Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres

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Data assimilation systems for convective-scale NWP are presented and discussed here for the following organizations:

1. Météo-France, the national weather service of France.
2. The ALADIN and RC LACE consortia with participation of the weather services of Algeria, Austria, Belgium, Bulgaria, Czech Republic, Croatia, France, Hungary, Morocco, Poland, Portugal, Romania, Slovakia, Slovenia, Turkey and Tunisia.
3. The HIRLAM consortium with participation of the weather services of Denmark, Estonia, Finland, France, Iceland, Ireland, Latvia, Lithuania, the Netherlands, Norway, Spain and Sweden.
4. The Met Office, the national weather service of the UK.
5. The COSMO consortium with participation of the weather services of Germany, Italy and Switzerland.
6. NOAA, the National Oceanic and Atmospheric Administration of the USA.
7. JMA, the Japan Meteorological Agency.

Aim of talk:

Survey briefly convective scale data assimilation methods at operational centers.

Survey briefly ongoing research at operational centers

Identify where the approaches differ and try to understand whether these differences are due to practical reasons or to differences in understanding of scientific problems.

Show that convective scale data assimilation is worth the effort.

Operational NWP models participating in the survey:

Group	Model	Numerics - (Physics)	Resolution
Meteo-France ALADIN, HIRLAM	ALADIN	Spectral, SL, SI (AROME or ALARO physics)	1.3 – 2.5 km 50-90 levels
COSMO	COSMO	Finite diff., C-grid, 3D Bott adv. Time-splitting	2.2 - 2.8 km 50-60 levels
Met Office	UKV	Finite diff., C-grid, SL, SI Variable resolution	1.5 km 70 levels
NOAA	CONUS-NAM HRRR	Finte diff., B-grid, F/B fast w. Finte diff. 5th order, C-grid, time splitting	3 km 3 km
JMA	MSM LSM	Finte diff., Split-explicit	5 km 2 km

Operational upper air data assimilation algorithms:

Group	Methods	Incr. res.	Other DA comp.
Meteo-France HIRLAM ALADIN	3D-Var; Berre(2000) statistical balance; EDA for BGE stat.	1.3 - 2.5 km	Bayesian retrieval of hum. profiles from radar refl.
COSMO	KENDA (LETKF); Adaptive multipl. and addit. Inflation; RTPP; Adapt. localization	2.2 - 2.8 km	Hydrost. Bal. Latent Heat Nudging
Met Office	Incr. 4D-Var; Stat. bal.; Lagged NMC for BGES	4.5 km	Jc-DFI Latent Heat Nudging
NOAA CONUS NAM NOAA HRRR	Hybrid incr. 3DEnVar NMC for BGEs Hybrid incr. 3DEnVar NMC for BGEs	9.0 km 12.0 km	Cloud analysis + Latent Heat Nudging -”- -”-
JMA MMA JMA LMA	Incr. 4D-Var;NMC for BGEs 3D-Var; NMC for BGEs	15.0 km 5.0 km	Jc-DFI Bayesian retr…… Soil control variab.!

Operational data assimilation cycling:

Group	DA cycle	Coupling to host model	Other
Meteo-France HIRLAM ALADIN	1 h cont. cycling 3 h cont. cycling 3-6 h cont. cycling	ARPEGE 0 h lag ECMWF 3-6 h lag ARPEGE 0h lag or ECMWF 6 h lag	Large scale mix Blendvar
COSMO DWD COSMO Suisse	1 h cont. cycling 1 h cont. cycling	ICON ensemble (20 km) 0 h lag ECMWF ensemble	
Met Offiice	1 h cont. cycling	MO global 3-8 h lag	
NOAA CONUS NAM NOAA HRRR	1 h cycling (restart from global t - 6 h) 1 h cycling (restart from 13 km parent model t-1h)	Parent domain (12 km) Parent domain (13 km)	
JMA MA JMA LA	3 h cont. cycling 1 h cycling (restart from MA t - 3h)	JMA GSM 3-6 h lag MSM 3-5 h lag	

Development of advanced data assimilation schemes

4D-Var HARMONIE:

- Multi-incremental, spectral space control variable, pre-conditioning by sqrt(B), (similar to ECMWF and HIRLAM)
- Large scale error constraint

Hybrid 4DEnVar:

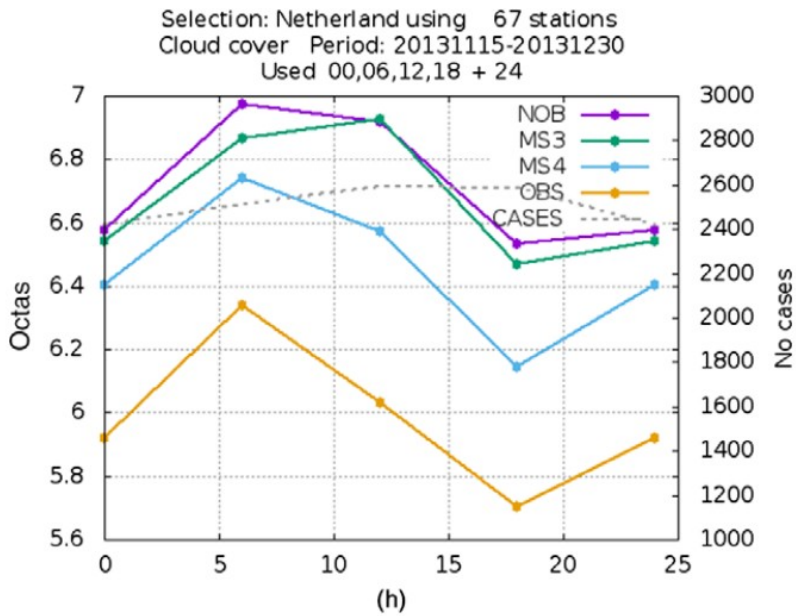
- Meteo-France: B pre-conditioning, control vector=model state, space-time localization (advection)
- HARMONIE: sqrt(B) pre-conditioning, α control vector, builds on HARMONIE 4D-Var
- JMA: Hybrid 4D-Var
- Met Office: Hybrid 4D-Var (similar to global)

Rapid update NOAA based on EnKF

Impact of HARMONIE 4D-Var

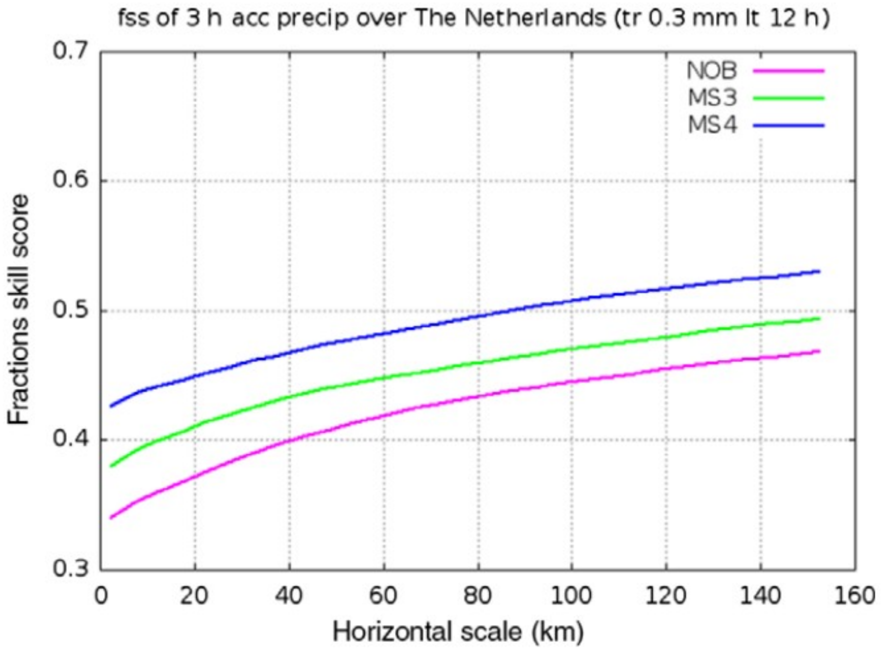
Daily cycle of Cloud cover

——---------- no data assimiation
------------- 3D-Var
------------- 4D-Var
------------- observations



3 h acc. Precipitattion

Fraction Scill Score
0.3 mm at 12h
------- no data assimilation
------- 3D-Var
------- 4D-Var

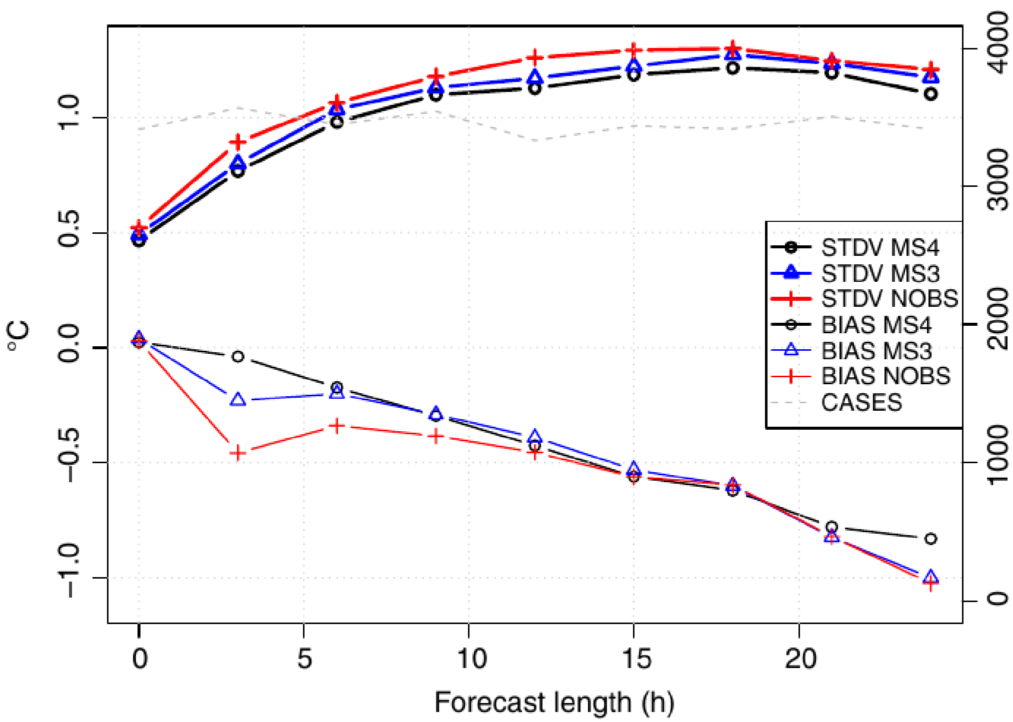


(Provided by Jan Barkmeijer et al.)

