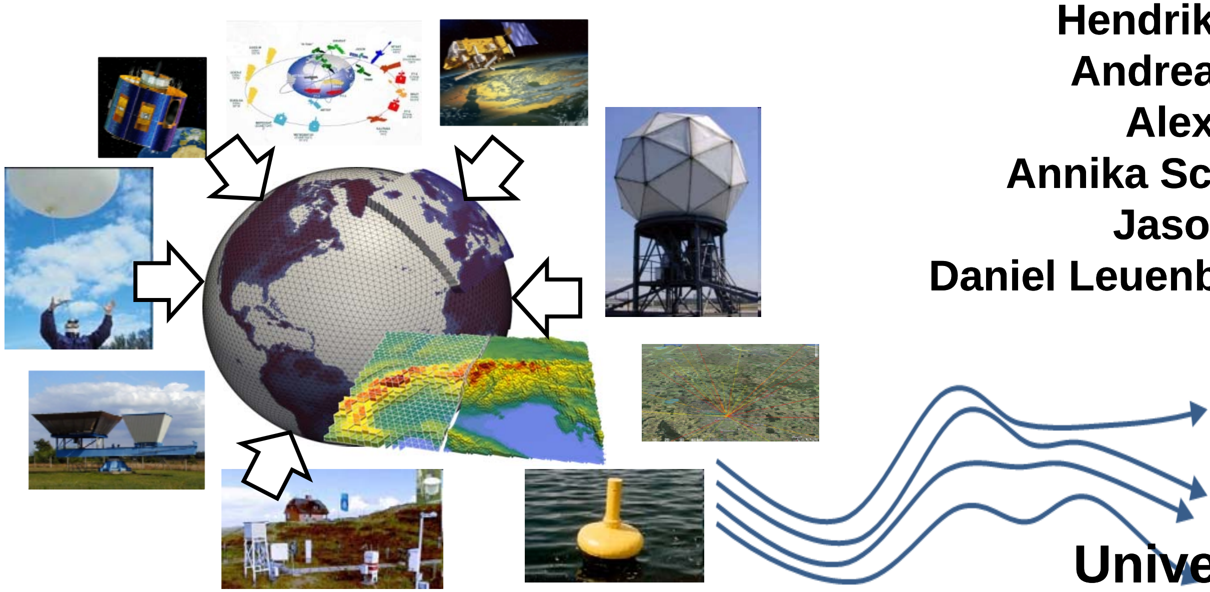
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

On Ensemble and Particle Filters for Large-Scale Data Assimilation

Roland Potthast
Hendrik Reich, Christoph Schraff
Andreas Rhodin, Ana Fernandez
Alexander Cress, Dora Foring
Annika Schomburg, Africa Perianez
Jason Otkin, Robin Faulwetter
Daniel Leuenberger, Hans Rüdi Künsch



DWD, Germany &
University of Reading, UK

Contents

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

- **Ensemble Systems** at Deutscher Wetterdienst (DWD)
  - I DWD Research Environment
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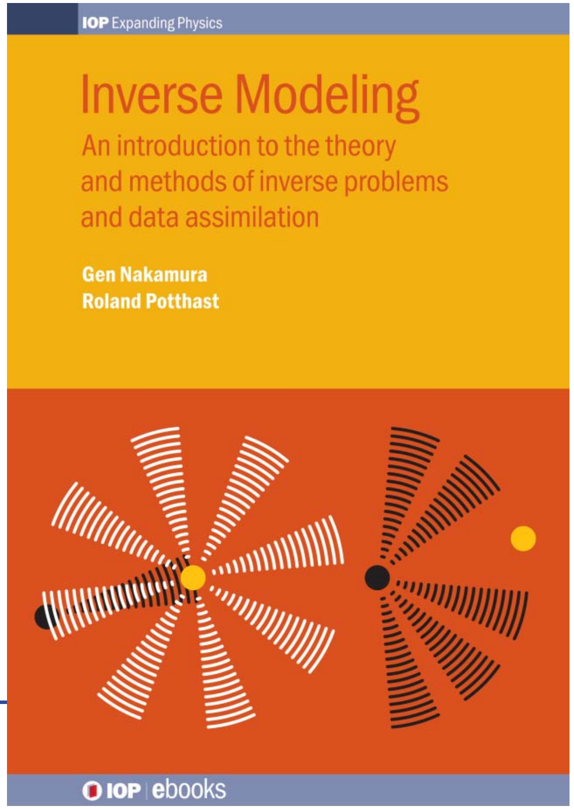
- **Research Projects** based on Ensemble Data Assimilation
- **IV Particle Filters** for NWP
  - Local Markov Chain Particle Filter
  - Gaussian-Particle Filter



Part I: Research Environment

- **Deutscher Wetterdienst (DWD) is the national weather service of Germany**

- **We are a part of the Ministery of Transport and Digital Infrastructure**

- **National and European Measurement Networks (e.g. Satellites) are controled and developed**

- **We develop our systems within a network of partnerships with other states, with research institutes and universities**

Deutscher Wetterdienst DWD

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Weather Prediction and Warnings for Central Europe.

DWD operates two

CRAY Supercomputers

Cray XC40, Intel Xeon E5-2670v2 10C 2.5GHz/E5-2680v3 12C 2.5Ghz, Aries interconnect,

Rank 128 on the TOP 500 supercomputer list in 2014/11.

Part I: Model Chain

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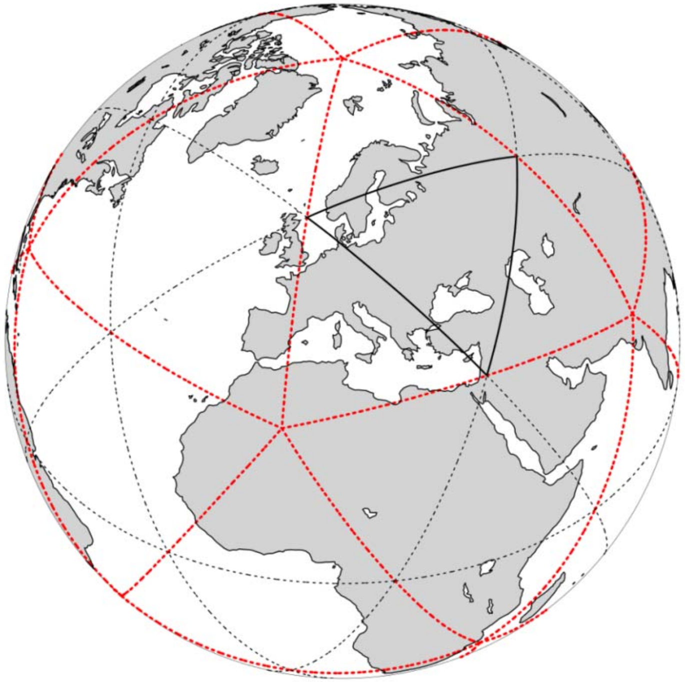
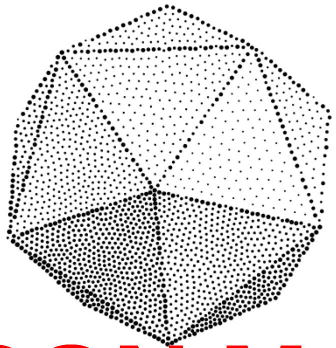
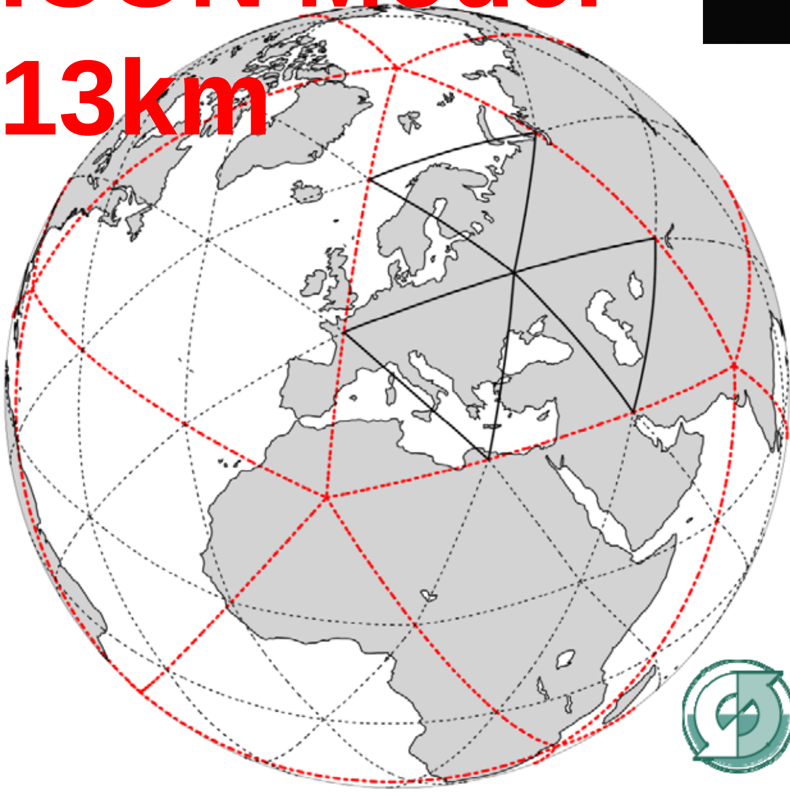




