

HarmonEPS developments

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and the HIRLAM EPS and predictability team

Salzburg, 2018

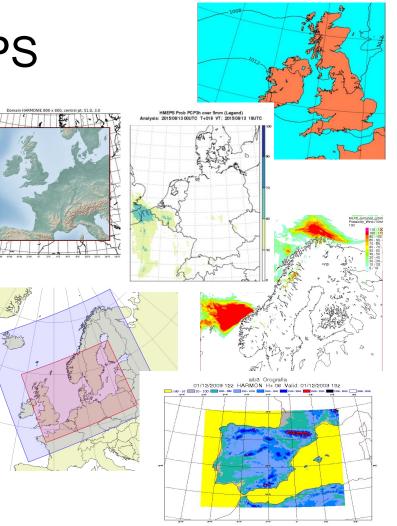
HarmonEPS

HarmonEPS with different configurations operational or being tested at several institutes:

MEPS - COMEPS - ySREPS - RMI EPS - KEPS - IREPS

Configurations vary, but typically:

- 10-20 members
- Arome, or Arome and Alaro
- 2.5 km
- 3D-Var
- SURFEX
- 2-3 days forecasts



HarmonEPS development

Four topics highlighted this year:

- EDA
- Effect of increasing the number of members
- Stochastically perturbed parameterizations SPP, and SPPT
- Calibration of MEPS 10m wind speed over Denmark

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Ensemble Data Assimilation (EDA) in HarmonEPS

Account for the uncertainty in the initial conditions by perturbing the observations. Observations used: conventional, AMSU-A, AMSU-B and IASI

Boundary nesting: SLAF

Members: 1+10

Area: MetCoOp

All members run their own surface analysis

Ensemble members start directly from EDA members, which are run at the same resolution

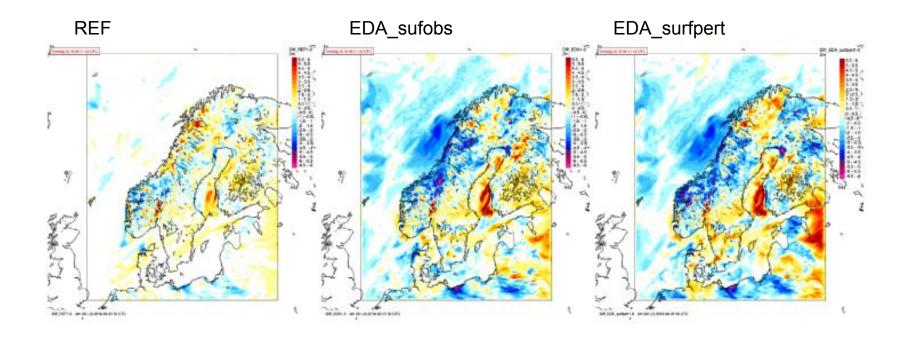
Experiments:

- REF reference exp, with surface perturbations
- EDA_surfobs EDA and 3DVar for all members
- EDA_surfpert As EDA_surfobs, but surface perturbation code instead of EDA at surface

Surface perturbations from Francois Bouttier et al, slightly modified

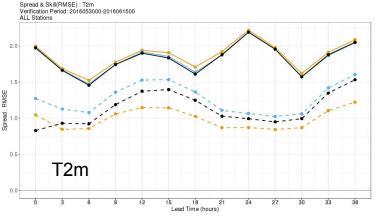
Inger-Lise Frogner, Roger Randriamampianina and Mate Mile

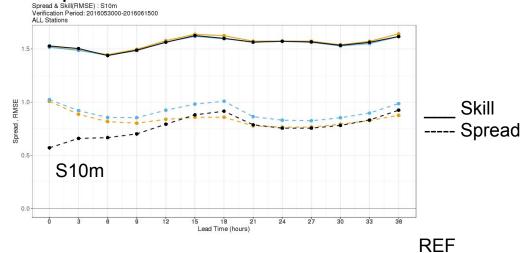
Example of perturbation size for one randomly chosen day, for T2m



- EDA introduces more evenly distributed perturbations throughout the area
- EDA does not introduce finer scale perturbations the spatial scales are qualitatively the same
- Perturbations are larger for EDA, slightly larger for EDA_surfpert

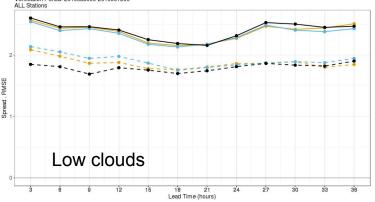
Effect on scores: Spread and skill





EDA surfobs





Good overall effect of activating EDA <u>EDA_surfpert</u> Increases spread throughout the forecast range, Particularly for the first ~12 hours.