Impact of HARMONIE 4D-Var

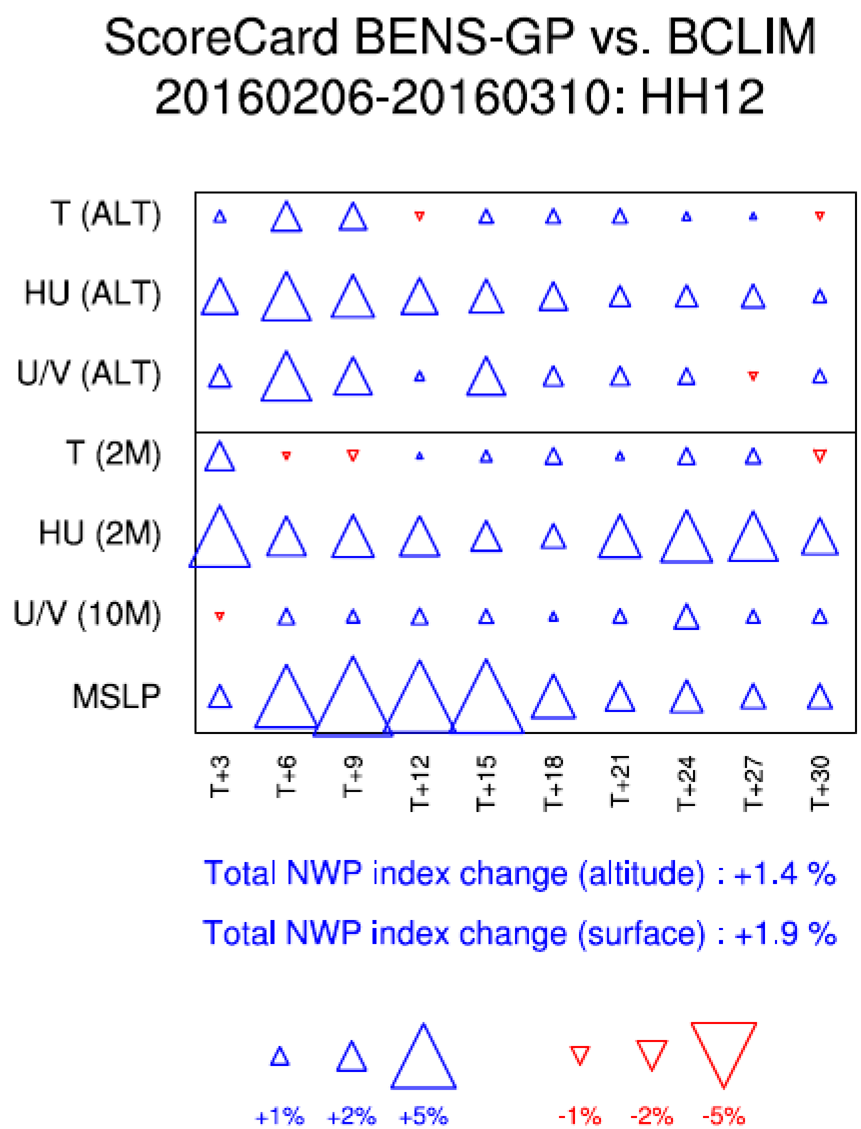
2 meter temperature
Bias and standard deviation

----------- no data assimilation
----------- 3D-Var
----------- 4D-Var



(Provided by Jan Barkmeijer et al.)

Impact of Meteo-France 3DEnVar



(Thibaut Montmerle, personal communication))

HARMONIE Hybrid EnVAR finally works !

Implementation as in

A hybrid variational ensemble data assimilation for the HIgh Resolution Limited Area Model (HIRLAM)

N. Gustafsson[1], J. Bojarova[2], and O. Vignes[2]

$$J\left(\delta \boldsymbol{x}_{\mathrm{var}}, \boldsymbol{\alpha}\right) = \beta_{\mathrm{var}} J_{\mathrm{var}}\left(\delta \boldsymbol{x}_{\mathrm{var}}\right) + \beta_{\mathrm{ens}} J_{\mathrm{ens}}(\boldsymbol{\alpha}) + J_{\mathrm{o}} \tag{6}$$

$$\frac{1}{\beta_{\mathrm{var}}} + \frac{1}{\beta_{\mathrm{ens}}} = 1.$$

$$J_{\mathrm{ens}} = \frac{1}{2} \boldsymbol{\alpha}^{T} \mathbf{A}^{-1} \boldsymbol{\alpha}$$

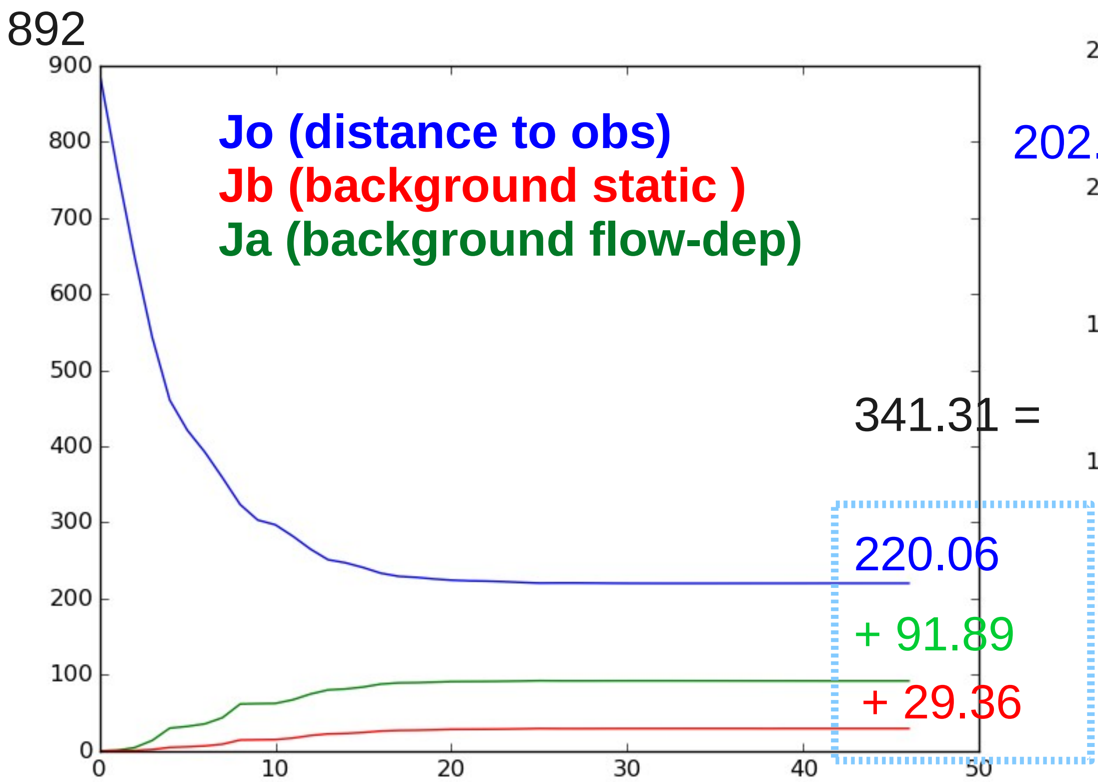
$$\mathbf{B}_{\mathrm{ens}} = \mathbf{A} \circ \mathbf{B}_{\text{raw-ens}}$$

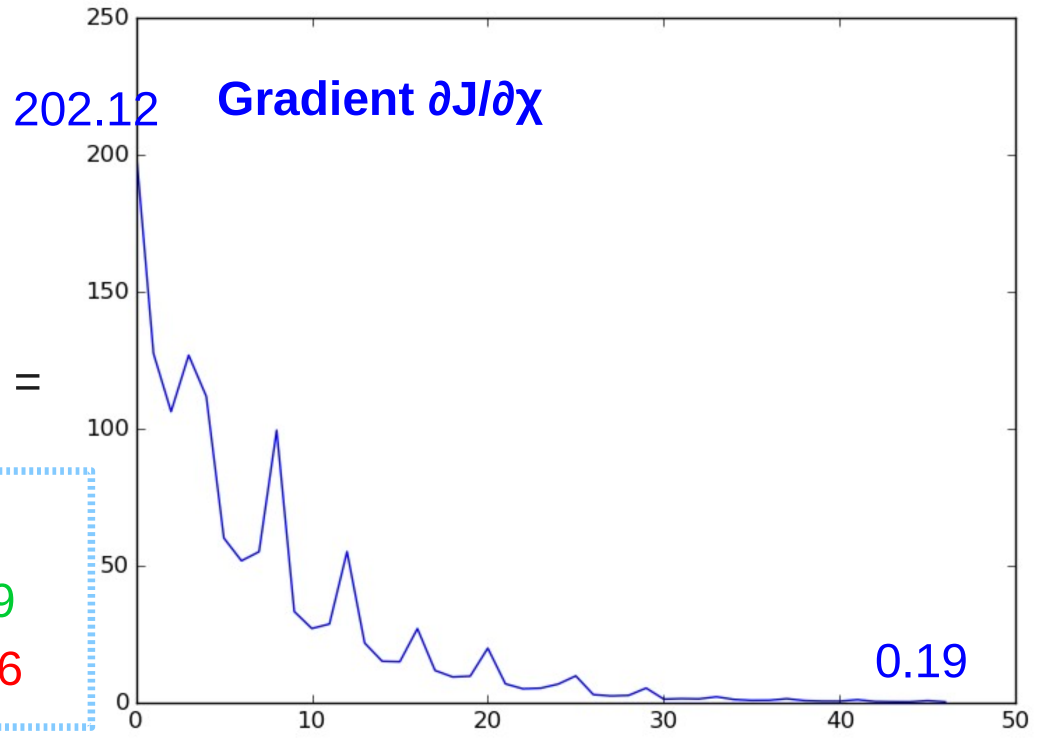
Ensemble : 10 members of BRAND perturbations
Localisation : spectrum of unbalanced surface pressure

(Provided by Jelena Bojarova)

Hybrid EnVar converges finally !!!!!