ICON Model 13km



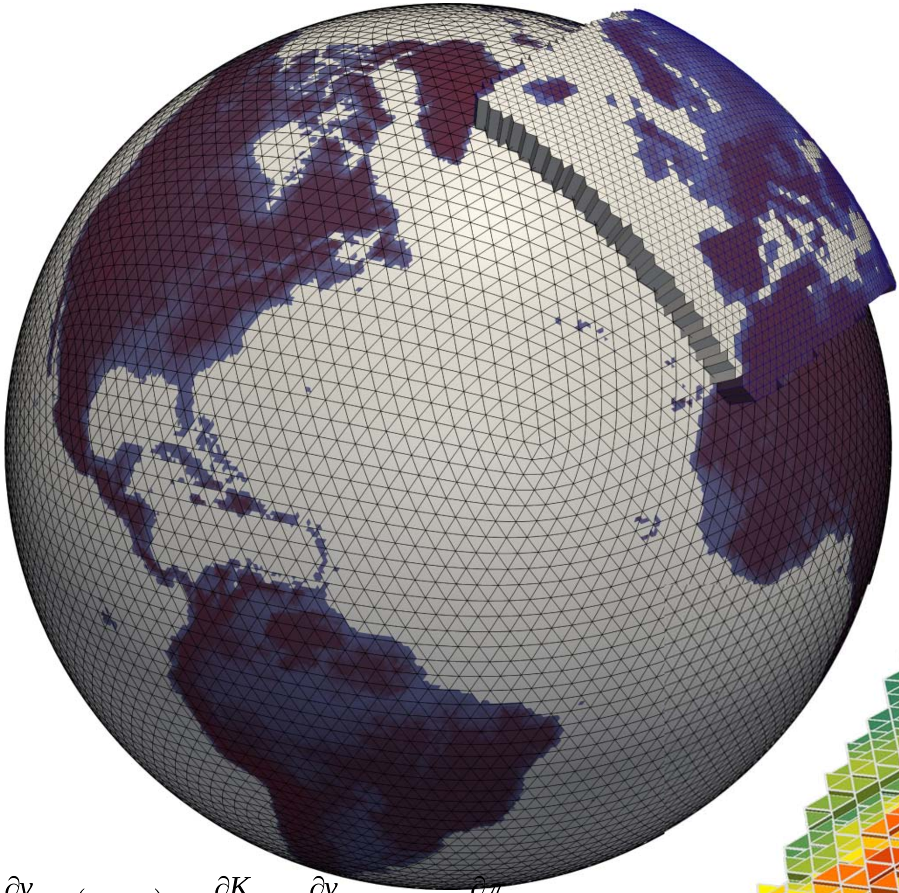
Karlsruhe Institute of Technology

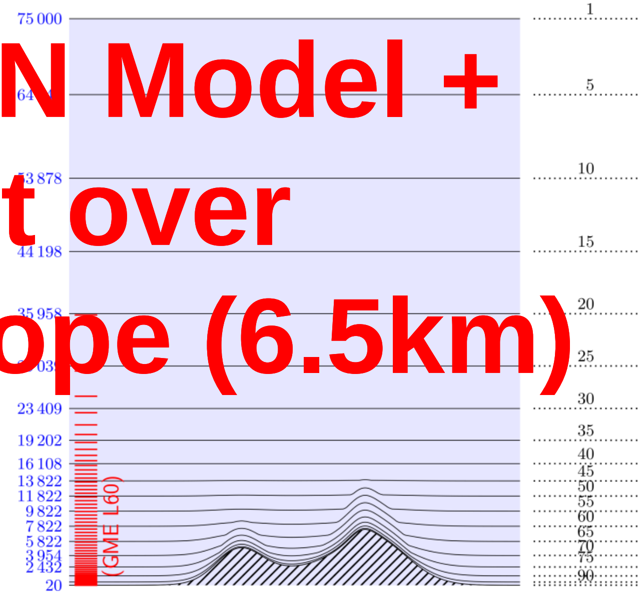
Max-Planck-Institut für Meteorologie

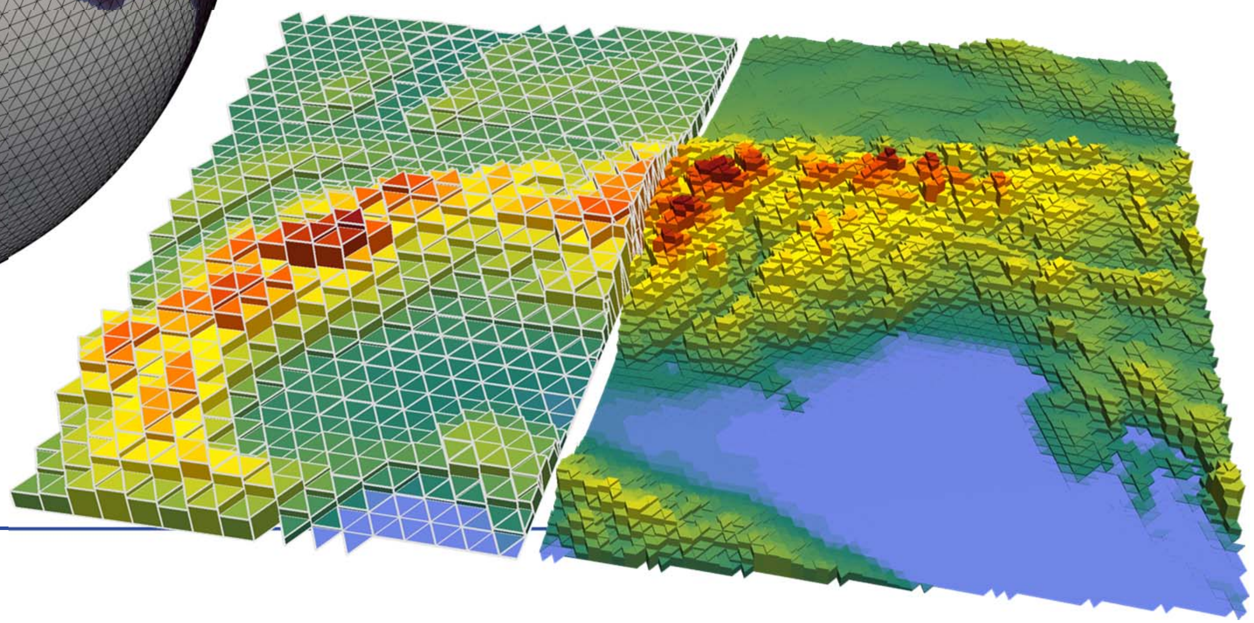
0-7 Days

Global Modelling

ICON Model + Nest over Europe (6.5km)







$$\frac{\partial v_n}{\partial t} + (\zeta + f)v_t + \frac{\partial K}{\partial n} + w\frac{\partial v_n}{\partial z} = -c_{pd}\theta_v \frac{\partial \pi}{\partial n}$$

$$\frac{\partial w}{\partial t} + \vec{v}_h \cdot \nabla w + w\frac{\partial w}{\partial z} = -c_{pd}\theta_v \frac{\partial \pi}{\partial z} - g$$

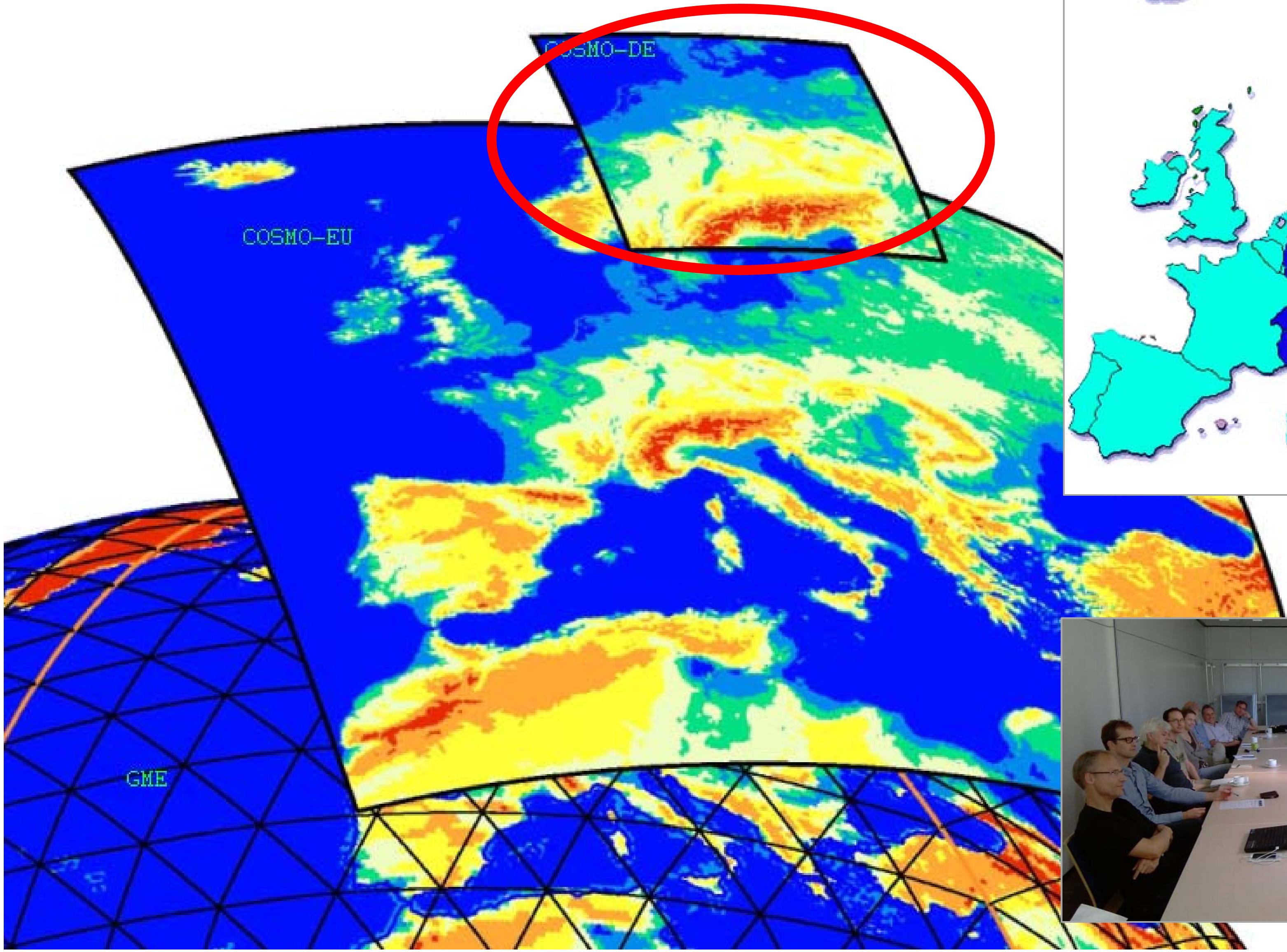
$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\vec{v}\rho) = 0$$

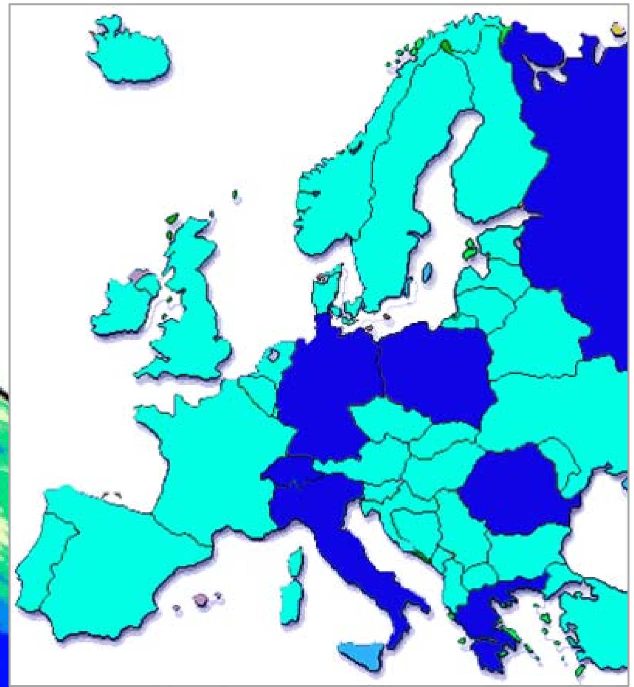
$$\frac{\partial \rho\theta_v}{\partial t} + \nabla \cdot (\vec{v}\rho\theta_v) = 0$$

02-24 Hours

High Resolution Modelling

Deutscher Wetterdienst
Wetter und Klima aus einer Hand





02-24 Hours

High Resolution Modelling

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

$$\frac{\partial v_n}{\partial t} + (\zeta + f)v_t + \frac{\partial K}{\partial n} + w\frac{\partial v_n}{\partial z} = -c_{pd}\theta_v \frac{\partial \pi}{\partial n}$$

$$\frac{\partial w}{\partial t} + \vec{v}_h \cdot \nabla w + w\frac{\partial w}{\partial z} = -c_{pd}\theta_v \frac{\partial \pi}{\partial z} - g$$

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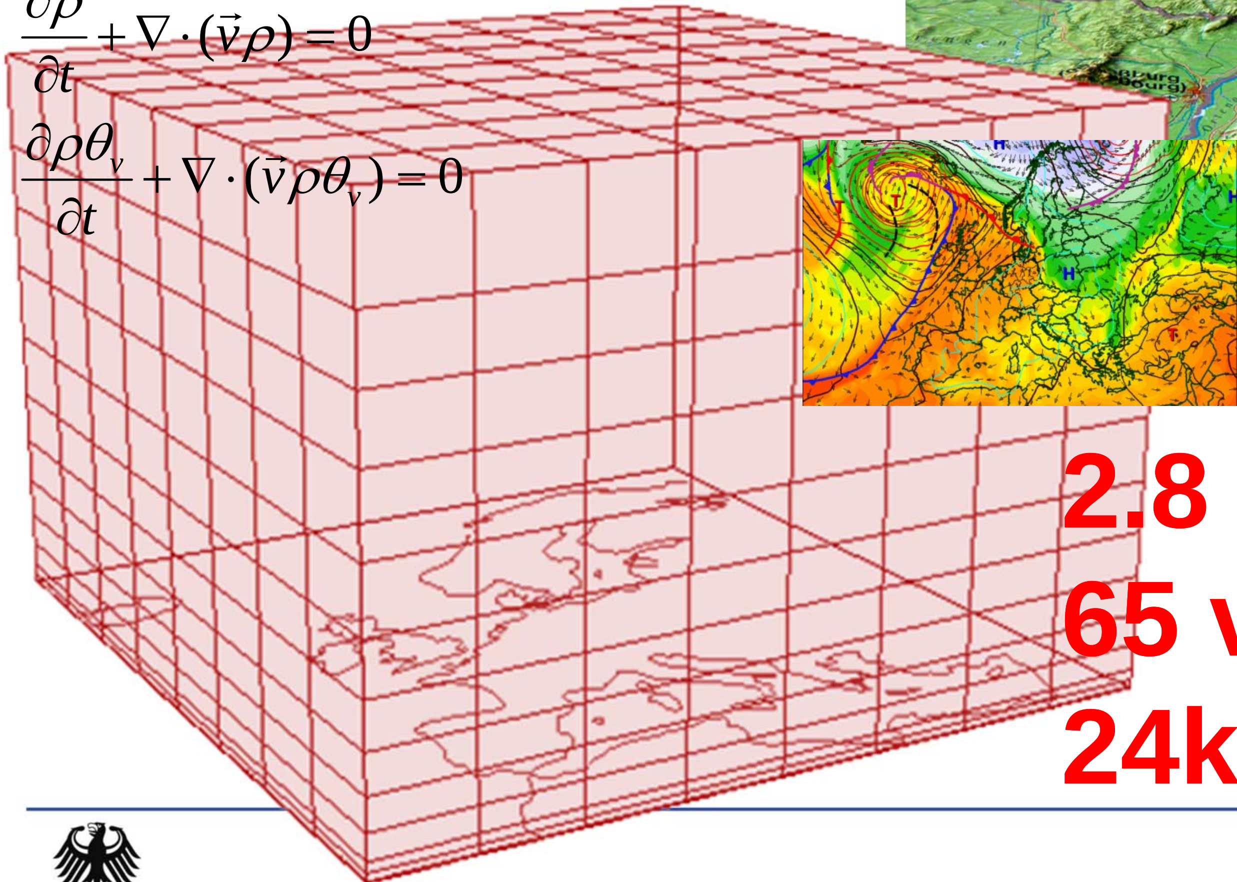

