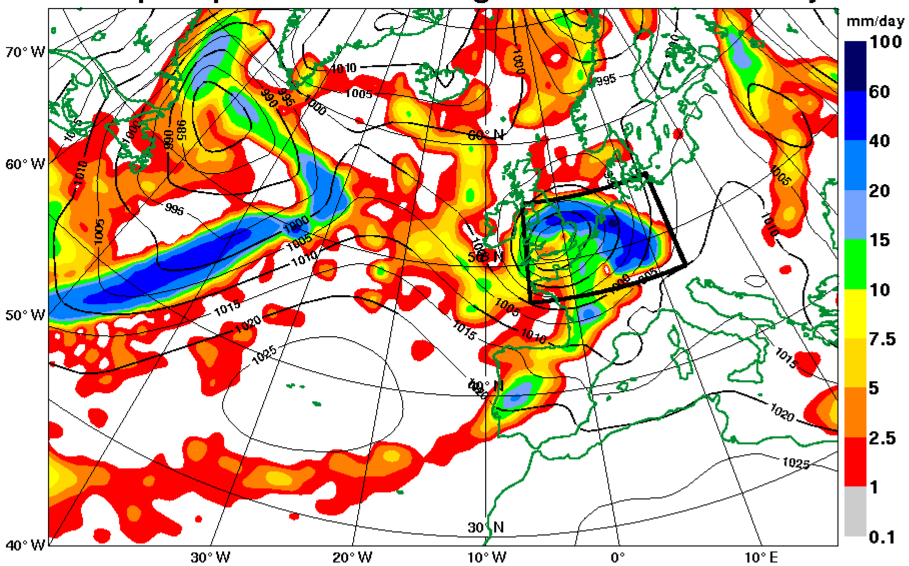
Adjoint sensitivity of a physical aspect to the model control variables

The time integration of the adjoint model allows the computation of adjoint sensitivities of any physical aspect (J) inside a target geographical domain to the model control variables ($\mathbf{x}$) several hours earlier.

Adjoint sensitivities for a European winter storm:

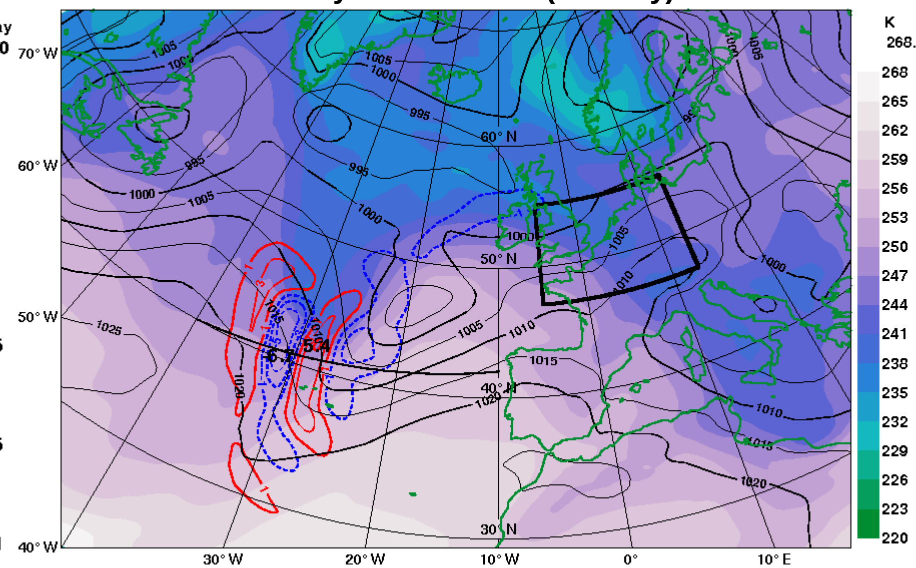
J = mean 3h precipitation accumulation inside black box.

Mean precipitation inside target box = 16.39 mm/day



$\partial J/\partial \mathbf{x}$ after 24 hours of “backward” adjoint integration

Sensitivity with respect to 500-hPa temperature
T159L91 Sensitivity units: 0.0001*(mm/day)/K



The dipolar pattern of sensitivities indicates that a strengthening of the cross-frontal temperature gradient would result in a precipitation increase inside the black box, 24 hours later.