YQ%LGP=.TRUE. YQ%LSP=.FALSE.	=>	YQ%LGP=.FALSE. YQ%LSP=.TRUE.	+	Qtrans





$J(\chi) = 2Jb + 2Ja + Jo$

$\min_{\chi} J(\chi) \Rightarrow$ **$\partial J/\partial \chi = 0$**

Example 20120613_21 DKCOEXP

(Provided by Jelena Bojarova)

Details in upper-air data assimilation – similarities and differences

(1) DA cycling and handling of larger scales:

- Groups with access to 0 h lag LBCs seem to be able to handle larger scales without any further action
- Groups using "old" LBCs need special efforts for larger scales (LSMIX, Jk, BlendVar).
- NOAA and JMA LA apply DA restarts (spinup problems?)

(2) Background Error Statistics in 3D-Var and 4D-Var:

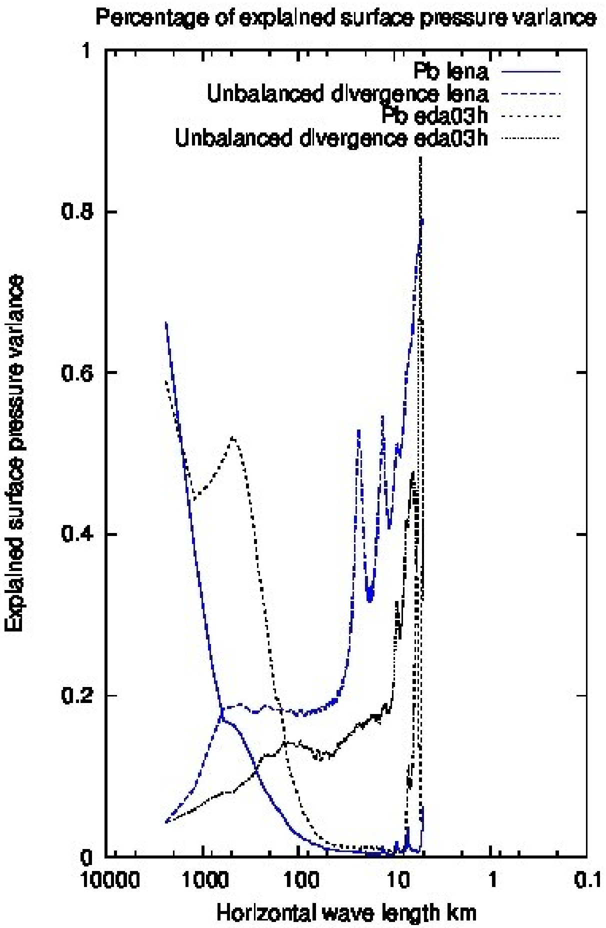
- Some groups express satisfaction while other groups are more critical (Poster by Bojarova and Gustafsson).
- Ensemble techniques to generate BGEs differ
- BGEs on model levels in steep orography ?
- Vertical transforms to do inversions better (Met Office)
- Moisture balances (ALADIN)
- Moisture control variable (ECMWF and Met Office)

Structure functions derived from different ensembles

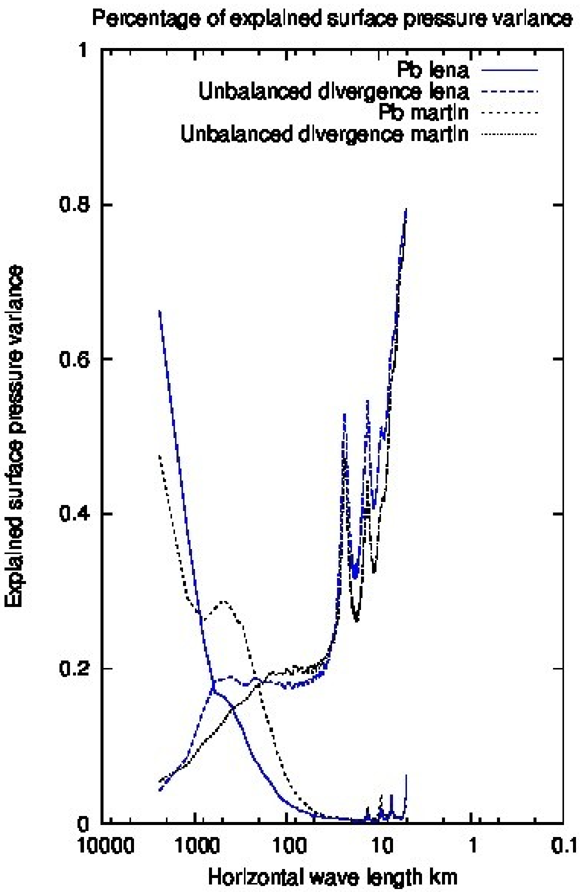
EDA with perturbed observations
BRAND: additative inflation of control BG

Surface pressure variance explained by
- vorticity (solid line)
- unbalanced divergence (dashed line)

EDA perturbations (6 hour DA cycle)

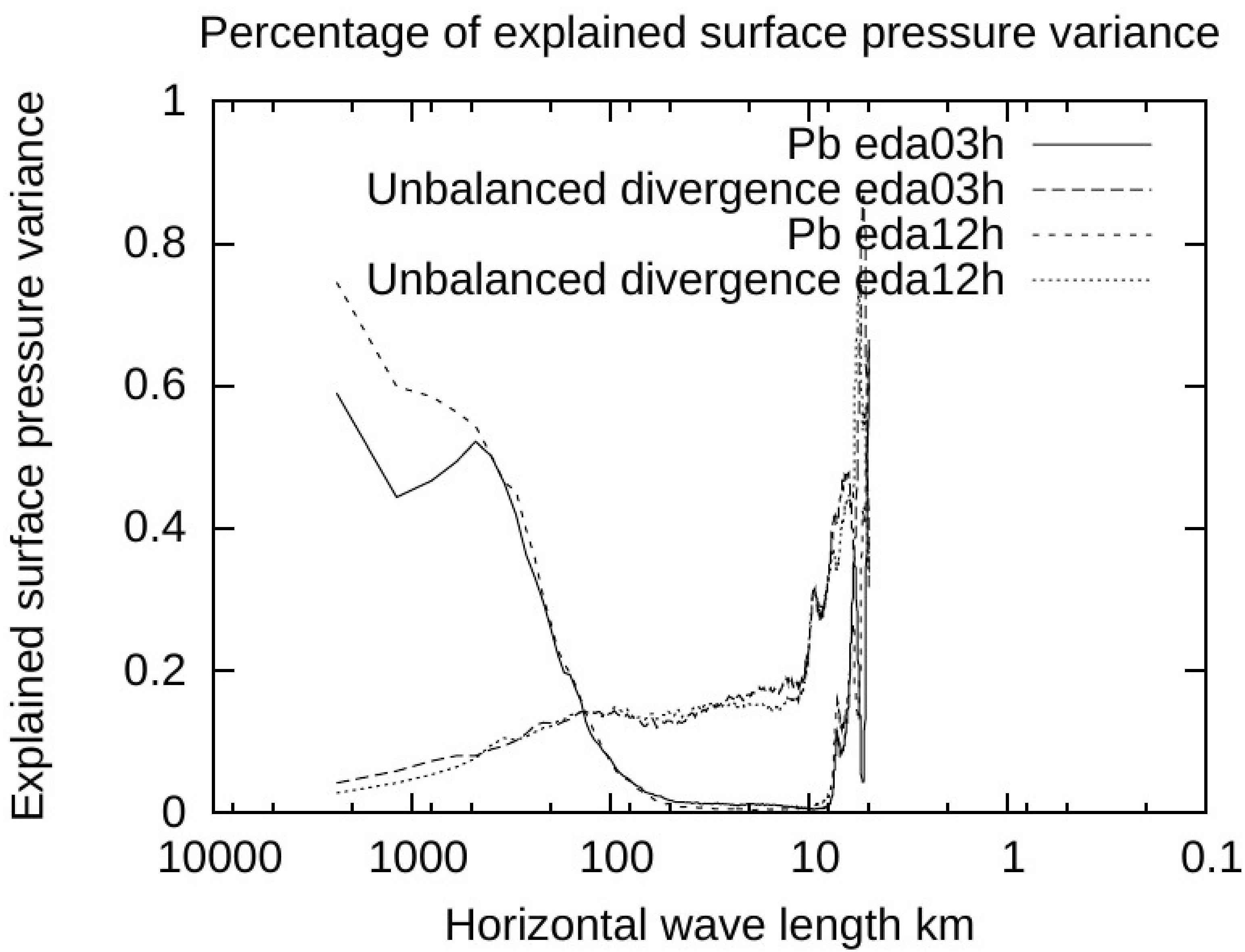


EDA perturbations (3 hour DA cycle)



(Provided by Martin Ridal and Jelena Bojarova)

Effect of further spinup



Details in upper-air data assimilation – similarities and differences (cont.)

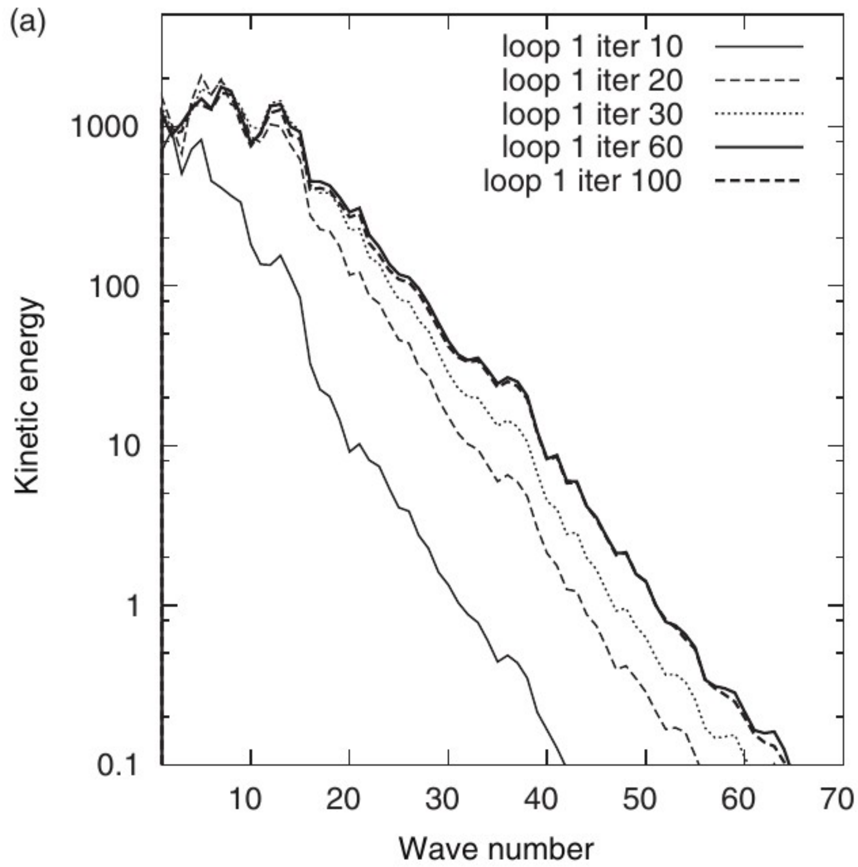
(3) 4D-Var

JMA: NL model resolution 5 km; innovations at 5 km; increment resolution 15 km; NL (!) forward model every iteration. Motivation: Non-linearities,