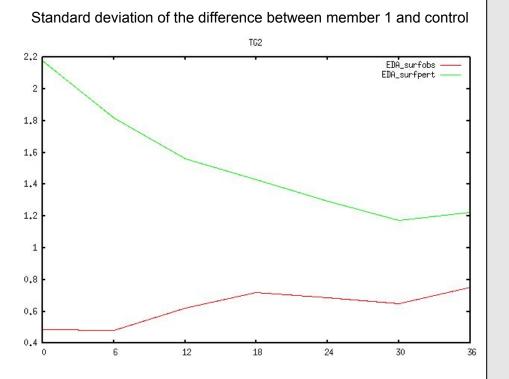
Surface perturbations scheme gives higher spread than perturbing the surface observations.

Why is the surface perturbation scheme better than EDA at the surface, for all lead times?

Why is the surface perturbation scheme better than EDA for the surface - for all lead times? Possible explanations:

- For surface EDA we only perturb the observations of T2m and RH2m
- For the surface perturbation scheme however, we perturb many more parameters (SST, surf. moisture, LAI, roughness length over land, albedo, …). Although they are kept constant throughout the forecast, except for the prognostic variables which are freely evolving, they are different for different members.
- EDA_surfobs have somewhat larger perturbations than EDA_surfobs, but why do we see the effect throughout the forecast range?
- Look at a parameter with longer memory, like deep soil temperature (TG2)

TG2 – for one random date (2016060100)



- Larger initial perturbation for EDA_surfpert
- EDA_surfpert have larger scales initially (not shown)
- The difference mbr1-cntl decreases with time for EDA_surfpert, it slightly increases for EDA_surfobs, but EDA_surfpert is still larger at the end of the forecast range
- Are the EDA_surfpert perturbations too big for the model to maintain?

Further work:

- Tuning of the initial size of the surface observation perturbations, together with perturbing more parameters like SST
- Combination of EDA_surfobs and EDA_surfpert

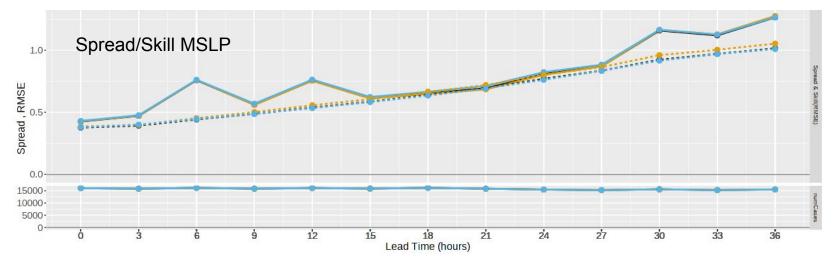
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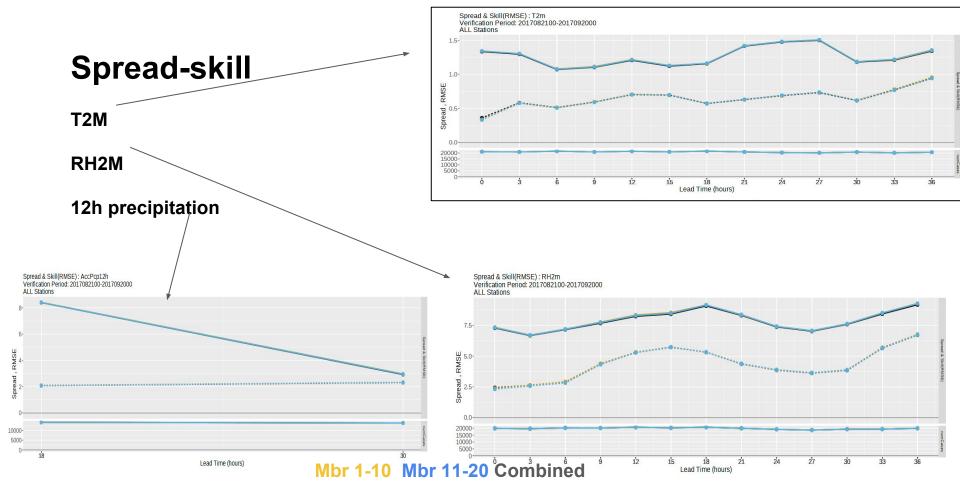
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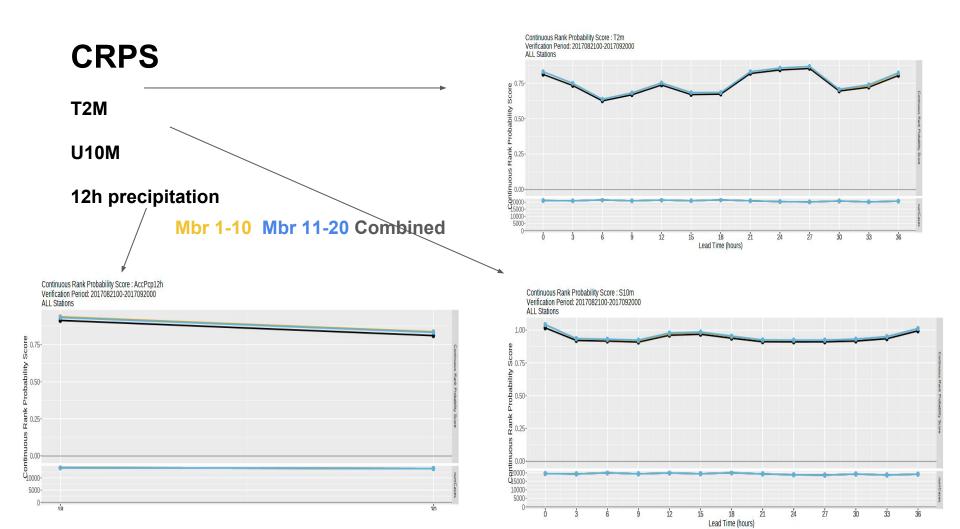
Effect of increasing the number of members - 20 vs 10 members