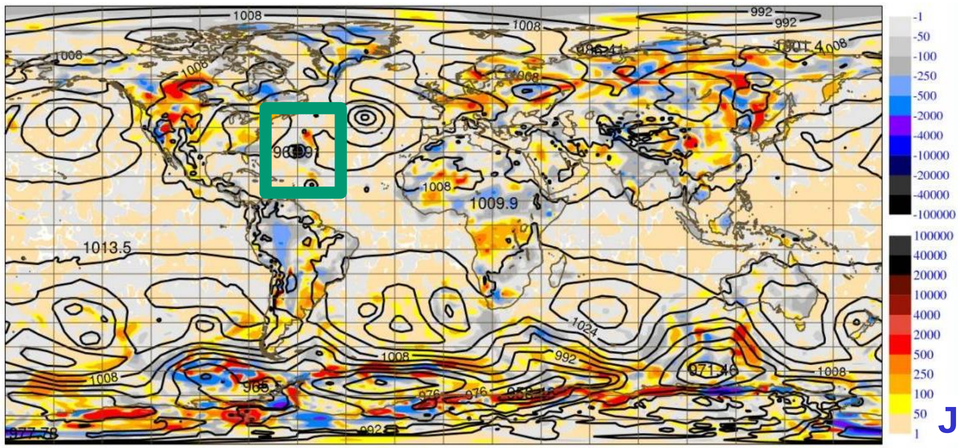
Janisková and Lopez, 2013

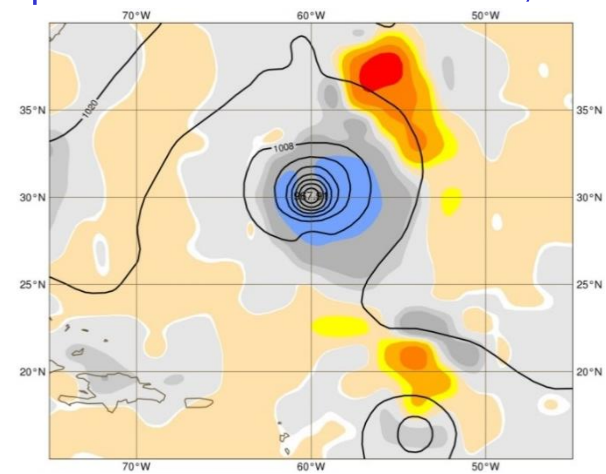
Adjoint sensitivity of forecast error to the initial conditions

i.e. to the analysis, $\partial J/\partial \mathbf{x}$, where J is a measure of the forecast error (e.g. energy norm)