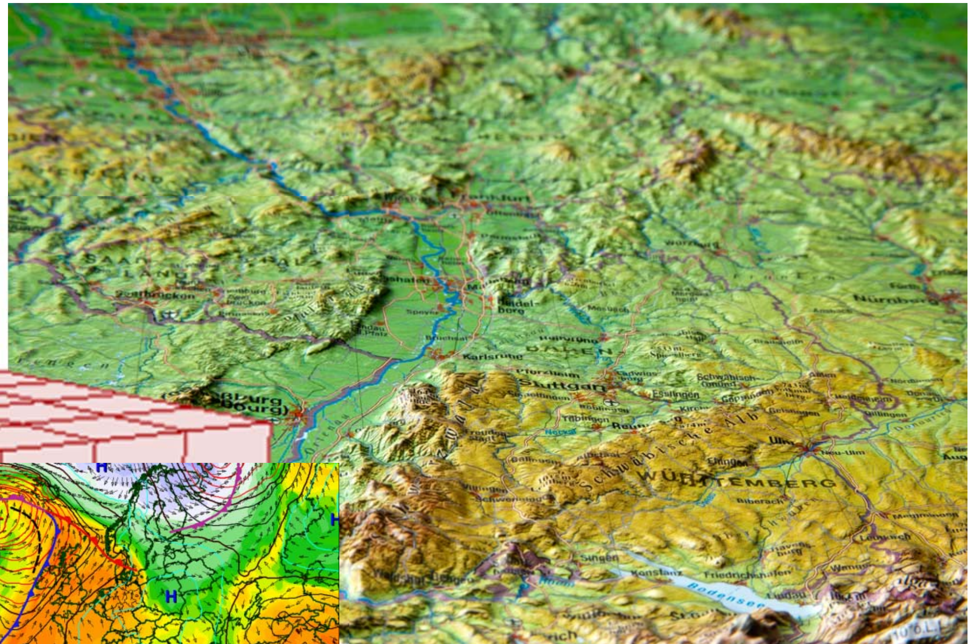

2.8 (2.2 or 1)km
65 vertial layers
24km height

Part I: Research Network

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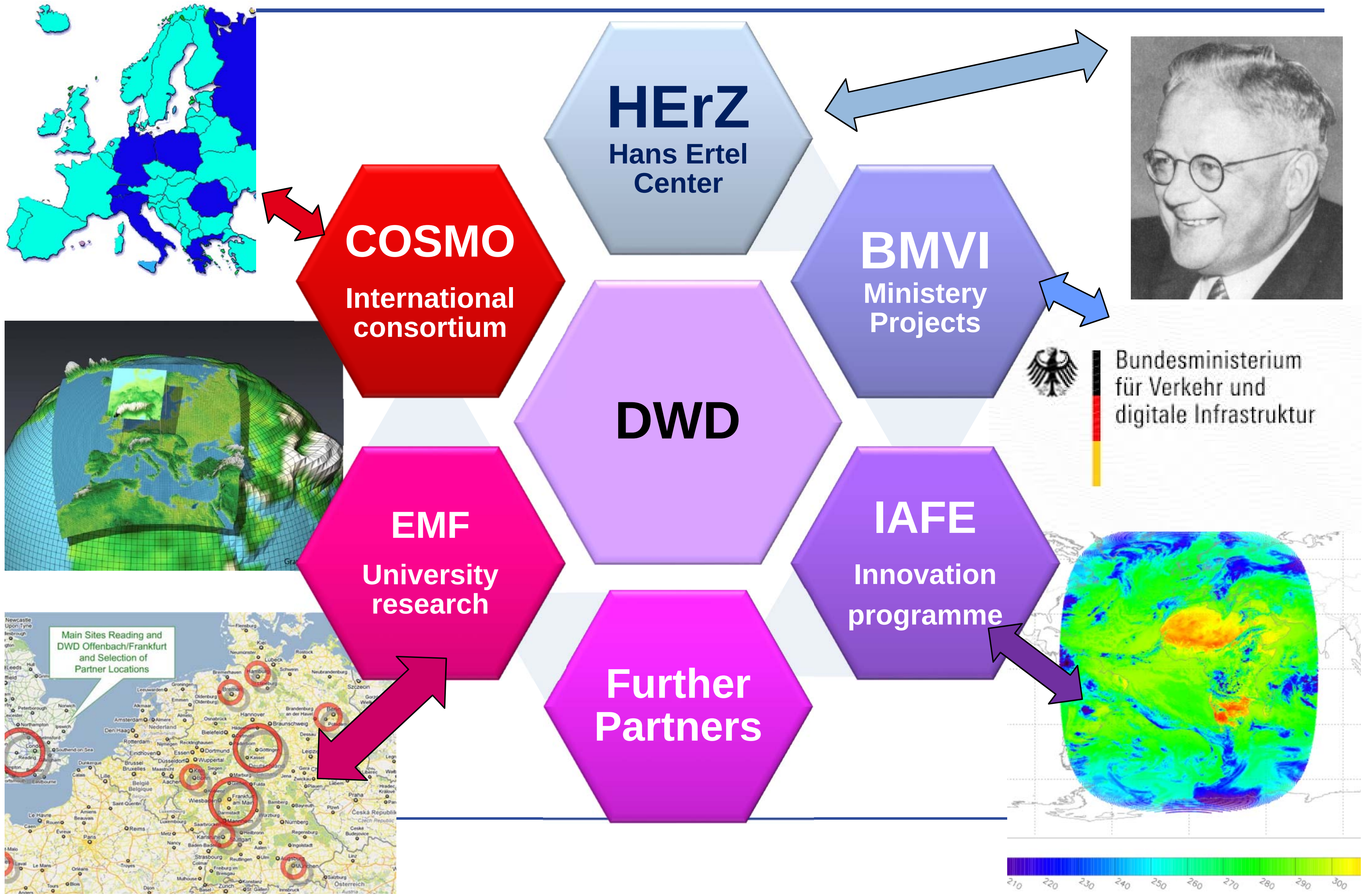
Wetter und Klima aus einer Hand



CONSORTIUM FOR SMALL SCALE MODELING

COSMO

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

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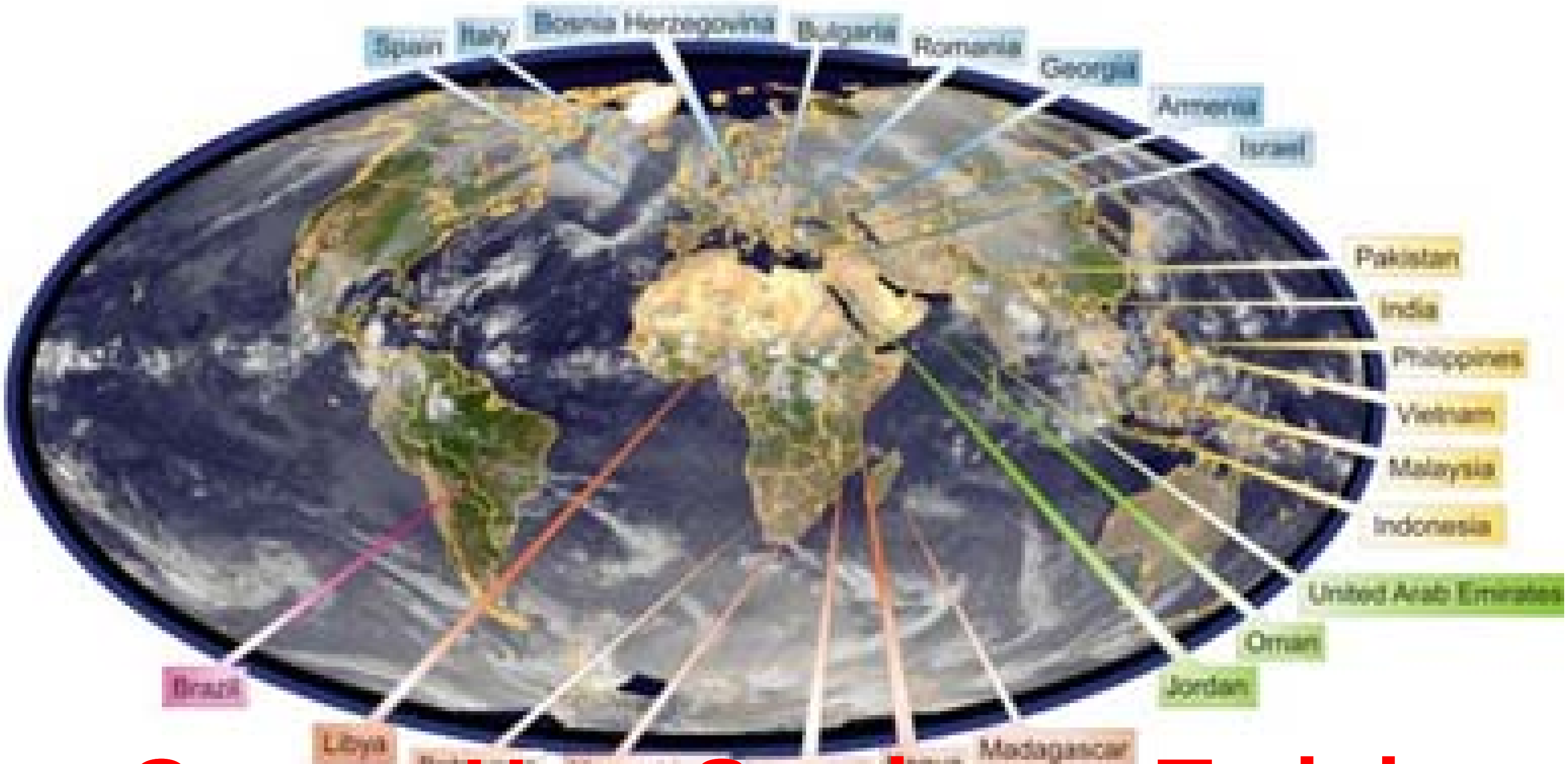
40 Countries



Cosmo User Seminar + Training Course + Symposium

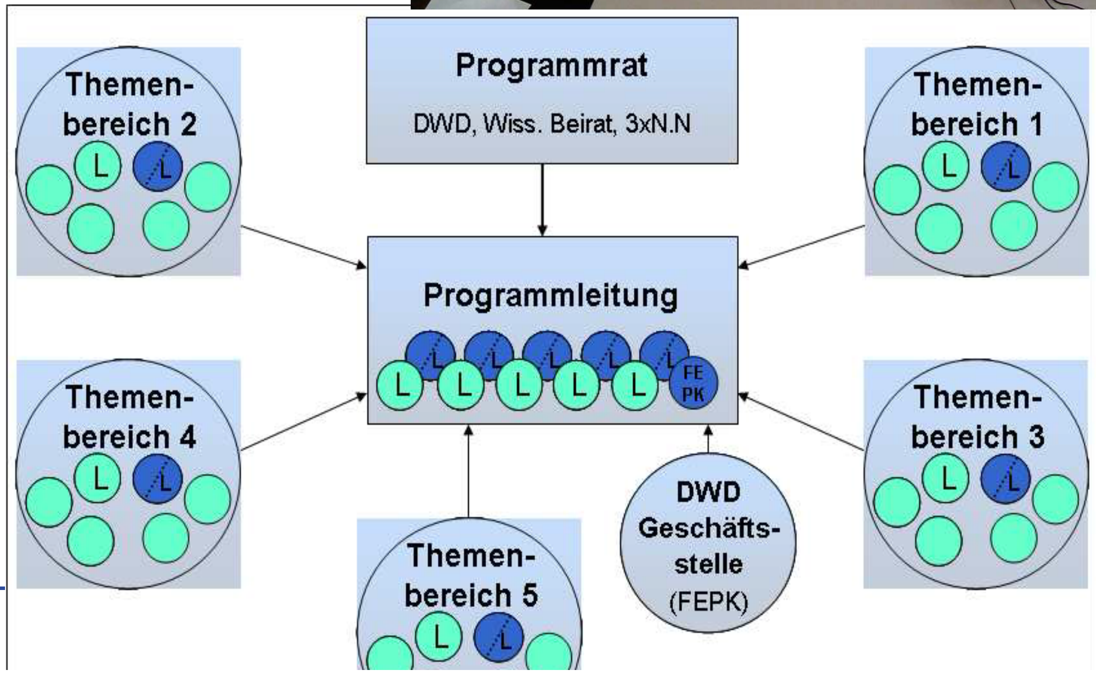
LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN
FAKULTÄT FÜR PHYSIK
METEOROLOGIE

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Research Network 2

Hans Ertel Center for Weather Research (HErZ)

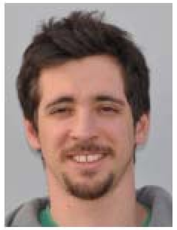
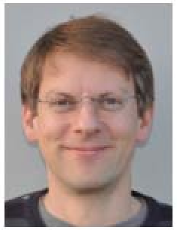
- ➔ **MPI Hamburg**
- ➔ **LMU Munich**
- ➔ **Uni Bonn**
- ➔ **Uni Frankfurt**
- ➔ **Uni Berlin**



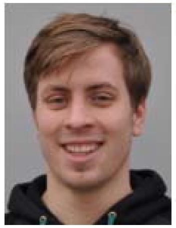
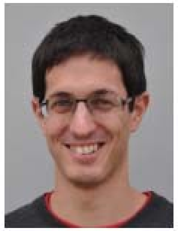
SEE Talk of Hendrik Reich

Research in HErZ-DA and associated projects

Subproject A: Assimilation of potential high-impact observations

HErZ funded

HErZ associated

n issues
s
biases
s
mulations
ping

Enviro
condit
of con
- MSG
chan
- GNNS total delay (vert. integrated water vapour)
- Novel MODE-S aircraft wind and temp. obs.