- Nesting in ENS member 0-20
- Surface perturbations on

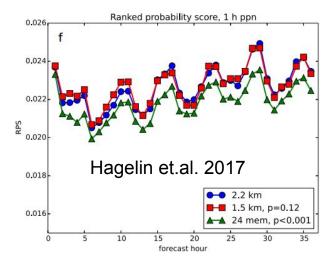


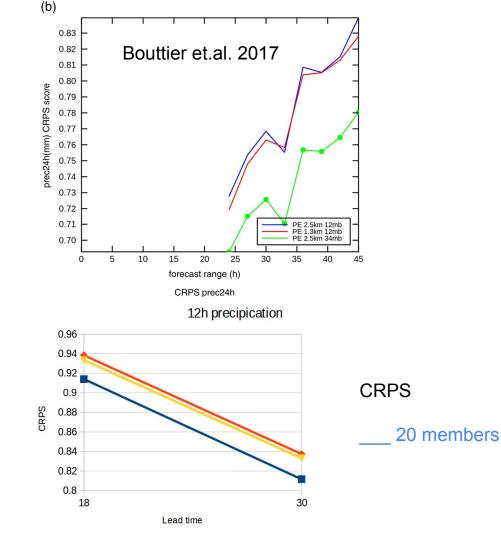
Mbr 1-10 Mbr 11-20 Combined





Compares with Meteo France/ UKMO results for precipitation





Minor improvements in scores - is it worth the extra cost?

- More members important for
 - Rare events
 - DA more EDA members are desirable to reduce the sampling noise in estimates for data assimilation errors (but so far we don't use EDA for this purpose)
 - \circ $\,$ $\,$ For users with low cost loss ratios $\,$
 - For multivariate events An example are forecast probabilities for the amount of energy produced by renewables. Here correlated probabilities of both *cloud cover* and *wind speed* are needed
- Forecasters expressed the wish for more members, as the probabilities are noisy with only 10 members

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Development work on representing model error:

- SPPT is available in HarmonEPS (1 pattern, 3 at ECMWF) now also with SPG Stochastic Pattern Generator (*M. Tsyrulnikov and D. Gayfulin. In Arome by Mihaly Szucs, in HarmonEPS by Ole Vignes)*
- **RPP** (Randomly perturbed parameters) our first attempt at perturbing parameters by stochastically varying the parameter for each member and each cycle, but kept constant in time and space
- **SPP** Stochastically perturbed parameterizations
 - IFS framework for SPP is implemented in HarmonEPS
 - log-normal distribution
 - As RPP but varying in time and space according to a 2D random pattern