Dry processes + dry energy norm

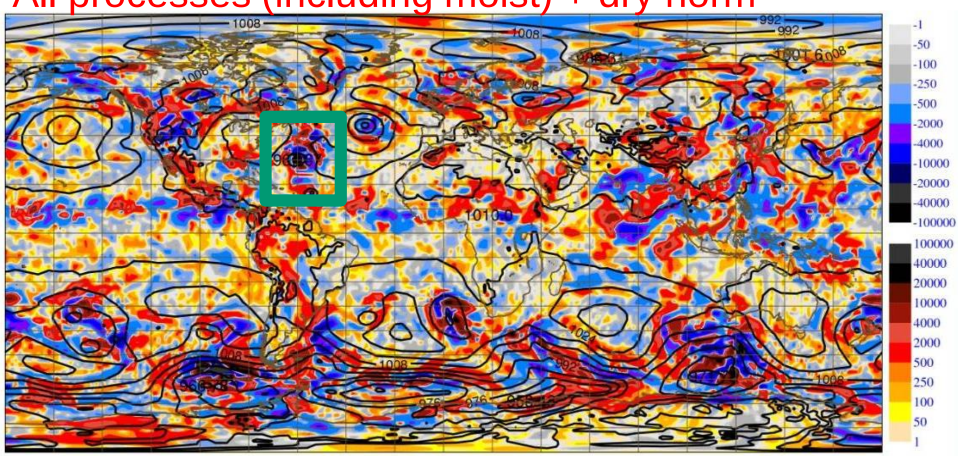
Example: 20100828 at 21:00UTC, L91

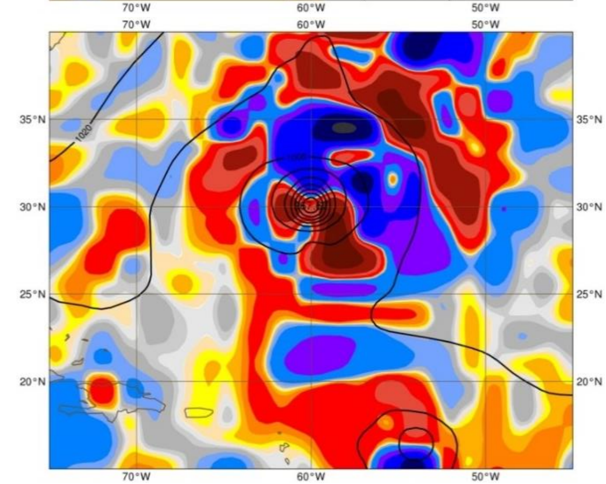




J kg^{-1} / (g kg^{-1})

All processes (including moist) + dry norm





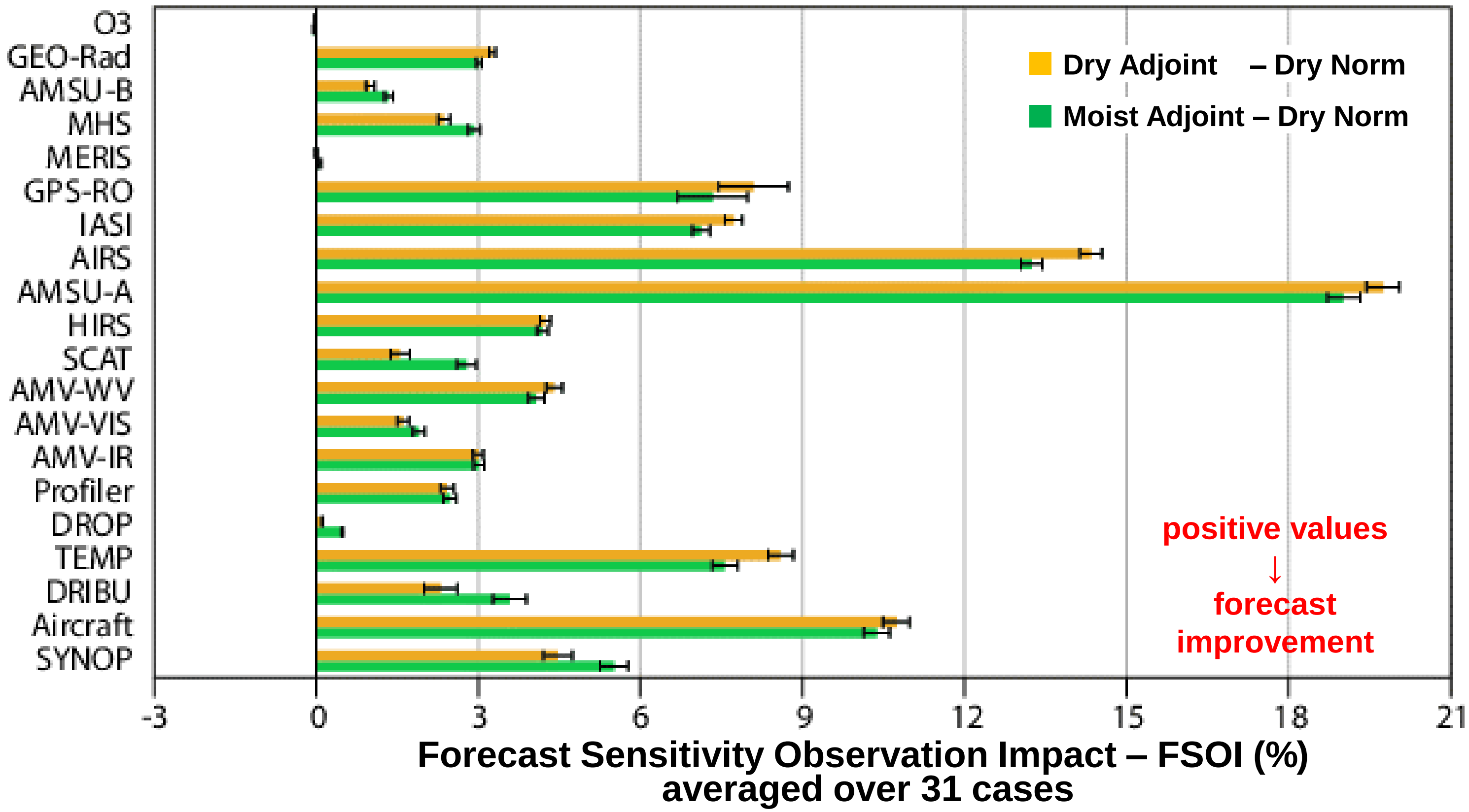
Using a more sophisticated adjoint model → more flow-dependent and more realistic sensitivities