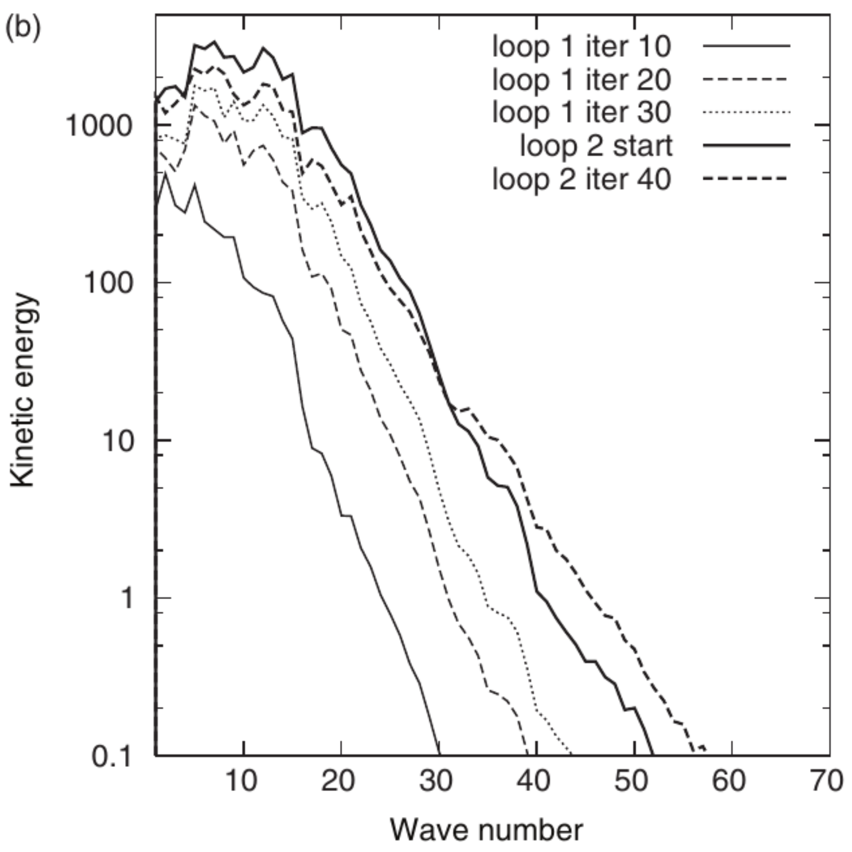
Met Office: NL model resolution 1.5 km; innovations at 1.5 km; increment resolution 4.5 km; linear perturbation model + adjoint during minimization

HARMONIE: NL model resolution 2.5 km; multi-incremental minimization; outer loop with innovation calculation at full model resolution; inner loop quadratic minimization with TL and AD models (including some NL model re-calculations at low resolution); 5 km inner loop resolution so far

Kinetic energy spectra of assimilation increment for different iteration numbers; HIRLAM 4D-Var 24 km model



1 outer loop iteration
100 iterations at 48 km



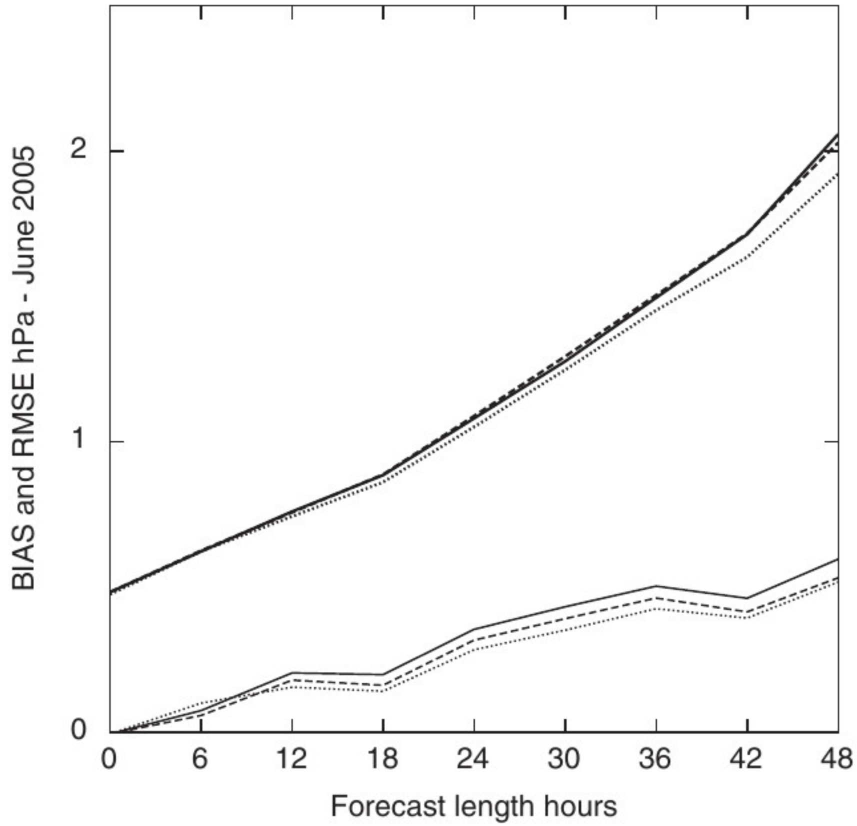
2 outer loop iterations
60 iterations at 96 km
40 iterations at 48 km

(Gustafsson et al., 2012)

Forecast verification scores (BIAS and RMSE) for different outer loop configurations

June 2005
Mean Sea Level Pressure

Full line: 100 iterations at 66 km
Dashed line: 100 iterations at 44 km
Dotted line: 50 iterations at 66 km + 50 iterations at 44 km

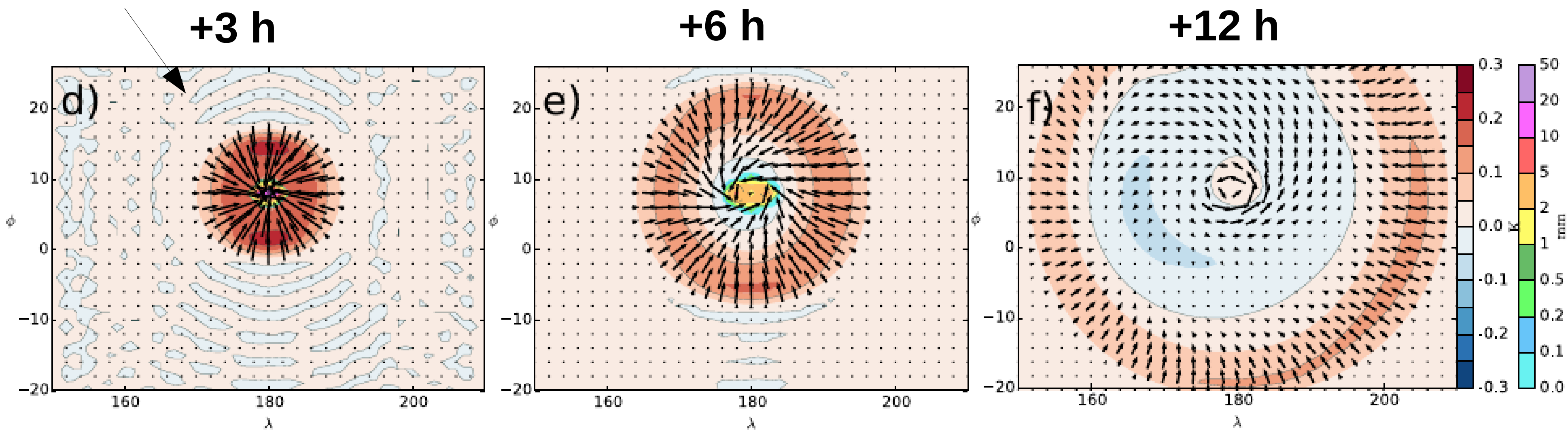


Gustafsson et al. (2012)

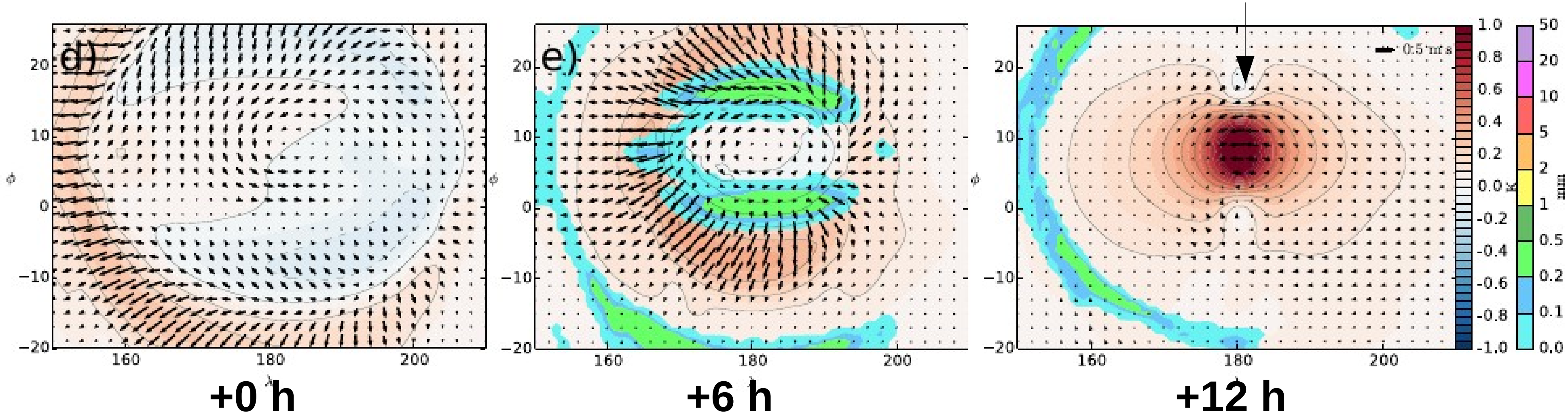
“Inverse adjustment” by 4D-Var

Equatorial domain shallow water model; moisture and condensation added.