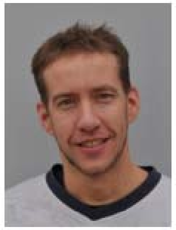
of convection)
- w2W project on error sources

systems)

Black: Proposed
Green: Externally funded complementary projects

- Feature-based scores
- Different assimilation settings
- Operator refinement
- Model error repr. *from B*

Subproject B: Accounting for model error in DA



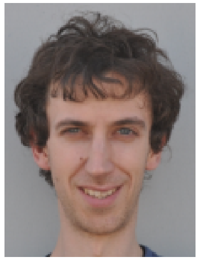
HErZ finanziert

Post-Doc Conservation in DA

HErZ associated

Work on stochastic perturbation schemes (LMU and w2W)

Subproject C: Predictability and ensemble generation



PhD
Repr. of model error, predictability

PhD
Observation impact

HErZ funded

HErZ associated

related model errors
visualization of uncertainty in 3D data

Subproject D: AMV height assignment

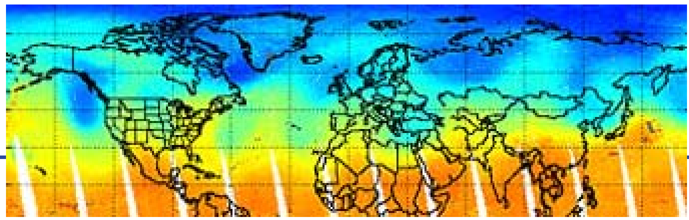
LIPSO
day

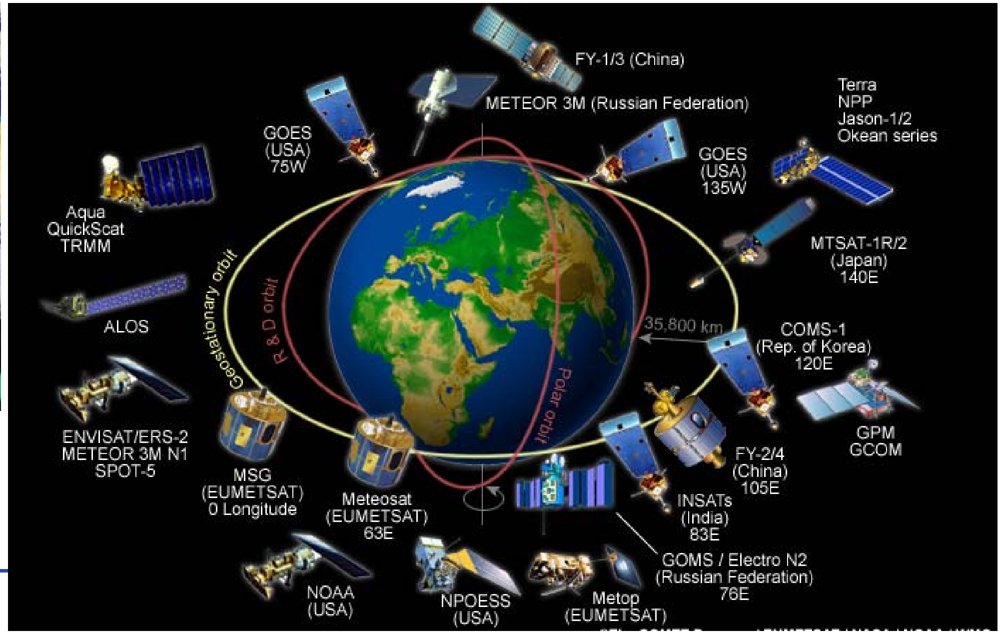
HErZ funded (2015)

Research Network 4:

IAFE Innovation in Applied Research and Development

Research and Development in Data Assimilation of Satellite Data





Innovation Programme (IAFE) +Eumetsat Positions Survey

Now filled ..

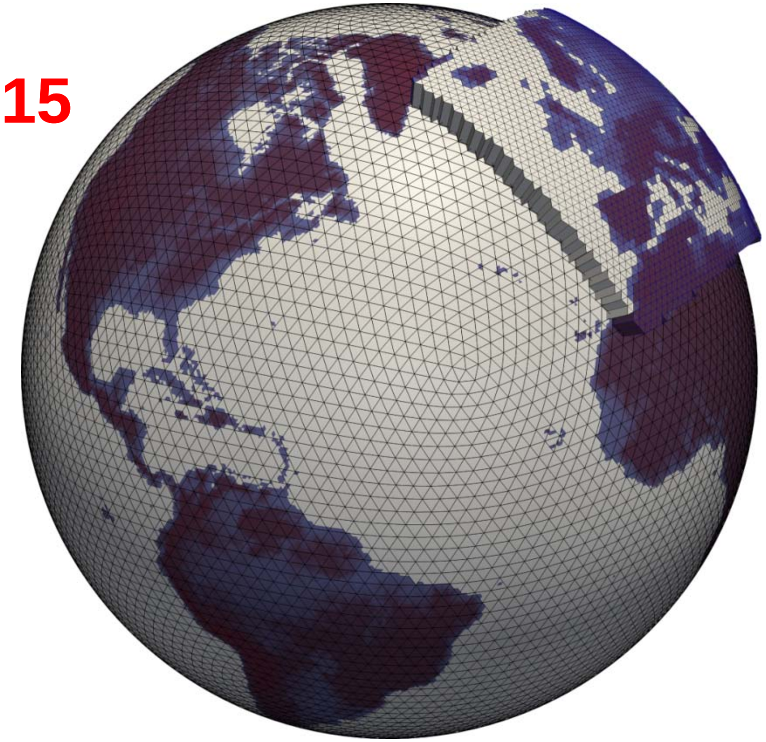
Nr	Position	Length in Years
1	SAT-GNSS-HUM	4
2	SAT-IR-ICON 1	4
3	SAT-IR-ICON 2	2 (+2 tbc)
4	SAT-IR-KENDA	4
5	SAT-MW-ICON 1	2 (+2 tbc)
6	SAT-MW-ICON 2	1+3
7	EUMETSAT Fellowship	1+2

Part II: New Global Model ICON

- Operational since Jan 20, 2015

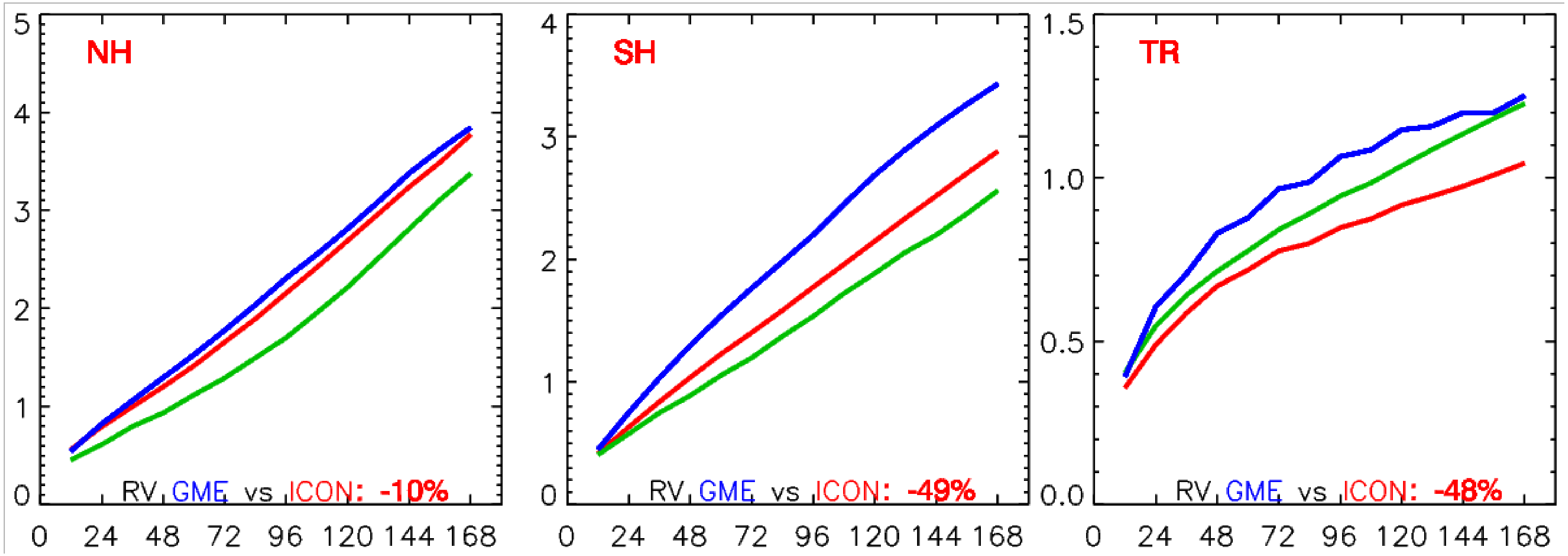
- Non-Hydrostatic
- 13km resolution globally
- 75km height
- 90 vertical levels

- Still a lot in the pipeline!!



Temperature at 700 hPa, RMSE in K

Blau: GME, rot: ICON, grün: IFS



Operational!

Part II: Global
Ensemble Data Assimilation (EDA)

- EnVar
- 40 Members
- 1 Deterministic

Global EDA (EnVar) Development

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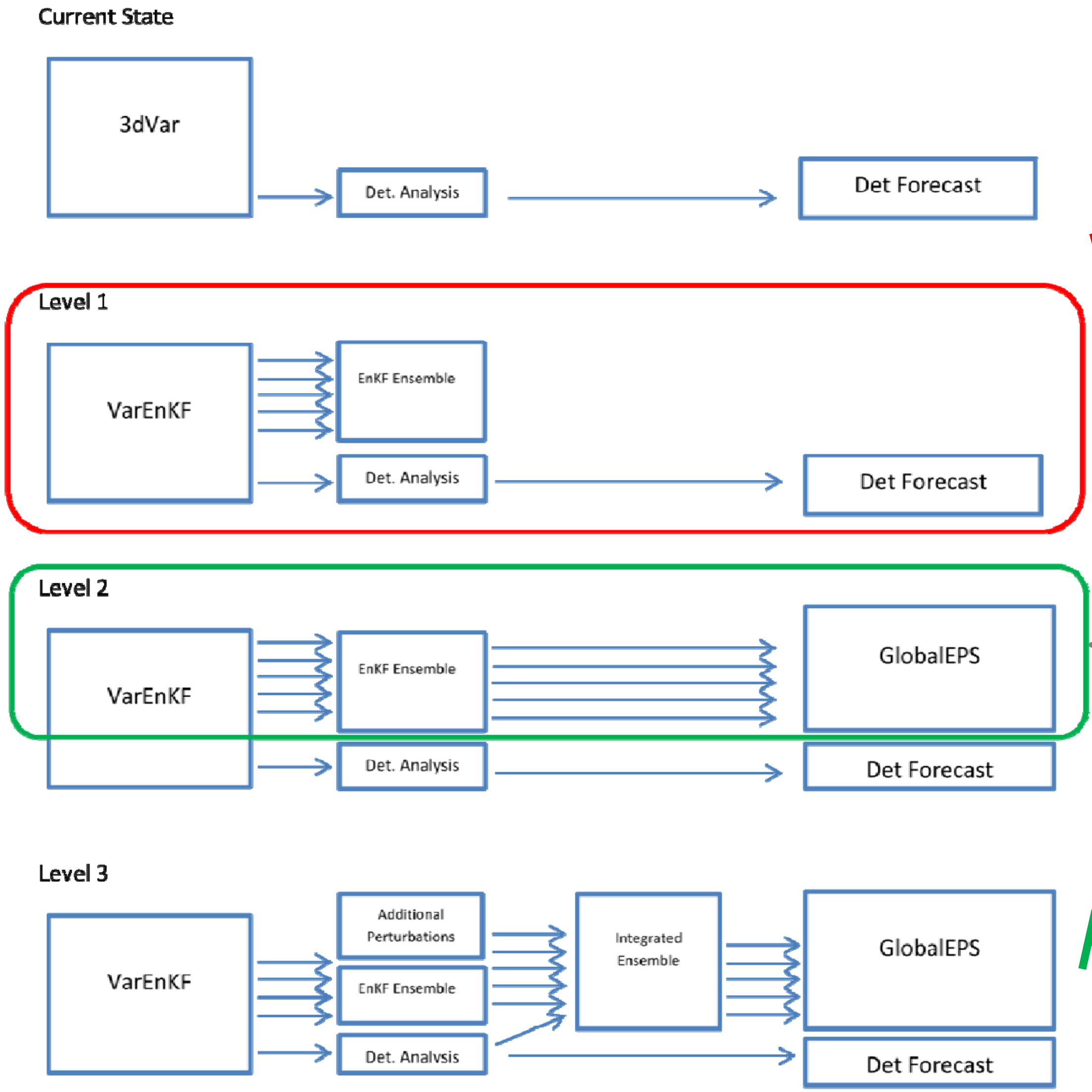
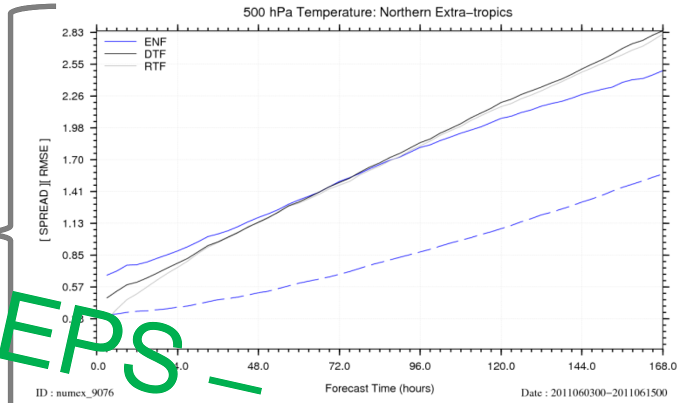
Wetter und Klima aus einer Hand
DWD