Janisková and Lopez, 2013

Adjoint-based technique measuring the observation influence on forecasts

- <u>Data assimilation diagnostics</u> – using adjoint model for monitoring sensitivity of the cost (objective) function J with respect to observations

(Baker & Daley 2000, Langland & Baker 2004, Cardinali & Buizza 2004, Morneau et al. 2006, Xu & Lagland 2006, Zhu & Gelaro 2008, Cardinali 2009)



Technique influenced by simplified adjoint model used to carry the forecast error information backwards → *impact of some observations increased when using moist processes*

<u>*Janisková and Cardinali, 2015*</u>

Physics parameter optimization using 4D-Var

Goal: to adjust the value of (some) physics parameters (PP) by cycling 4D-Var data assimilation (typically over one or two months), under the constraint of all routinely available observations.

The PPs to be optimized need to be added to the control vector of the 4D-Var data assimilation and its cost function:

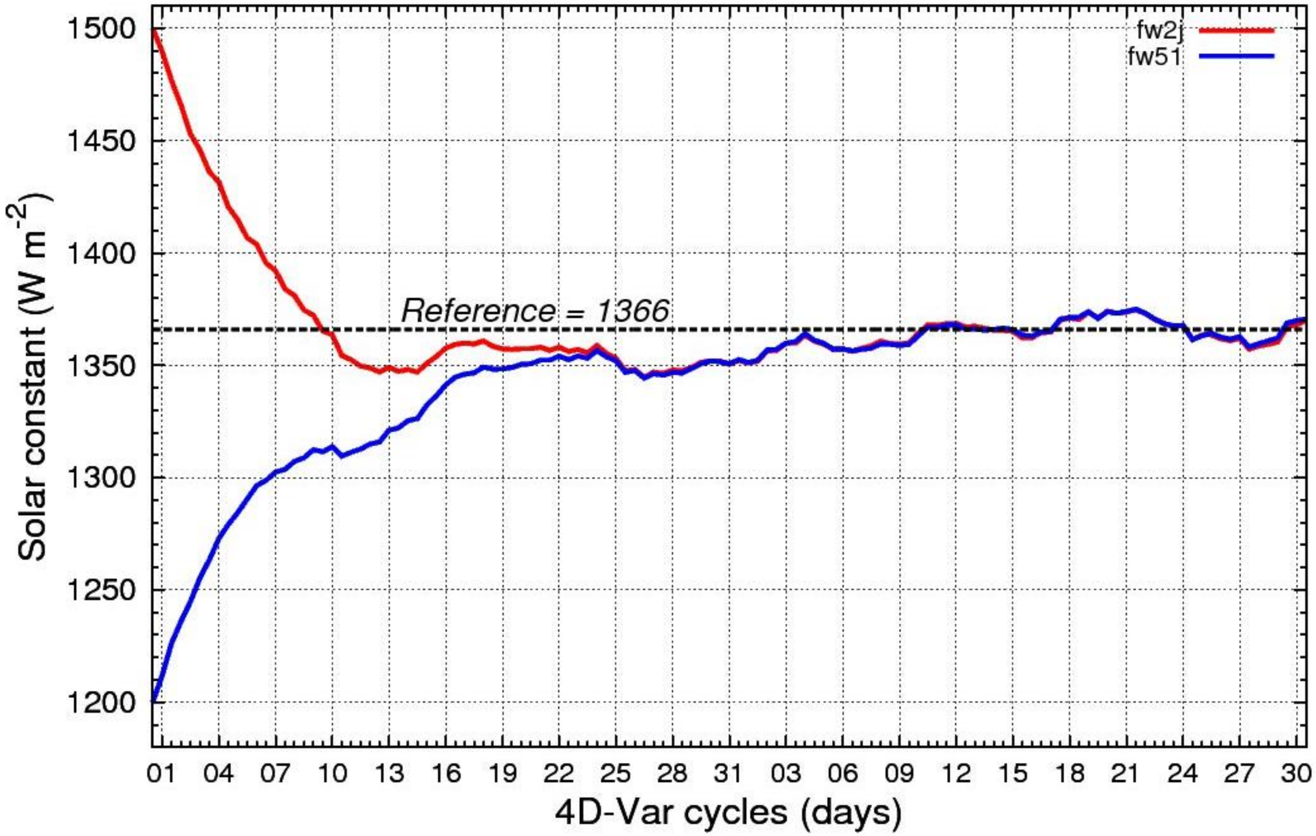
$$J = \frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T \mathbf{B}_{\mathbf{x}}^{-1}(\mathbf{x}-\mathbf{x}_b) + \frac{1}{2}(\mathbf{p}-\mathbf{p}_b)^T \mathbf{B}_{\mathbf{p}}^{-1}(\mathbf{p}-\mathbf{p}_b)$$
$$+ \frac{1}{2}\left(H(\mathbf{x},\mathbf{p})-\mathbf{y}_o\right)^T \mathbf{R}^{-1}\left(H(\mathbf{x},\mathbf{p})-\mathbf{y}_o\right)$$