Forward non-linear model sensitivity experiment from
a temperature perturbation at +0h



4D-Var data assimilation experiment
with a temperature observation at +12h



For more details see poster by Ziga Zaplotnik!

Details in upper-air data assimilation – similarities and differences (cont.)

(4) EnKF and EnVar

- Ensemble resolution: Full model resolution ensemble (COSMO) – Global ensemble (NOAA)
- Ensemble generation technique
- Localization (Observation space, model space, time/space) and inflation (multiplicative, additative, RTPP)

Details in upper-air data assimilation – similarities and differences (cont.)

(5) Radar data assimilation and adjustment

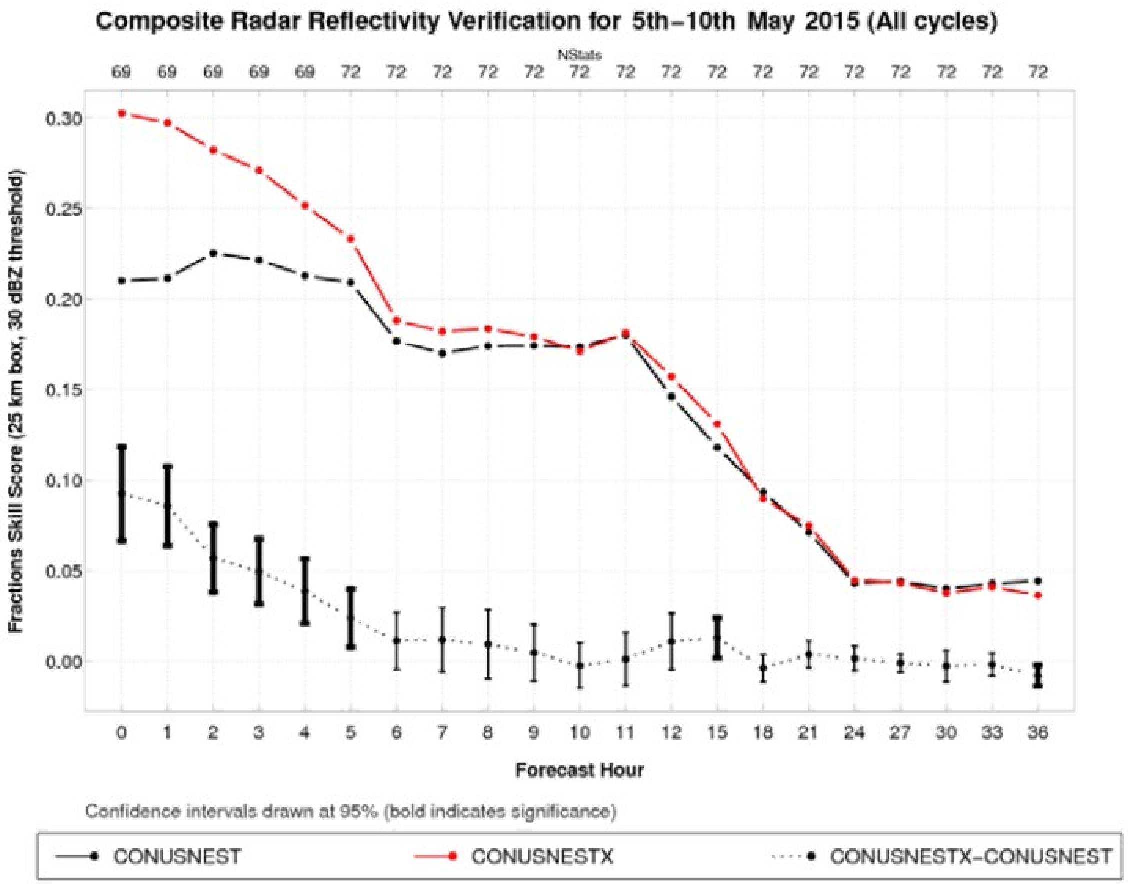
- Meteo France, HARMONIE and JMA 1DVar solution:
  - Retrieve humidity profiles from radar reflectivity
  - Assimilate these humidities and radar winds together with all other observations
    (“nature balance” in case of dense data)
  - Statistical balance constraints

- Latent Heat nudging
  - Convert radar reflectivities to latent heating rates
  - Use these latent heating rates during model integration
  - Let the model do the adjustment

Impact of Latent Heat nudging

Fractions Skill Score (FSS) verification of radar reflectivity
NOAA CONUS NEST, 5-10 May 2015

--------- operational with latent heat nudging during DFI
--------- experiment without latent heat nudging during DFI



Details in upper-air data assimilation – similarities and differences (cont.)

(5) Balances - Need for initialization?

- AROME does not use initialization and this is defended by Meteo France (“nature balance” with dense observations)
- COSMO uses hydrostatic balancing
- UKV uses JcDFI
- NOAA uses digital filter (with latent heat nudging)
- JMA uses JcDFI for 4D-Var

Problems

- HARMONIE-Arome: significant short range noise
- How to separate signal and GW noise with short windows?
- NLNMI approach?
- Diagnostic balance relations (Pagé et al., 2007)?

Impact Studies – Is convective-scale data assimilation worth the effort?

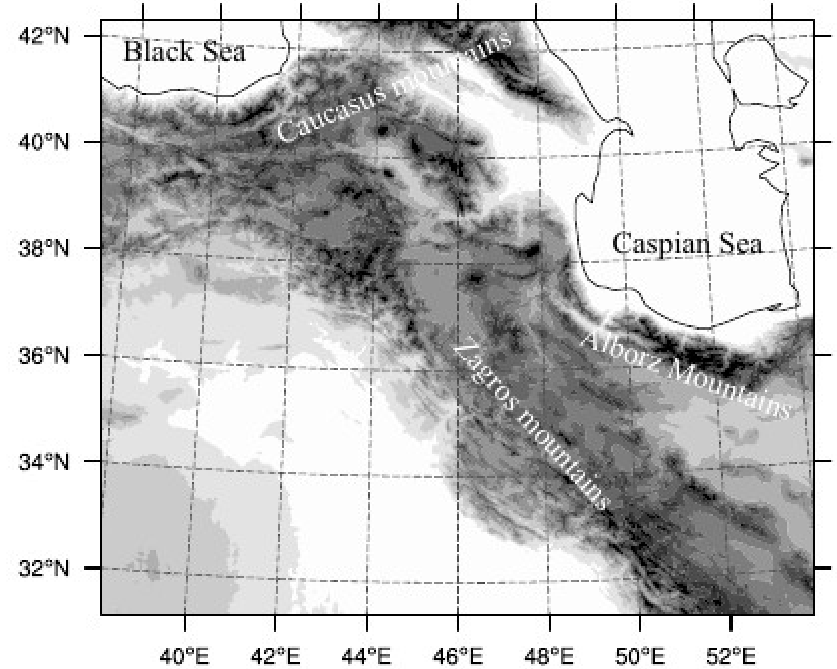
Data assimilation versus downscaling?

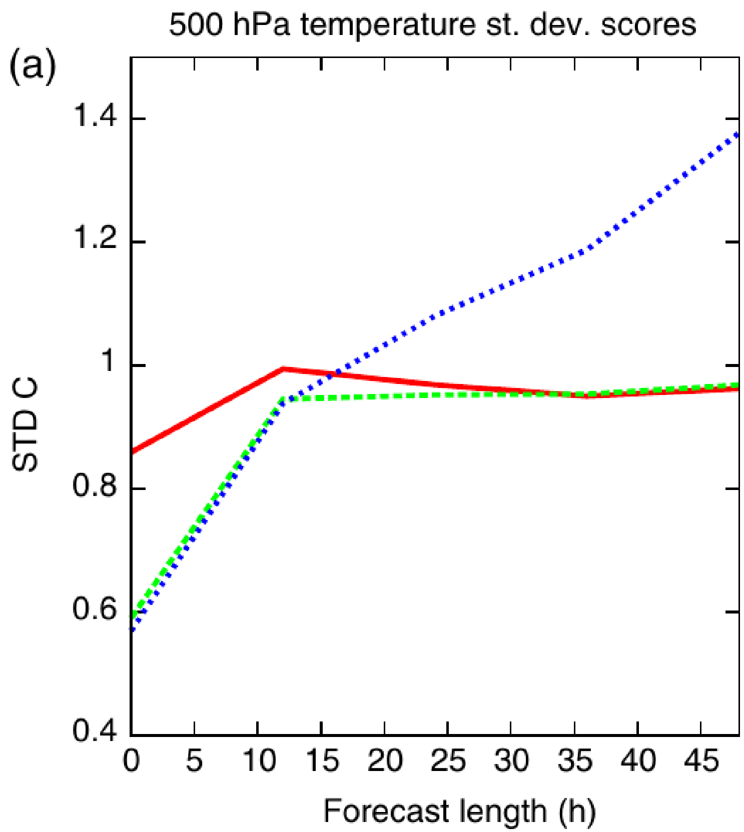
Impact of advanced methods versus simpler methods?

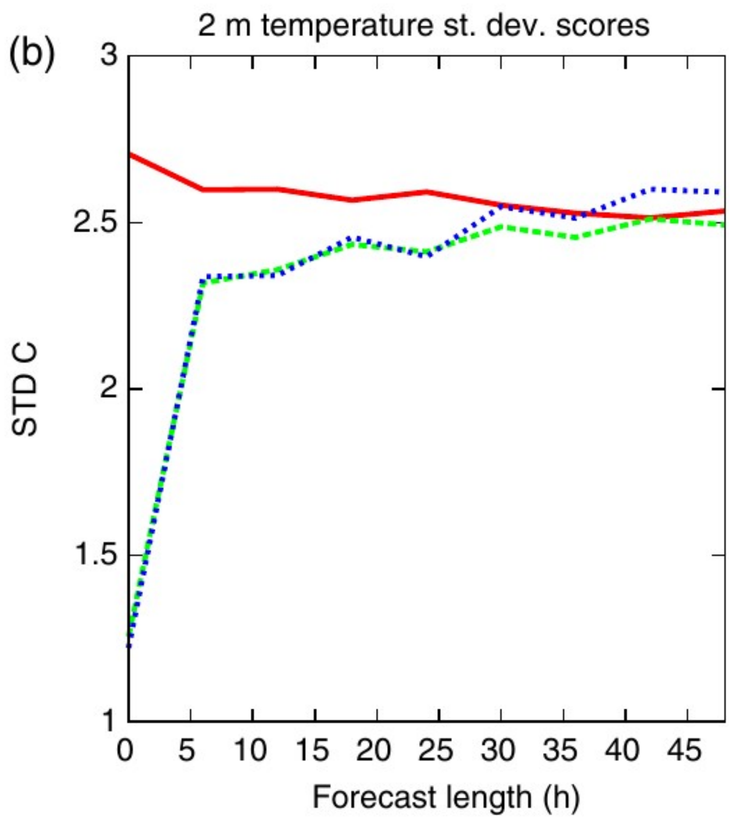
Impact of observations on convective scales?