Migration Done

Deterministic Forecast

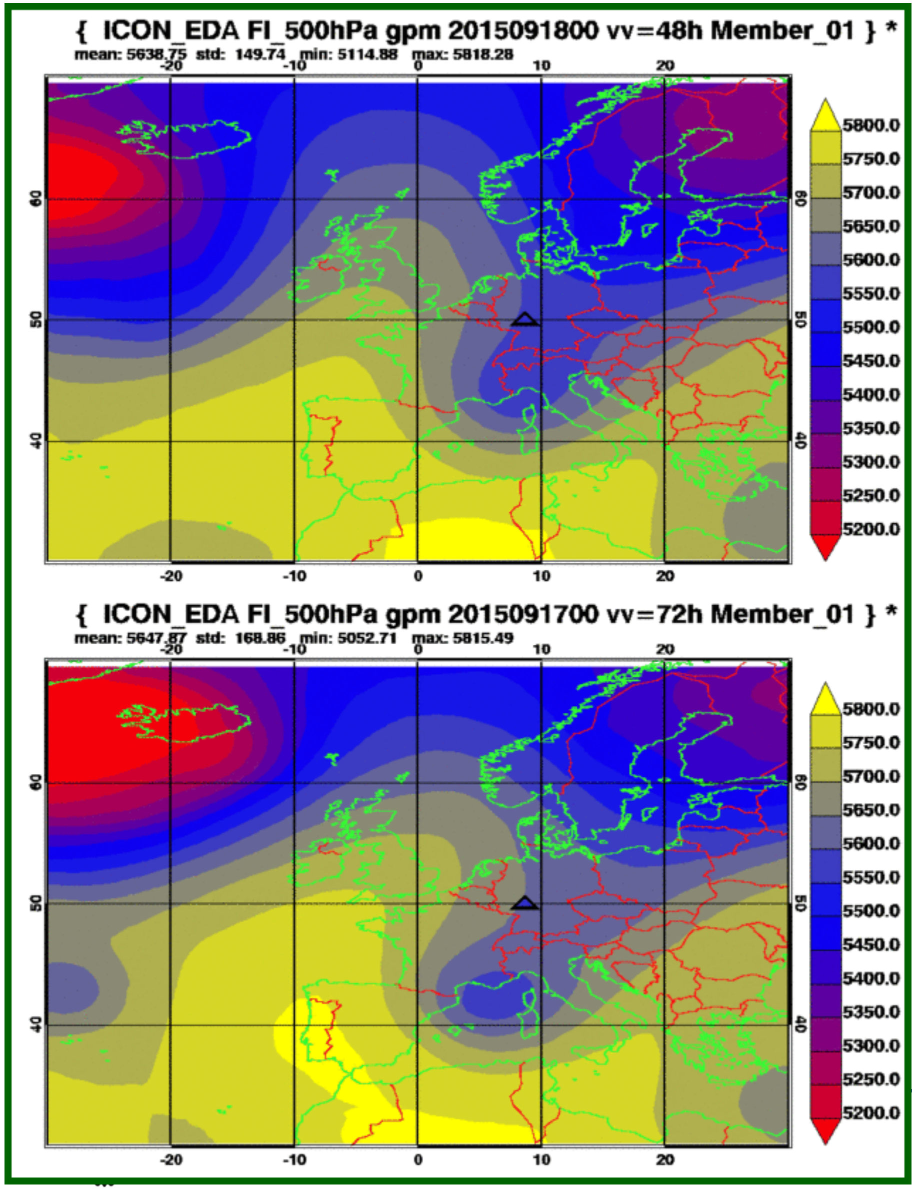


EPS – Ensemble Prediction

4. ICON Ensemble Datenassimilation

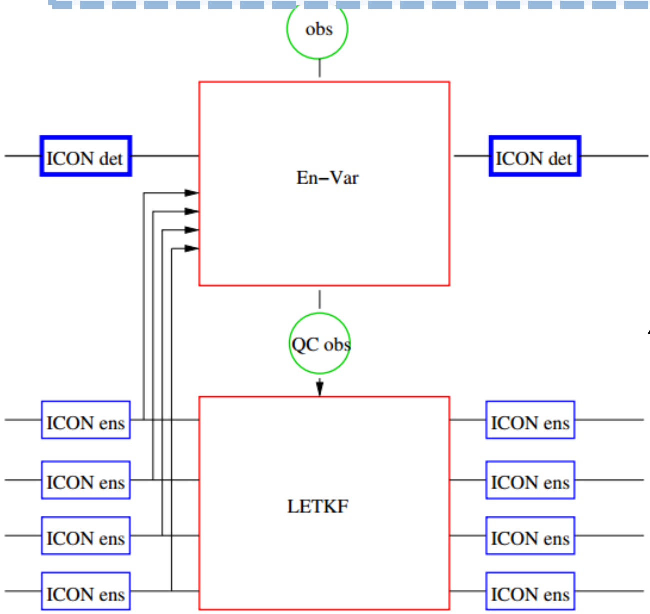
Pre-Operational since Sept 2015 : Rhodin, Fernandez, Cress, Anlauf, etc.

Ensemble Film by Bodo Ritter, FE14



We are running **ICON EDA** in our Parallel Routine since *10 Sept 2015*

- 40 Members each with 40km global resolution and 20km NEST over Europe
- 1 deterministic 13km member
- **EPS forecasts** 40 Members 7 Days + 1 Deterministic
- Output for convective-scale EDA/EPS
- **Hybrid System** active since Sept 24,2015



Grafics and
ICON EDA Head
Andreas Rhodin, FE12

4. ICON Ensemble Datenassimilation

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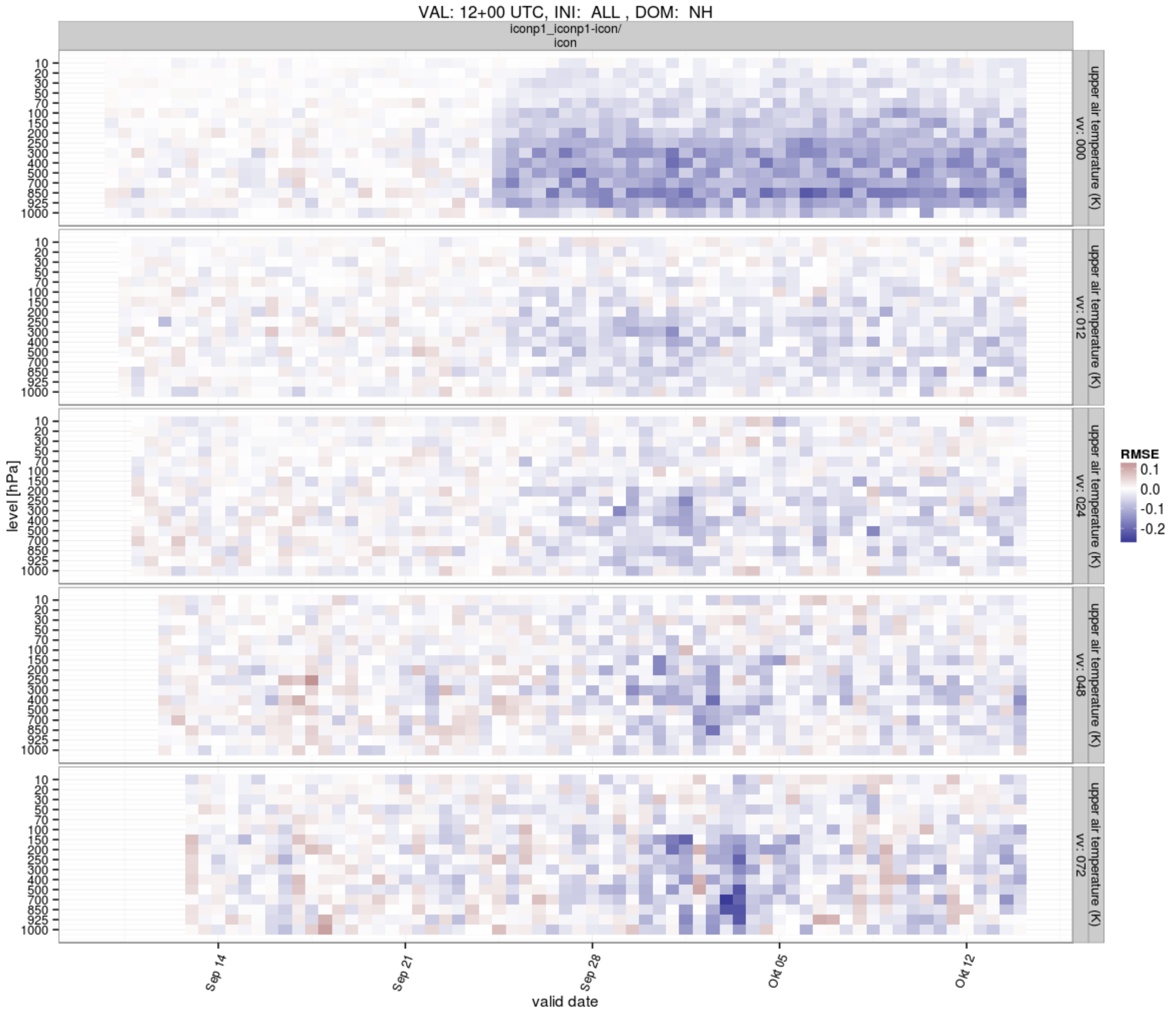
Verifikation: Felix Fundel, FE15, Michael Denhard, FE15 und A. Rhodin, FE12

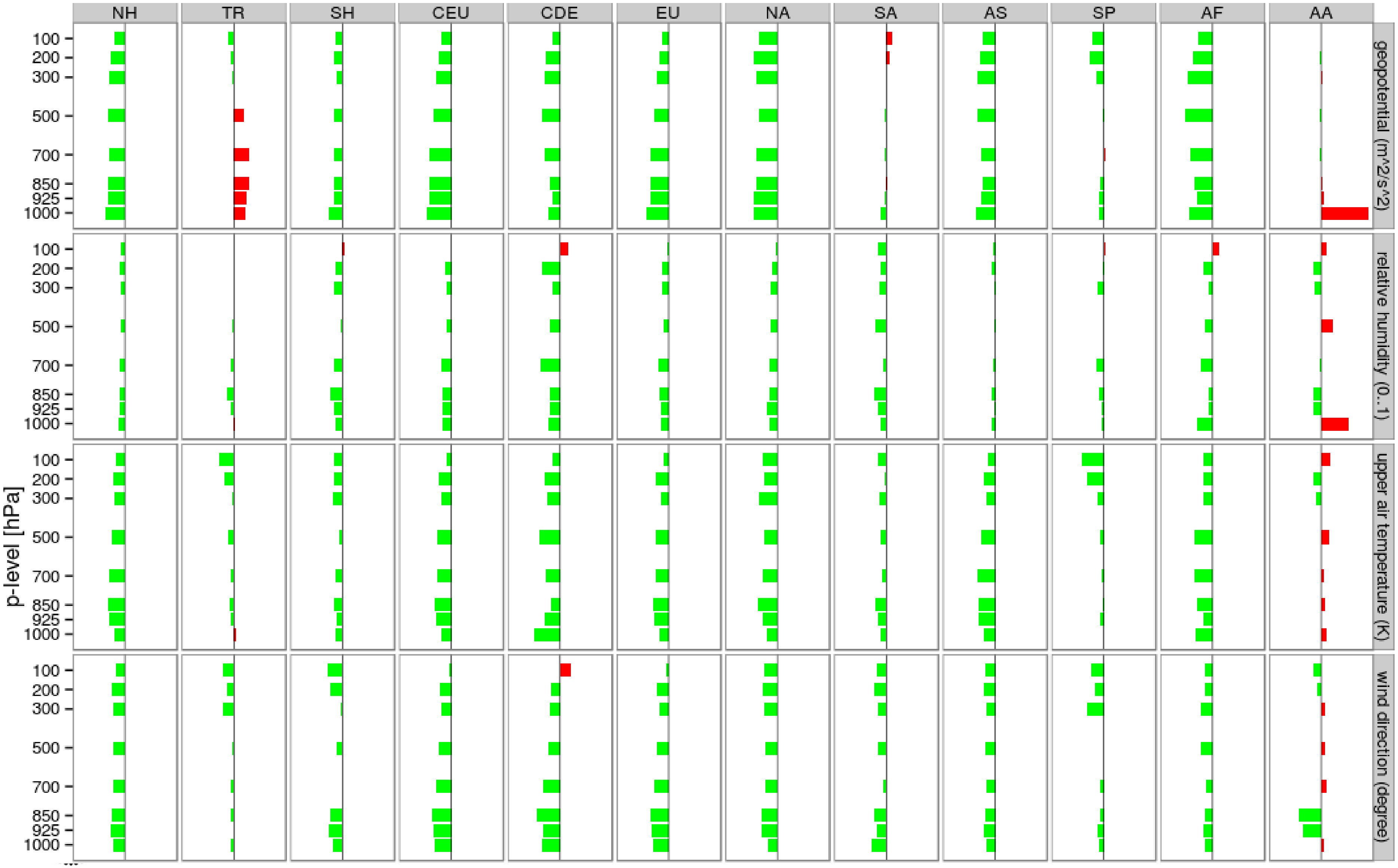


4. ICON Ensemble Datenassimilation

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Verifikation: Felix Fundel, FE15 und A. Rhodin, FE12