where B_p is the background error covariance matrix for PPs.

Limitations: Only parameters that are present in both the forecast model and the linearized simplified physics (TL & AD) can be treated in this way.

Discrepancies between the full non-linear physics and the TL & AD physics (used in the minimization of *J*) might lead to sub-optimal results.

Feasibility test: 4D-Var optimization of solar constant



T511 L91 4D-Var experiment
Period: Oct-Nov 2012

Evolution of the optimized solar constant as a function of 4D-Var cycles with initial value:

1500 W m^{-2}

1200 W m^{-2}

---- reference, 1366 W m^{-2}

4D-Var is able to converge towards the reference value after a couple of months.

⇓

- New prospects for the objective optimization of some parameters of the model's physics.
- But to be tested whether the method successful when dealing with parameters:
  - *more uncertain or less well constrained by the observations,*
  - *associated with more non-linear processes (e.g. condensation)*

Summary (1)

- **Positive impact from including physical parametrization schemes into the linearized model has been demonstrated.**

- **Physical parametrizations become important components in current variational data assimilation systems:**
  - positive impact on analysis and subsequent forecast
  - enabling to assimilate observations related to physical processes (rain, clouds, ...)

- **Including linearized physical parametrization schemes into singular vector computations can lead to:**
  - more of the SVs structures associated directly with some atmospheric processes
  - better spread in EPS

- **Adjoint of physical processes used for sensitivity studies can provide:**
  - more flow-dependent and more realistic sensitivities
  - different tool for the validation of parametrization schemes
    (sensitivity to all governing parameters obtained at minimal computational cost)
  - diagnostic tool for:
    - analyzing sensitivity of a forecast error to initial conditions
    - monitoring the observation impact on short-range forecasts

Summary (2)

- **The linearized physics provides new prospects for the objective optimization of some physics parameters, but:**
  - limited to parameters present in both the forecast model and the linearized physics
  - uncertain for parameters associated with more non-linear processes or not enouh constrain by observations

BUT

Certain requirements/constraints/limitations must be considered.

- **Linearity of physical parametrization/observation operator,** since nonlinearities could:
  - cause convergence problems in variational assimilation based on strong assumption that the analysis is performed in quasi-linear framework
  - lead to spurious unstable modes in computation of singular vectors
  - limit the relevance and usefulness of adjoint sensitivity
- **Acuracy of physical parametrization/observation operator:**
  - to provide realistic enough sensitivities and model equivalent to observations
- **Computational cost for practical applications**