Currently the following 7 parameters can be perturbed in HarmonEPS SPP:

• Microphysics:

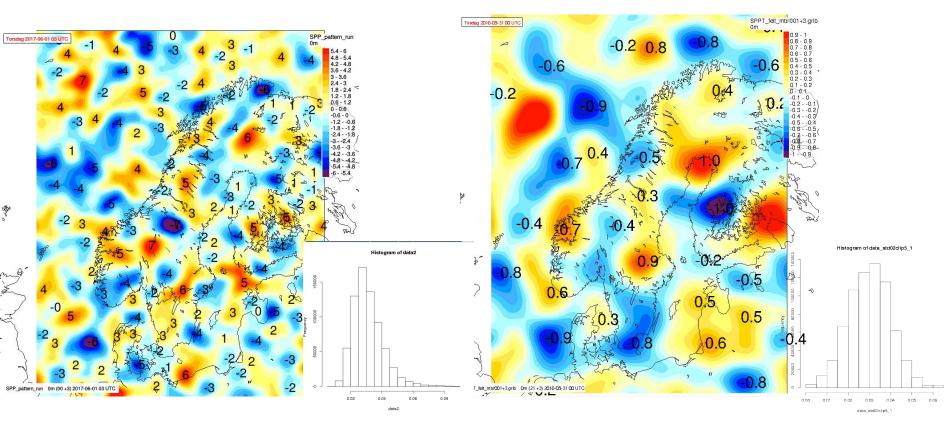
- VSIGQSAT saturation limit sensitivity
- ICE_CLD_WGT cloud ice content impact on cloud thickness
- ICENU ice nuclei concentration
- KGN_ACON Kogan autoconversion speed
- KGN_SBGR Kogan subgrid scale (cloud fraction) sensitivity

• Convection:

- CLDDPTH threshold cloud thickness for stratocumulus/cumulus transition
- CLDDPTHDP threshold cloud thickness used in shallow/deep convection decision
- Radiation:
- Turbulence:
- Dynamics:

Examples of patterns used:

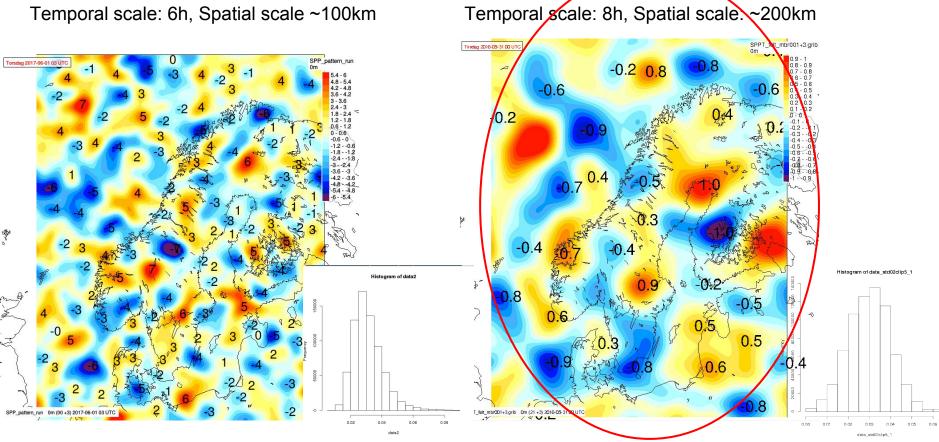
Temporal scale: 6h, Spatial scale ~100km



Temporal scale: 8h, Spatial scale: ~200km

Examples of patterns used:

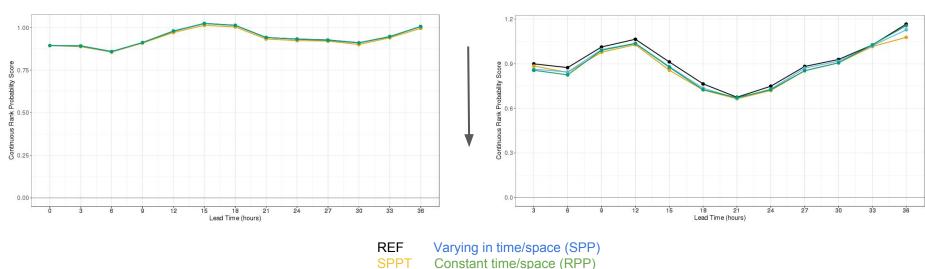
Temporal scale: 6h, Spatial scale ~100km