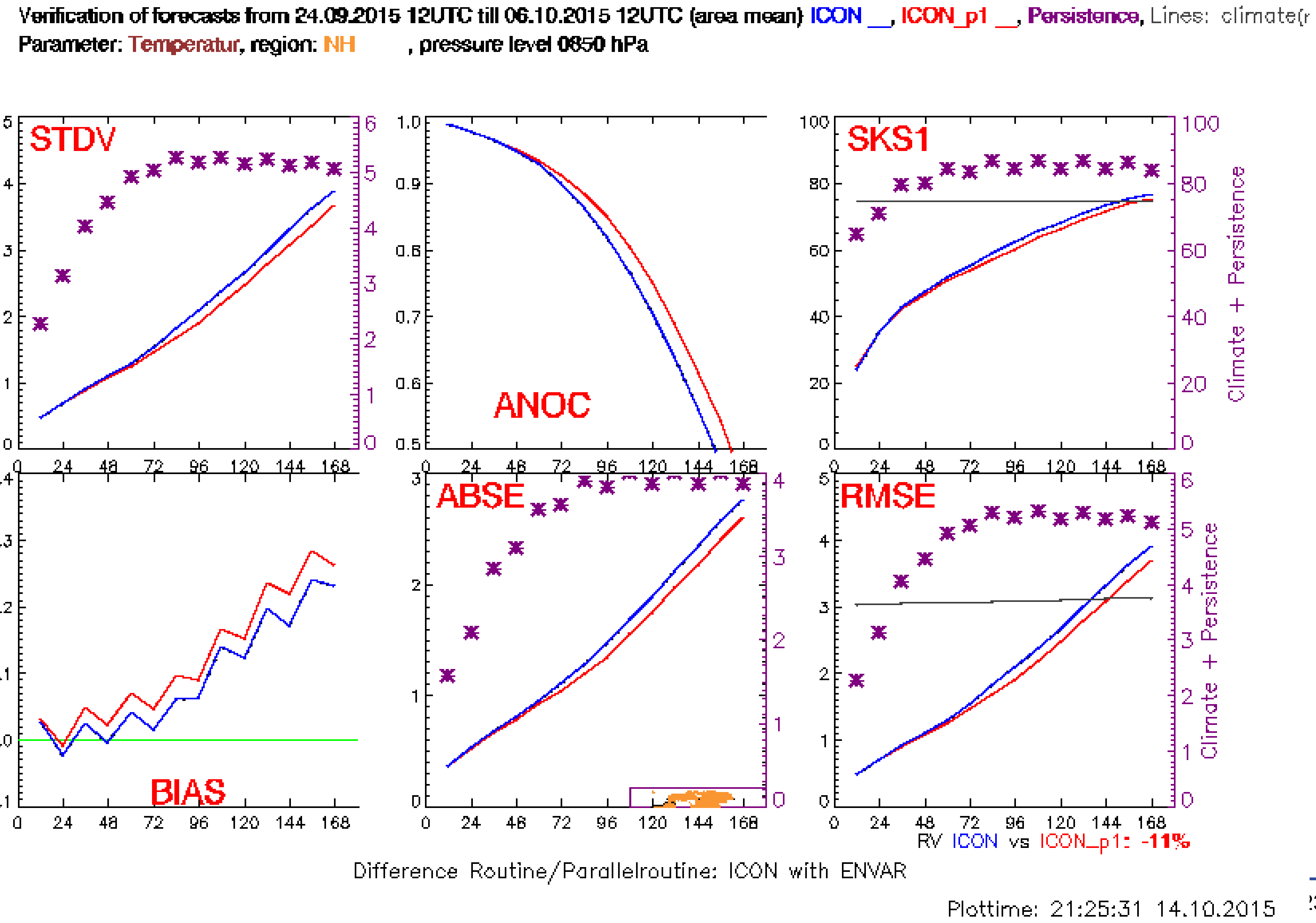
EnVAR Hybrid System Deterministic Forecast 13km Verification against TEMP



4. ICON Ensemble Datenassimilation

Verifikation: Michael Denhard und Uli Damrath, FE15

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



4. ICON Ensemble Datenassimilation

Verifikation: Felix Fundel, FE15, Michael Denhard, FE15 und A. Rhodin, FE12

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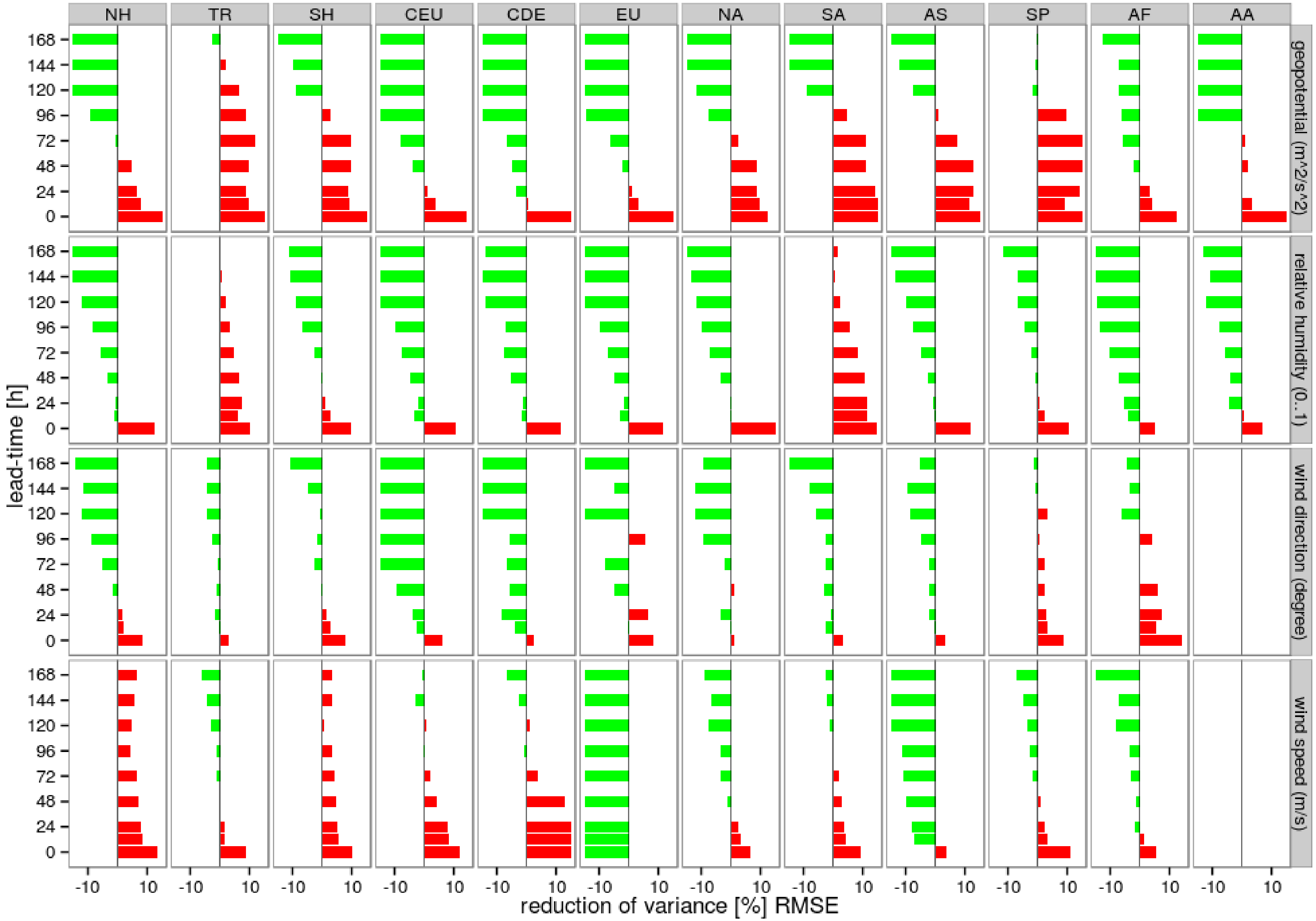
ICON EPS Ensemble Forecast 40/20km Verification Mean against TEMP

4. ICON Ensemble Datenassimilation

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Verifikation: Felix Fundel, FE15, Michael Denhard, FE15 und A. Rhodin, FE12