Data assimilation versus downscaling for a small model domain over Iran (HARMONIE-AROME)

----------- ERA Initial and Lateral Boundary Conditions (LBCs), No DA
----------- ERA LBCs, DA
----------- ECMWF operational forecast LBCs, DA



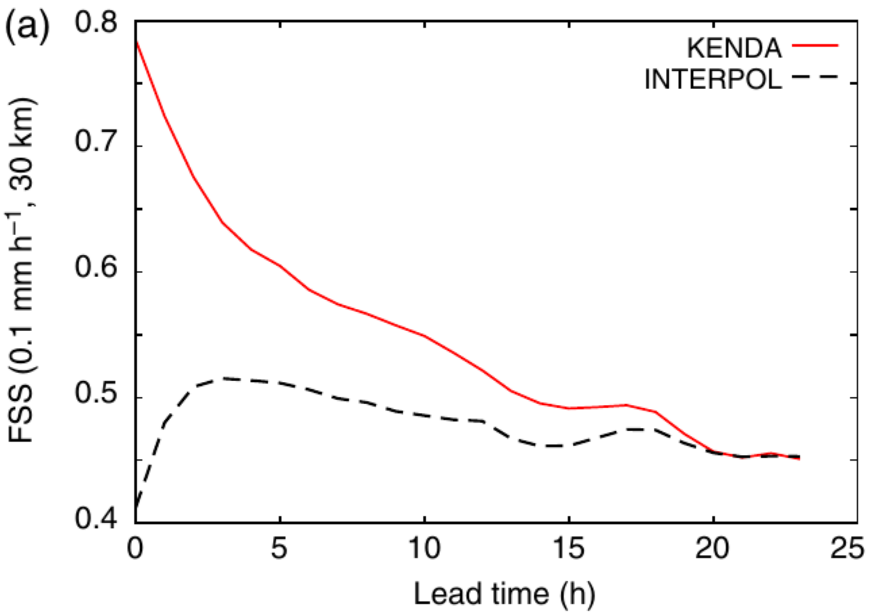




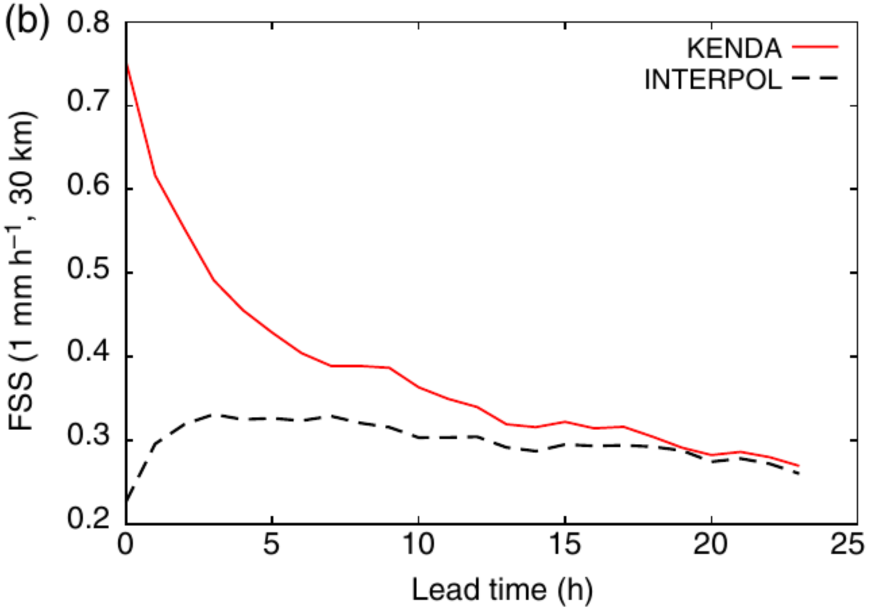
COSMO KENDA, 1 h precipitation, Fractions Skill Score (FSS), 30 km x 30 km, 26 May – 9 June 2016

KENDA initial data - full line
Interpolated initial data – dashed line

0.1 mm/h

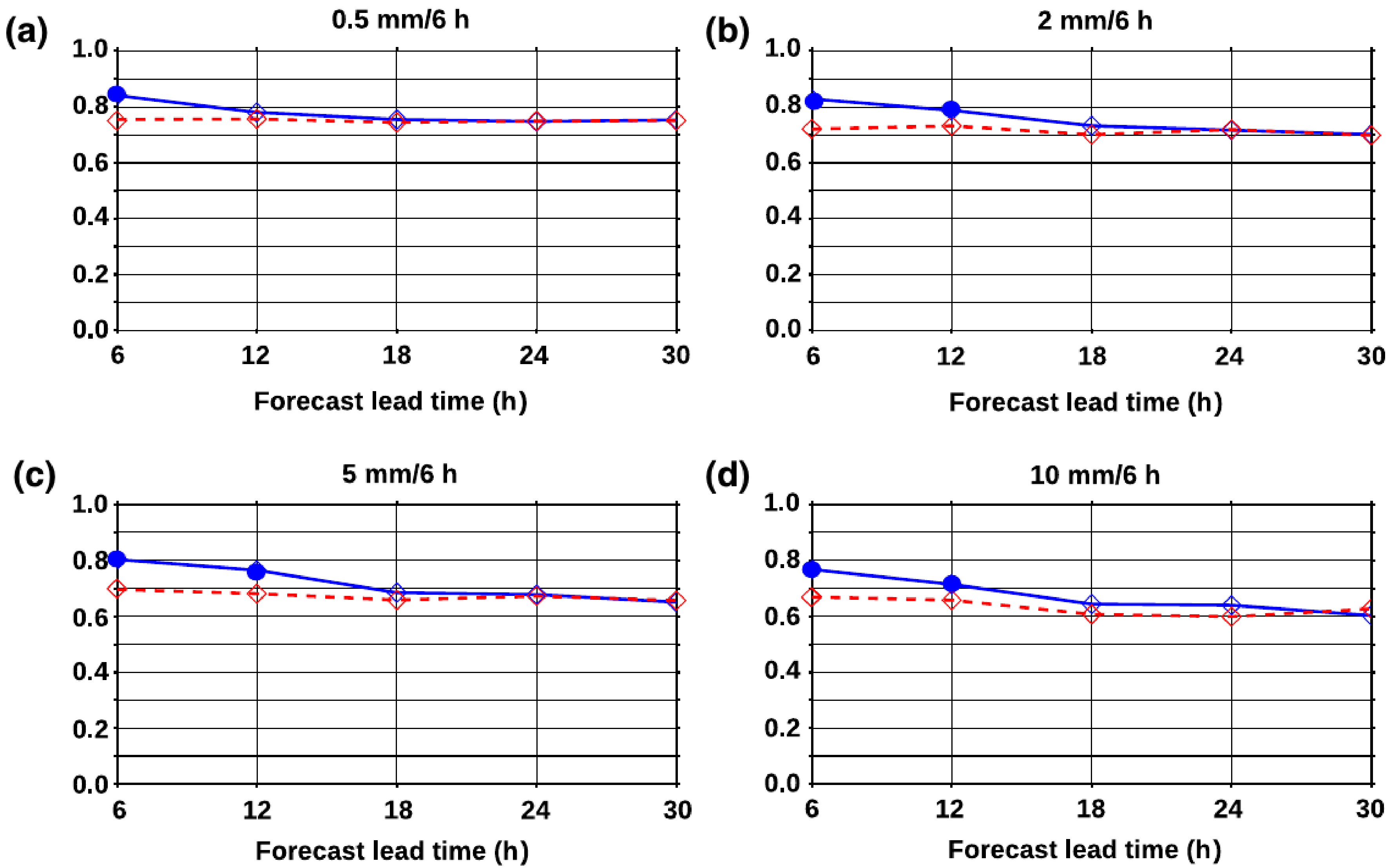


1.0 mm/h



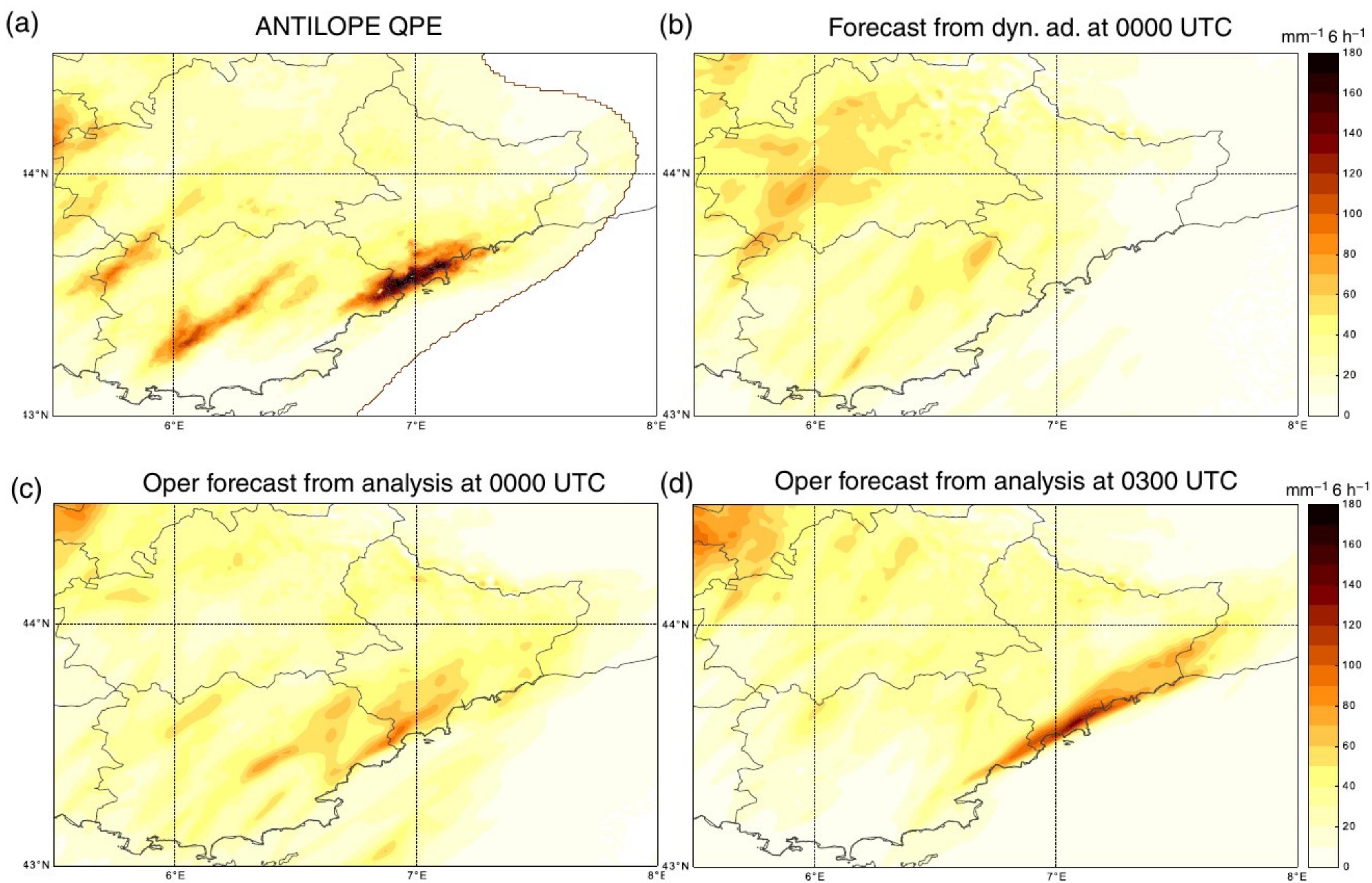
AROME-France, 6 h precipitation, Brier Scill Score, 50 km neighborhood, 1 May – 1 Nov 2016