Example perturbing one parameter VSIGQSAT - CRPS

S10m

Low clouds



Small, positive impact of SPPT on S10m (and other parameters)

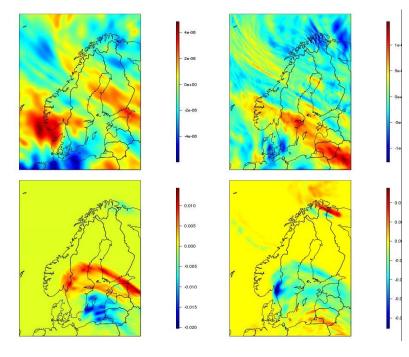
Very little impact of perturbing VSIQSAT, a parameter that allows lower relative humidity for (low) clouds to form, except for cloud related parameters where there is a small, but positive, impact of the same order as SPPT

Further work on upper air perturbations in HarmonEPS:

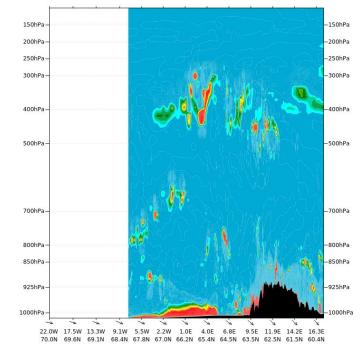
- Include more parameters in SPP
- Perturbing the dynamics SLHD
- Study closer the effect of the different perturbations, looking into spatial and temporal scales of the pattern, test new pattern generator (SPG), comparing SPP with SPPT
- Optimize SPPT, using SPG
- Develop tendency diagnostics

Examples of diagnostics

Standard deviation of 10 members SPP exp, total physics tendencies V-component of wind, four different levels



Cross section for one member from SPP exp, total physics tendencies V-component of wind



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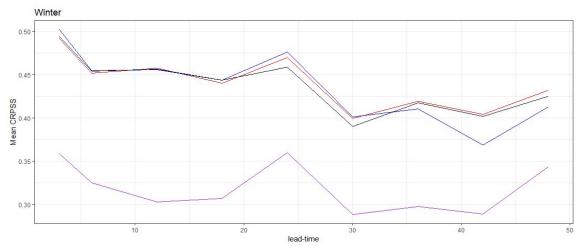
Calibration of 10m wind speed 2 months of training data but pooled all stations

- MEPS ensemble stations from Denmark (similar topography to the Netherlands)
- Comparing calibration methods
 - Truncated normal distribution (μ and σ depend on predictor variables, e.g. ensemble mean and std. dev. of wind speed, land type)
 - Quantile regression forests

(a tree-based ensemble method for estimation of conditional quantiles. It is a non-parametric method that yields an empirical Cumulative distribution function(CDF))

Verification – Continuous Ranked Probability Skill Score

 Statistical post-processing methods improve forecast skill compared to climatology and the raw ensemble for the bulk of the distribution

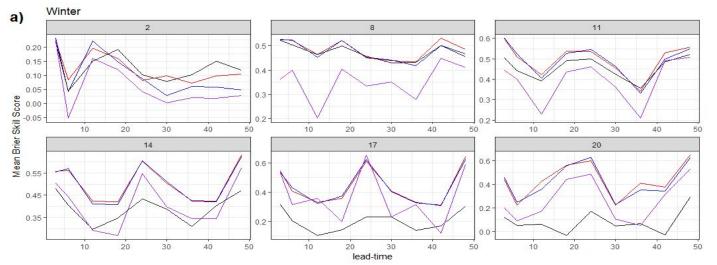


Trunc. Normal (2 predictors) Trunc. Normal (5 predictors) Quantile Regression Forests Raw MEPS



Verification – Brier Skill Score

- All methods more skilful than the raw ensemble for low wind speed thresholds (2, 8, 11 m/s)
- QRF less skilful for high wind speed thresholds (14, 17, 20 m/s) probably suffers most from small data set the most



Trunc. Normal (2 predictors) Trunc. Normal (5 predictors) Quantile Regression Forests Raw MEPS

Thank you