ICON EPS Ensemble Forecast 40/20km Verification Mean **Surface**

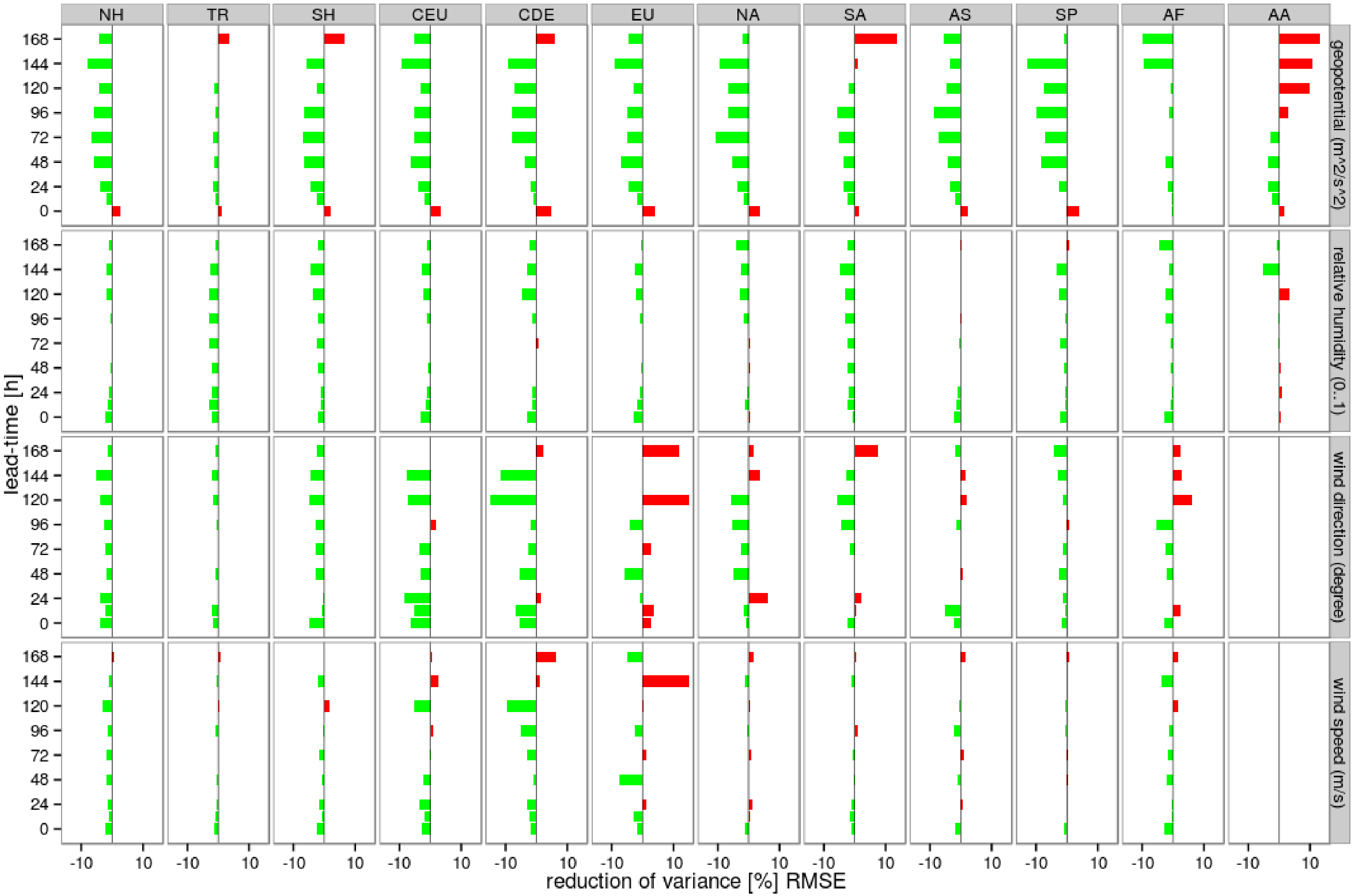


4. ICON Ensemble Datenassimilation

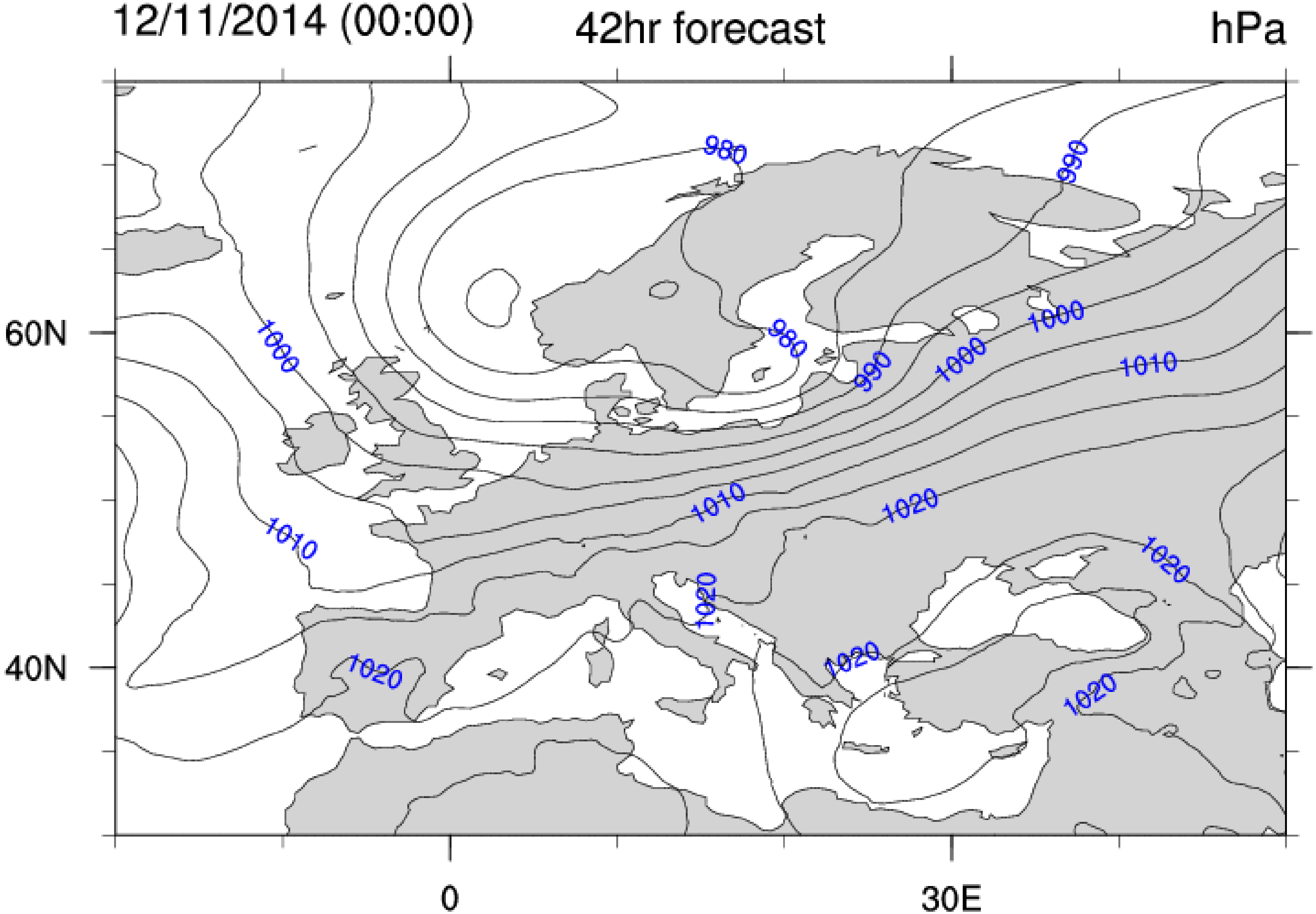
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Verifikation: Felix Fundel, FE15, Michael Denhard, FE15 und A. Rhodin, FE12

ICON EnVar Forecast 13km Verification Surface vs. Routine



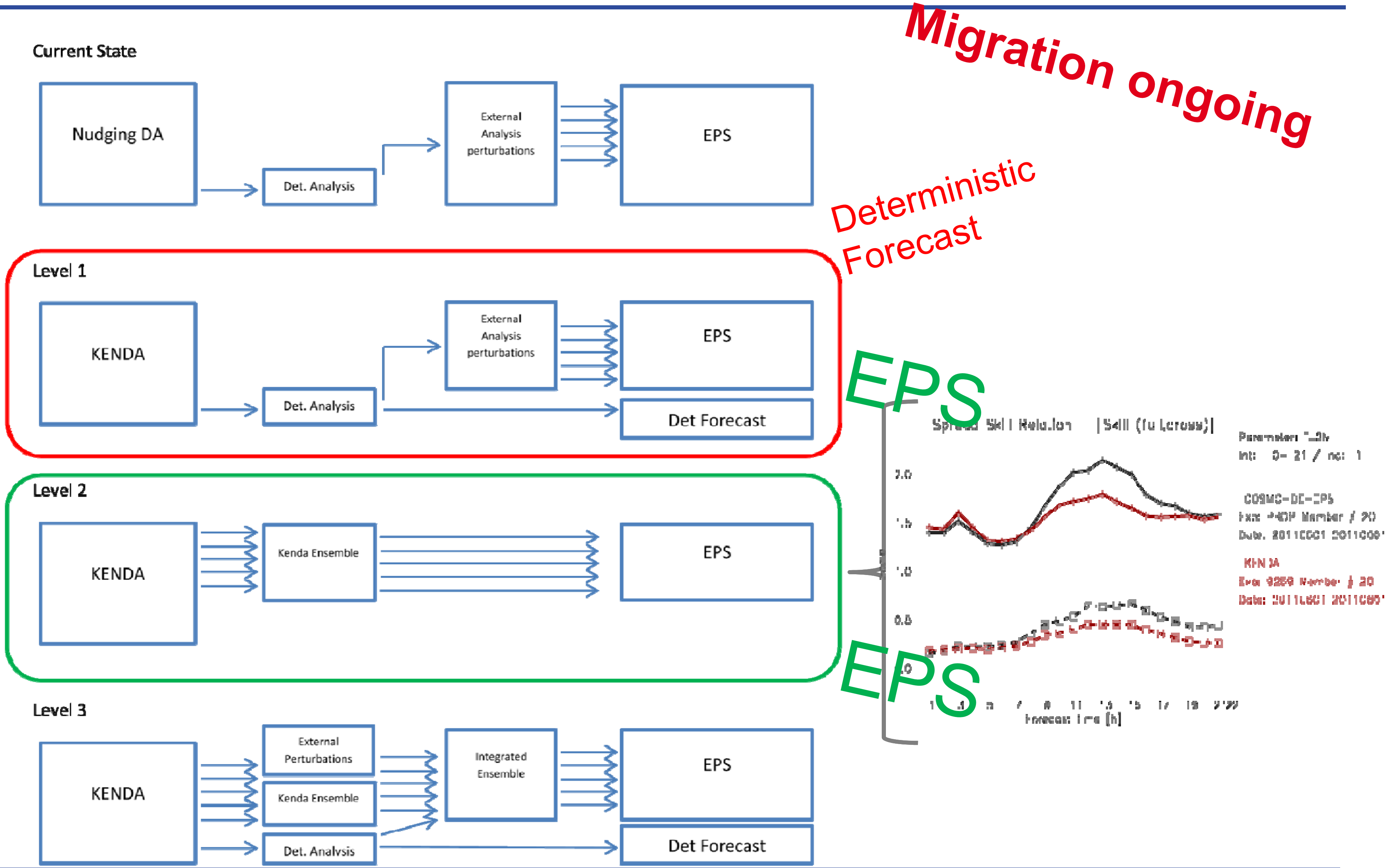
ICON Ensemble PMSL Mean Member 1



Part III: Kilometer Scale Ensemble Data Assimilation (KENDA)

- **LETKF + DetAnalysis**

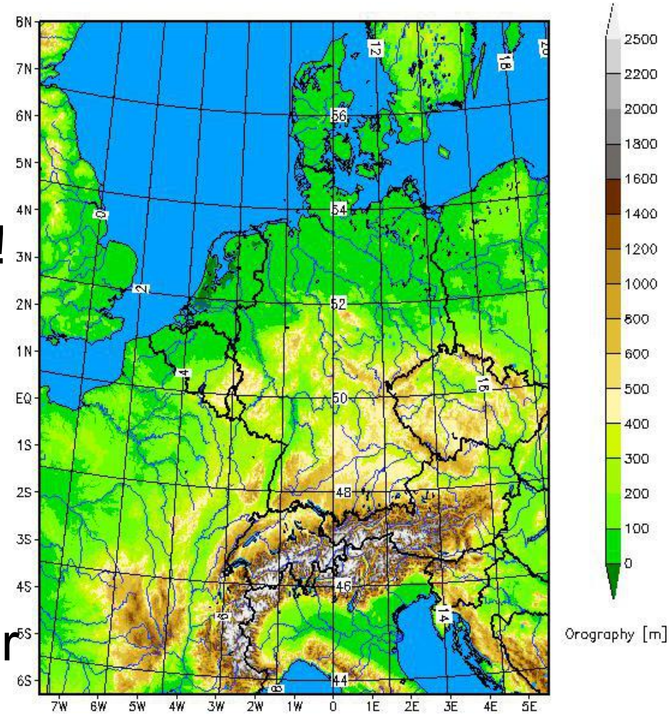
KENDA and EPS Development



KENDA for COSMO

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

1. **Full System** with **conventional data** ***running***
2. Work **Latent Heat Nudging**, done, works well!
3. Further **Observation Systems** under development
   (e.g. **SEVIRI, GPS/GNSS**, Lidar, …)
4. **Longer Periods/Winter Periods** to be tested.
5. **Technical work** on operational setup (member loss) done
6. **Archive/Storage** challenges remain severe
7. **Pattern Generator** and further **Refinements**
   (Localiyation, Covariance Inflation, …)



introduction of soil moisture (SM) perturbations
(+ SST pert.)

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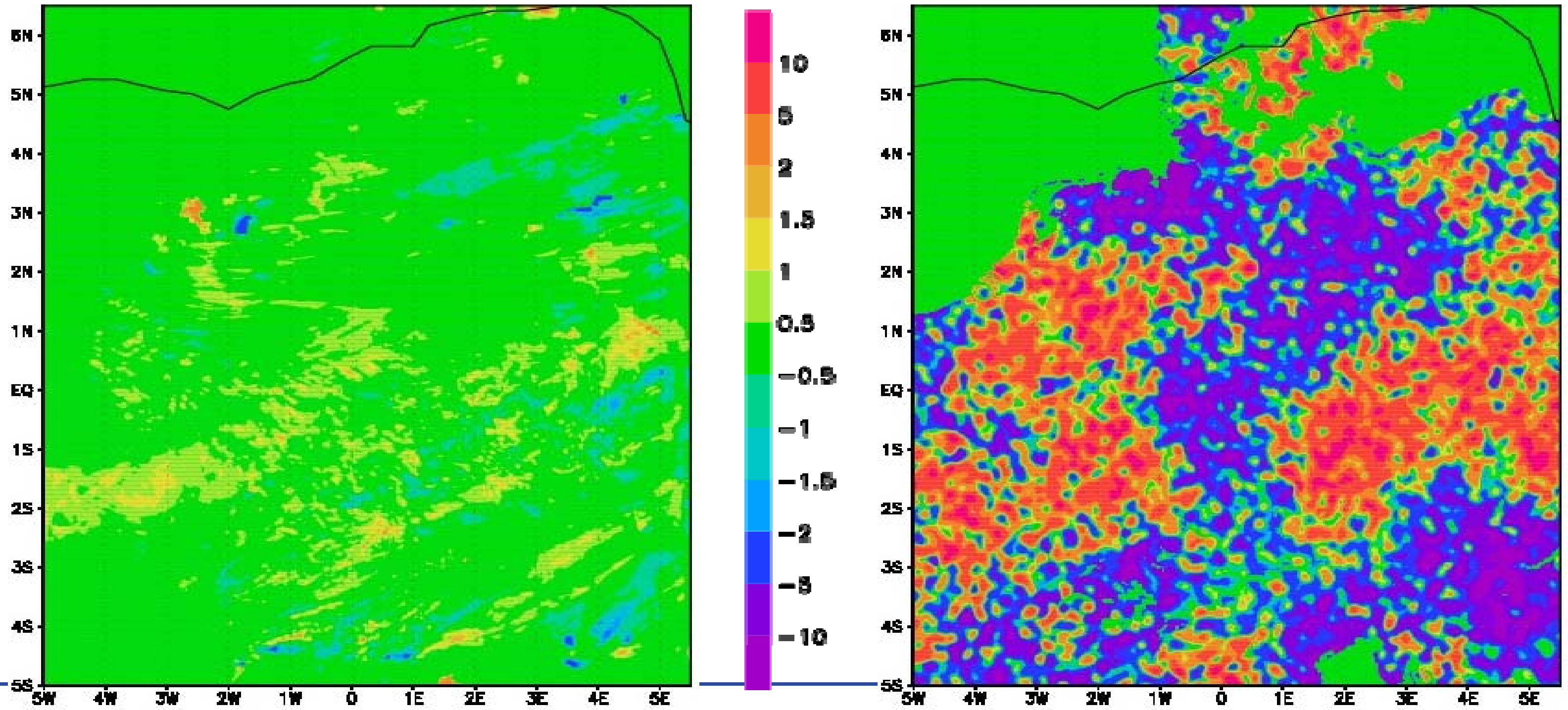
- simple superposition of Gaspari-Cohn (~ Gaussian) functions at each analysis g.p., with random amplitude and pre-specified horiz. / temporal correlation scale(s)
- scales : 100 km + 10 km ; 1 day ; std dev of amplitude: 0.1 soil moisture index

spread of soil moisture (WSO), layer 3 (3 – 9 cm), after 5 days

cycling without perturbations

cycling with SM perturbations



impact of including **LHN** in LETKF DA cycle (with ICON soil): score chart

	LETKF **LHN-det** vs. no-LHN		LETKF **LHN-all** vs. LHN-det	
variable	RMSE ETS / FSS	Bias FBI	RMSE ETS / FSS	Bias FBI
upper-air	=	=	=	=
surface	=	=	=	=
precip 0 UTC , 0.1 mm	(+)	(+)	(+)	=
precip 0 UTC , 1 mm	=	=	(+)	=
precip 12 UTC, 0.1 mm	**+**	**+**	**+**	=
precip 12 UTC, 1 mm	**+**	=	**+**	=