AROME initial data, blue full line
ARPEGE initial data, red dashed line



Case study, strong precipitation event over the Riviera

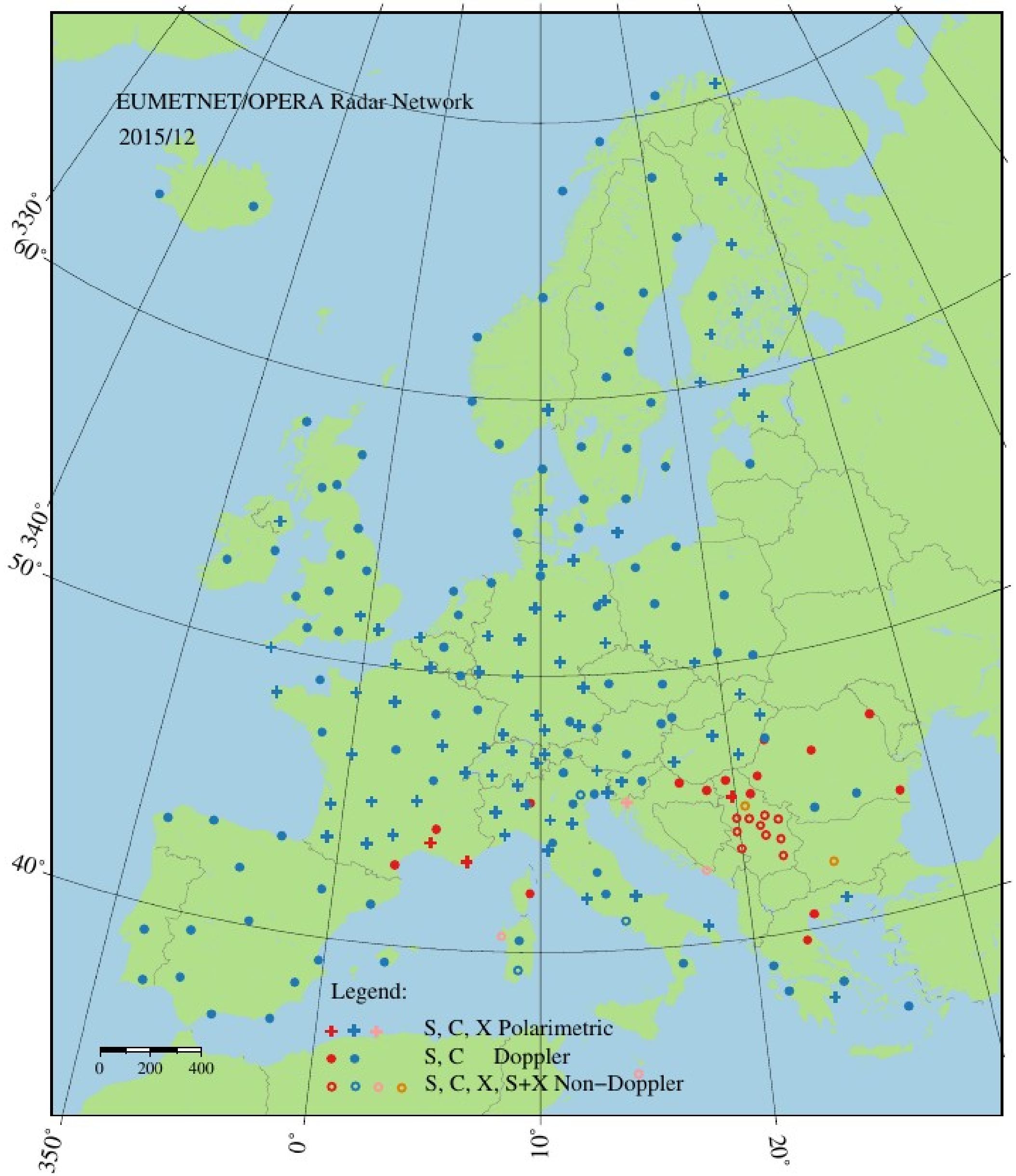
3 October 2015 15–21 UTC
(a) Radar + rain-gauge; (b) ARPEGE initial data 00UTC
(c) AROME initial data 00UTC; ARMOME initial data 03UTC



Improved utilization of observations

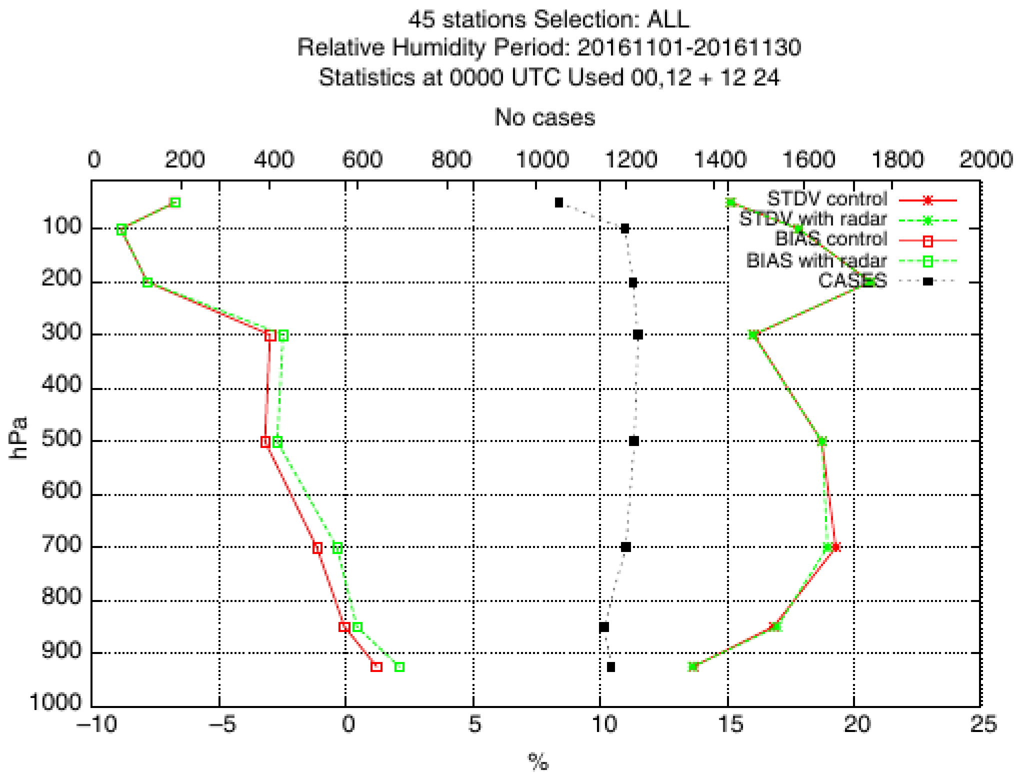
- Radar networks (OPERA)
- Dual polarimetric radars
- Mode-S
- Satellite image data
- Need for improved modelling of spatially correlated observation errors

The EUMETNET OPERA radar data network



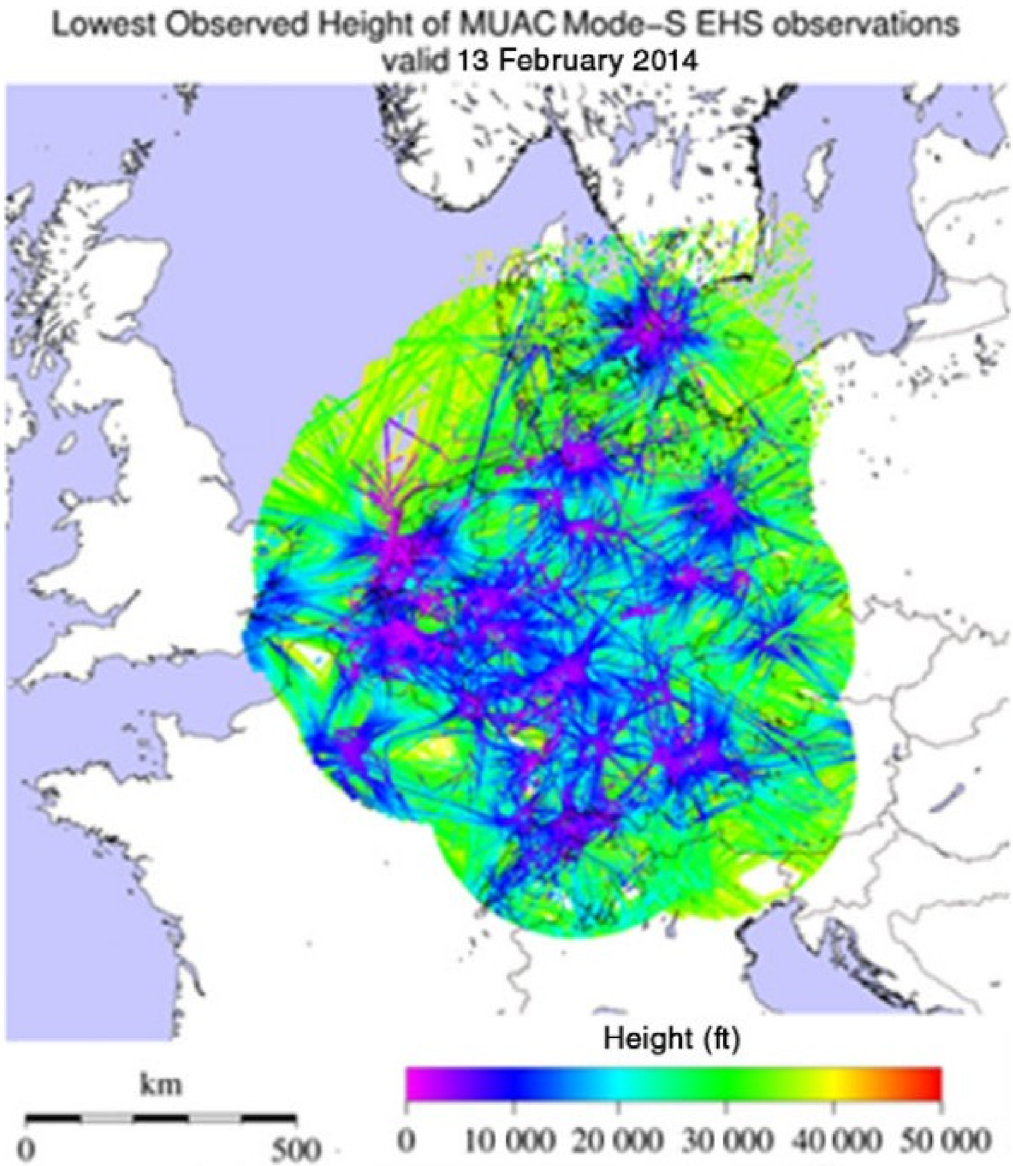
Impact from an international set of radar reflectivity data from the OPERA network

November 2016, relative humidity profiles



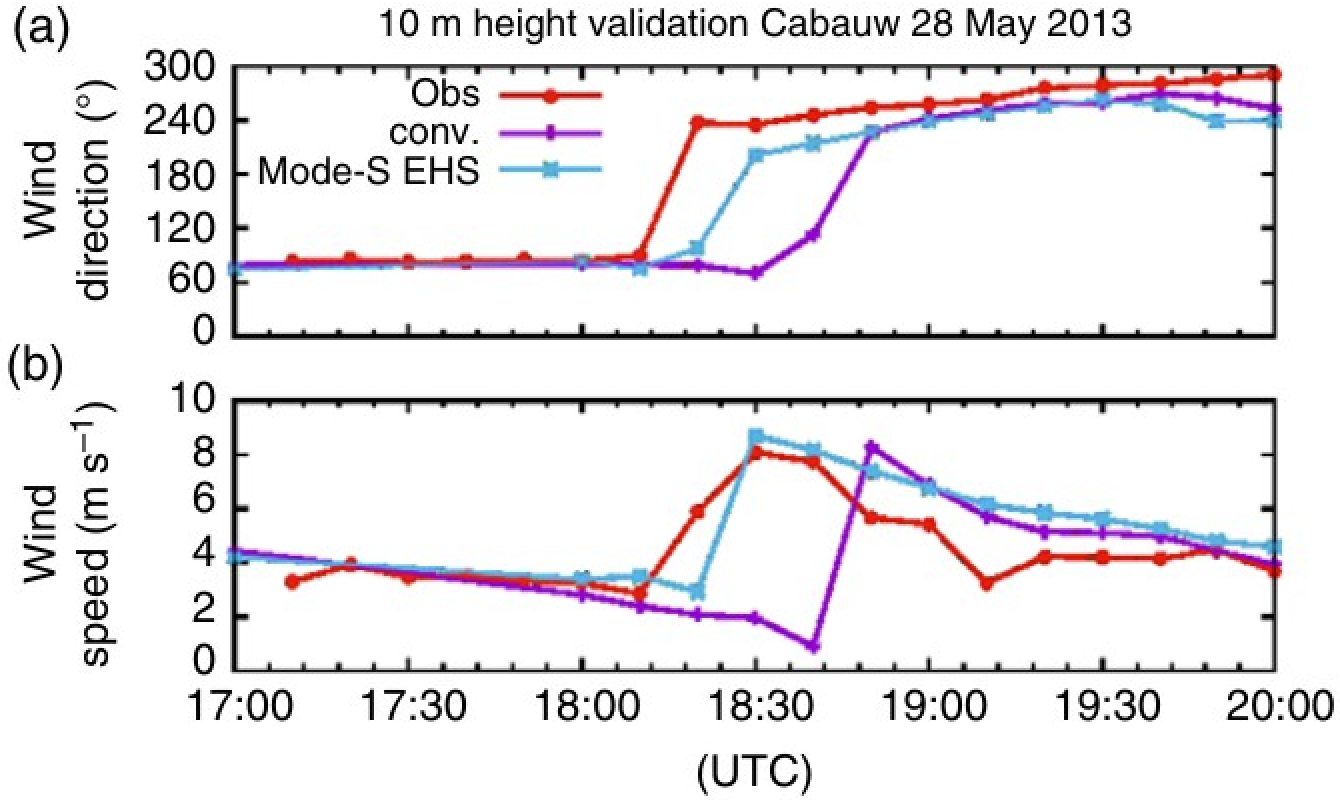
(From Ridal and Dahlbom)

Example of distribution of Mode-S aircraft observations in the vicinity of the Shiphol Airport



Example: Impact of Mode-S observations on 10 meter wind HARMONIE forecasts over the Cabauw tower in De Bilt

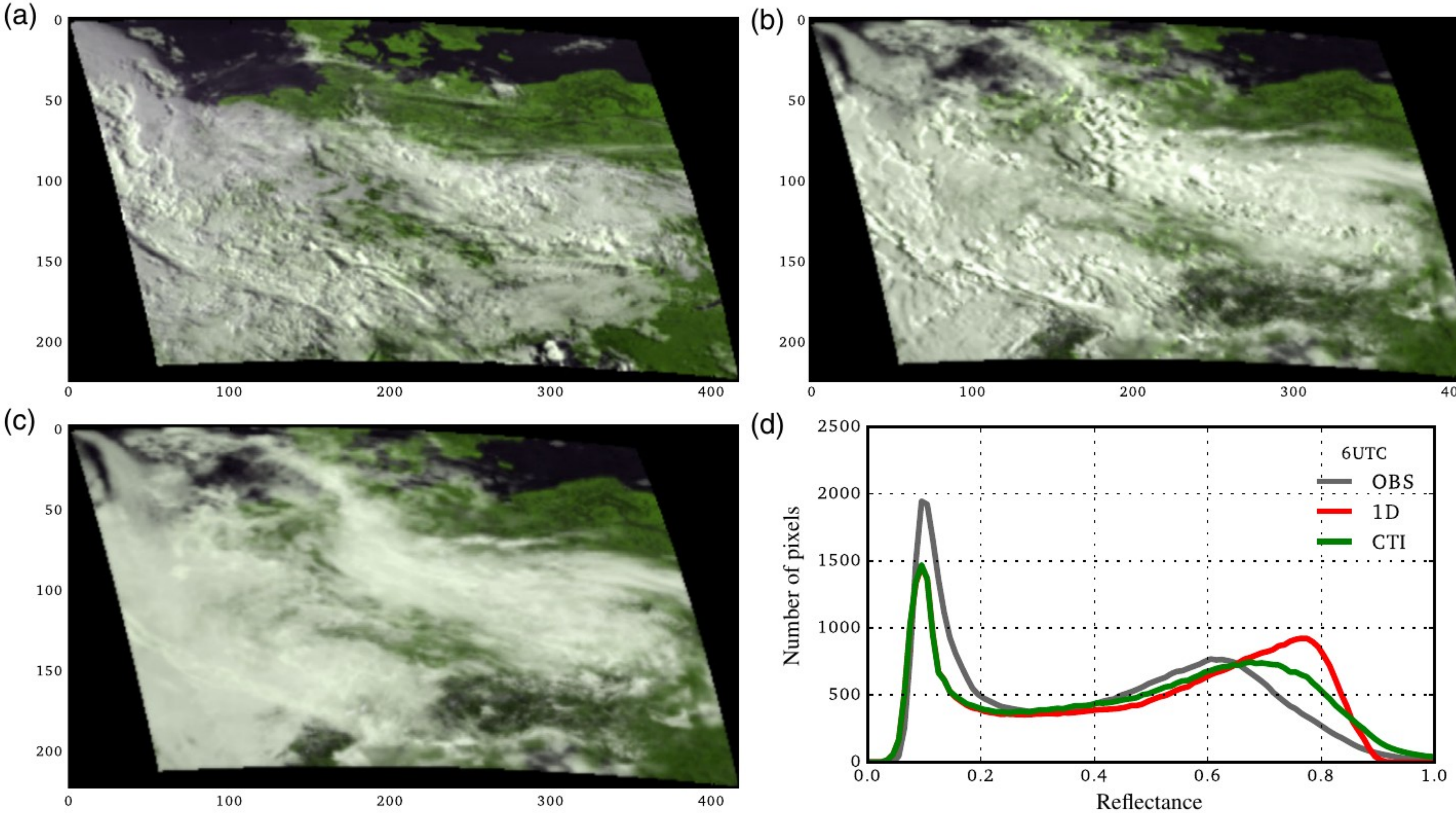
……………… Observation
……………… HARMONIE with conv. observations
……………… HARMONIE with conv. + Mode-S observations



Many types of satellite observations still to be assimilated!!

Example:

(a) SEVIRI observations on the COSMO-DE grid
(b) Synthetic image from COSMO output (with additional cloud top corrections)
(c) Synthetic image from COSMO output (without additional cloud top corrections)
(d) Reflectance histograms (a) grey, (b) green and (c) red



Convective-scale data assimilation - code development and maintenance

- DA developments for convective scales has followed global DA with a time lag of several years
- Not satisfactory; flow dependency for example is strongly needed at convective scales
- One reason is the sharing of huge investments into DA software with higher priority for the global version.
- This wish to share development resources may have delayed the development of more dedicated convective-scale methods.

Concluding remarks concerning convective scale data assimilation

- Different approaches are applied operationally at present
- Move towards EnKF and EnVar methods
- Impact studies show that convective scale DA is worth the effort

Core convective scale assimilation problems not discussed in this talk:

- Multi-scale assimilation methods
- Space-time covariance localization
- Improved observation error statistical models

Thank you!