→ benefit from adding LHN small for 0-UTC runs, large for 12-UTC runs
→ deterministic forecast improves if LHN also added to all ens members in LETKF

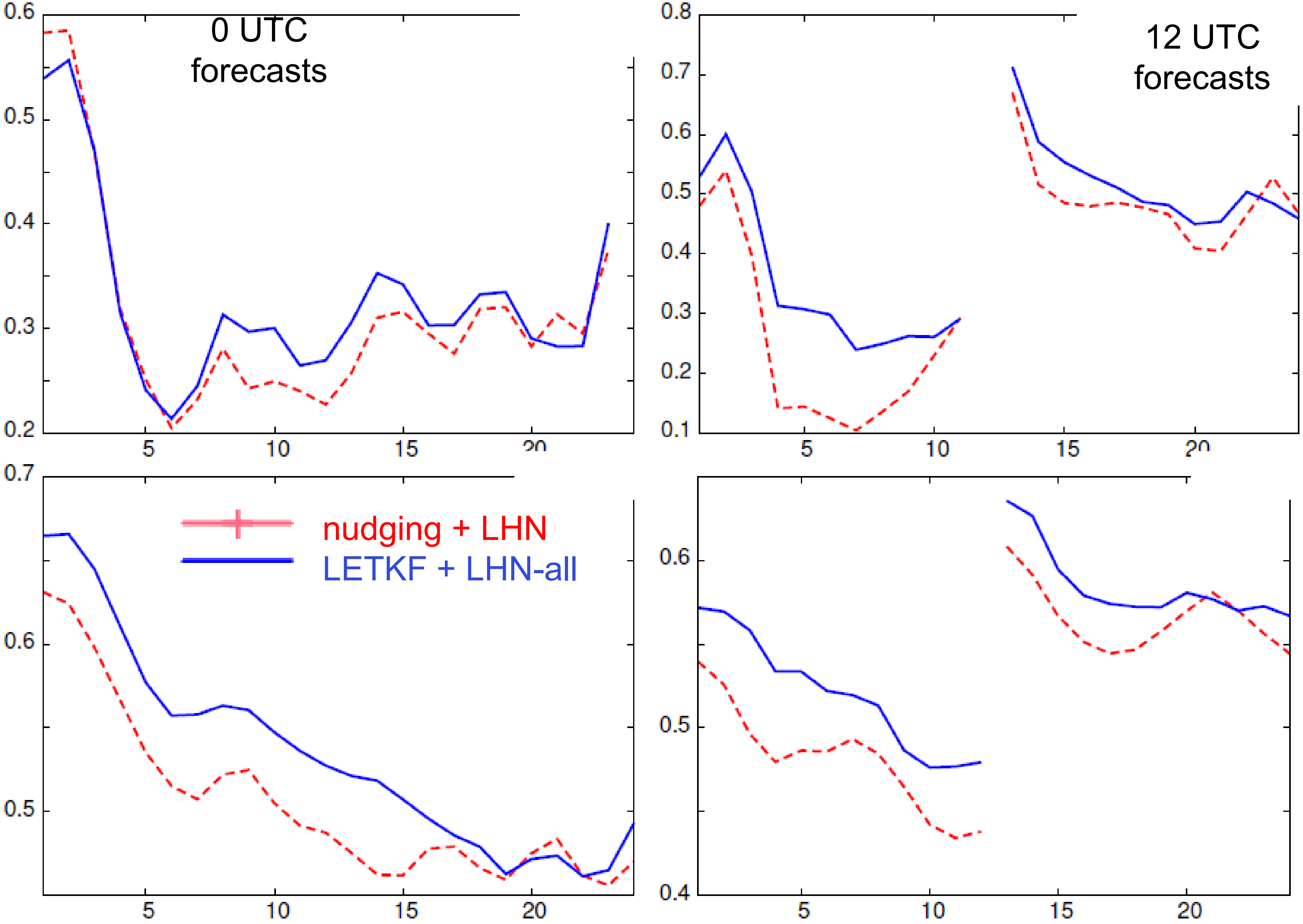
LETKF + LHN-all vs. Nudging + LHN : verification against radar precipitation

Period 1, 6 Days

FSS 11 g.p. (30 km)

0.1 mm

Period 2, 12 Days



LETKF + LHN-all vs. Nudging + LHN : KENDA score chart

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	variable	T2012		T2014	
		rmse	bias	rmse	bias
upper air	geopotential	=	=	=	=
	temperature	=	=	(+)	(+)
	relative humidity	=	=	=	–
	wind speed	+	=	+	=
	wind direction	+	=	(+)	=
surface	2-m temperature	=	=	+	=
	2-m dew point	=	=	+	+
	10-m wind	=	=	=	=
	surface pressure	–	=	+	=
	total cloud	=	=	=	=
	low cloud	+	+	–	=
	mid-level cloud	+	+	=	=
	high cloud	–	–	–	–
radar	precip 0 UTC runs	+/(–)	+	++	++
	precip 12 UTC runs	++	++	++	++

LETKF:

→ overall comparable / better results

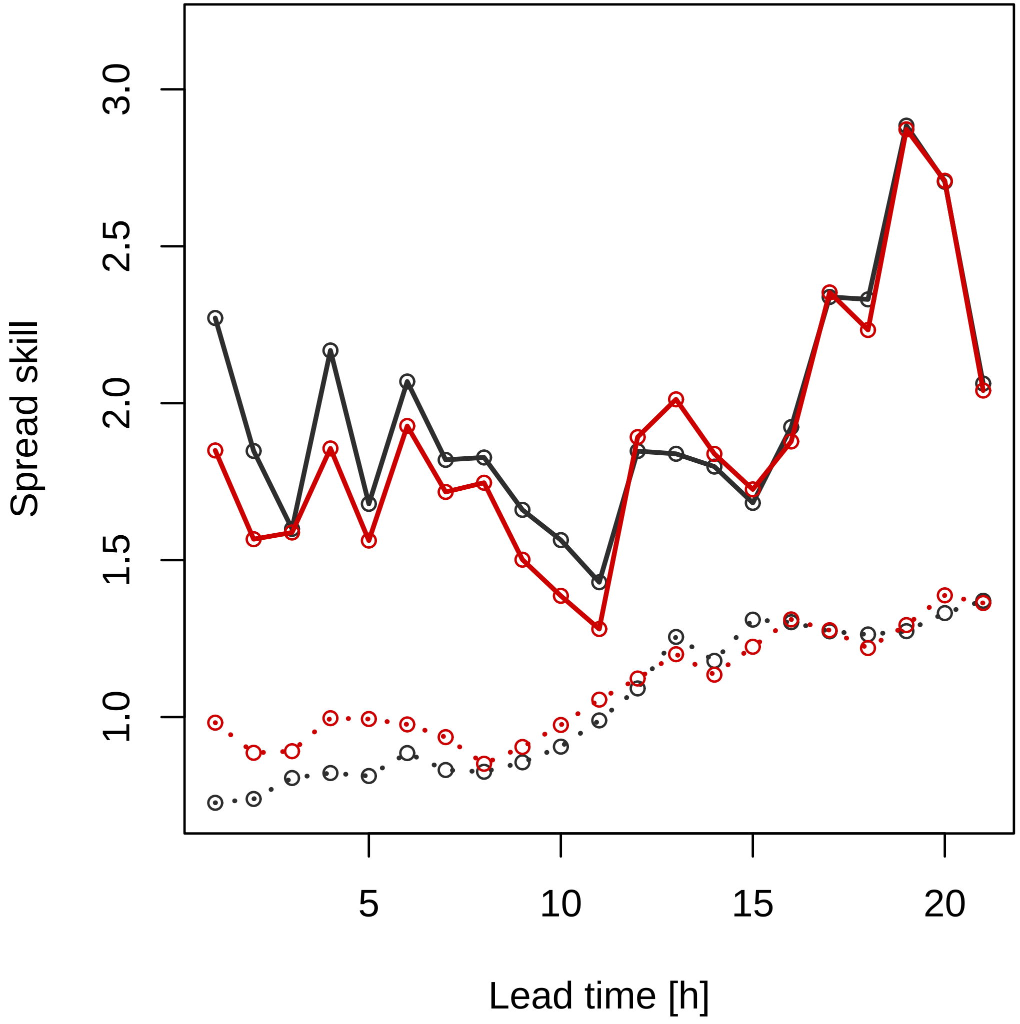
→ Mixed view for surface pressure

→ Problem with high clouds

Stable Improvement

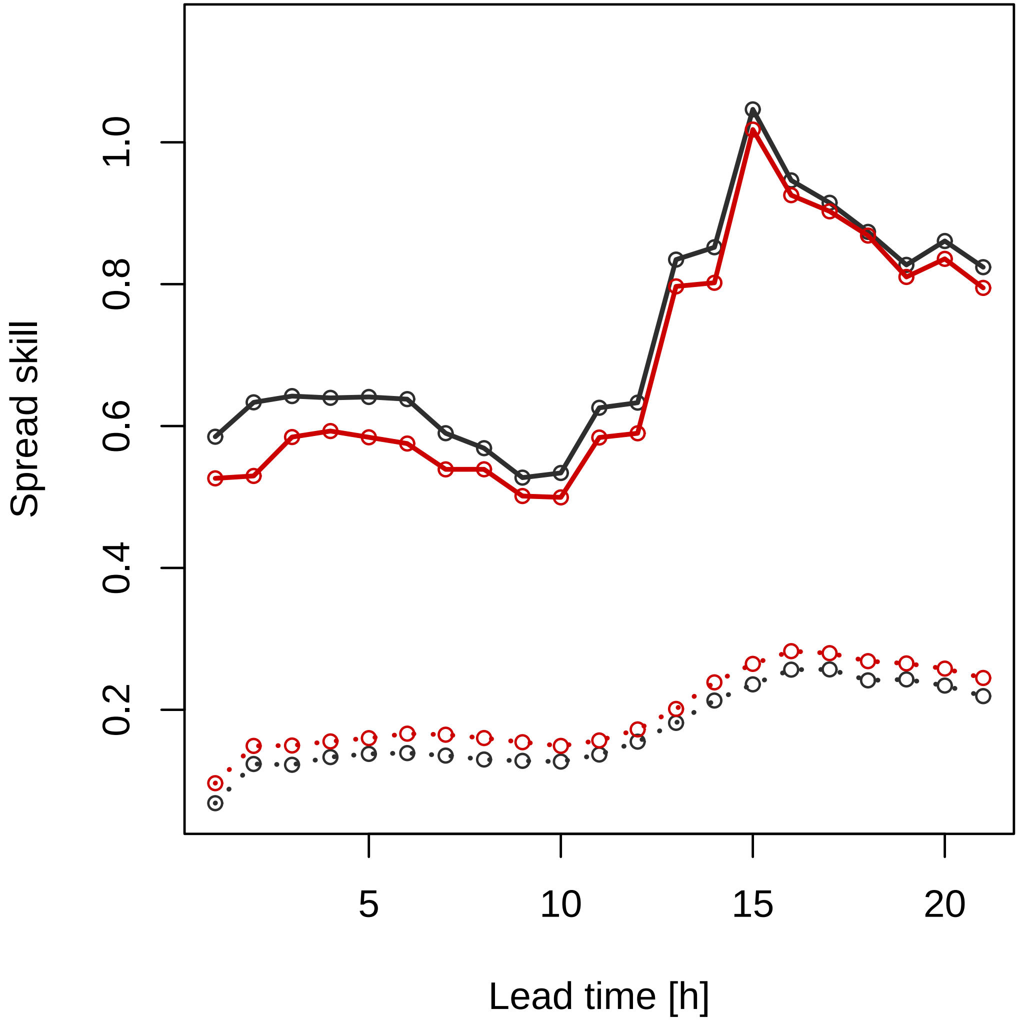
EPS 10-250 m Wind: RMSE + Spread

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



Nudging + BCEPS
KENDA

EPS Precipitation: RMSE + Spread



Nudging + BCEPS
KENDA

Part IV: Particle Filter

- Can a Particle Filter work for NWP?
- Yes, the EnKF is already working (as shown above)!
- The question is how to calculate the posterior ensemble!
- DWD is developing a Local Markov Chain Particle Filter
- MeteoSwiss + ETH Zurich + DWD are working on an Ensemble Kalman Particle Filter
- Uni Potsdam is developing a Particle Filter for our System

Part IV: Particle Filter

- You get a **prior distribution** p(x) by some prior ensemble

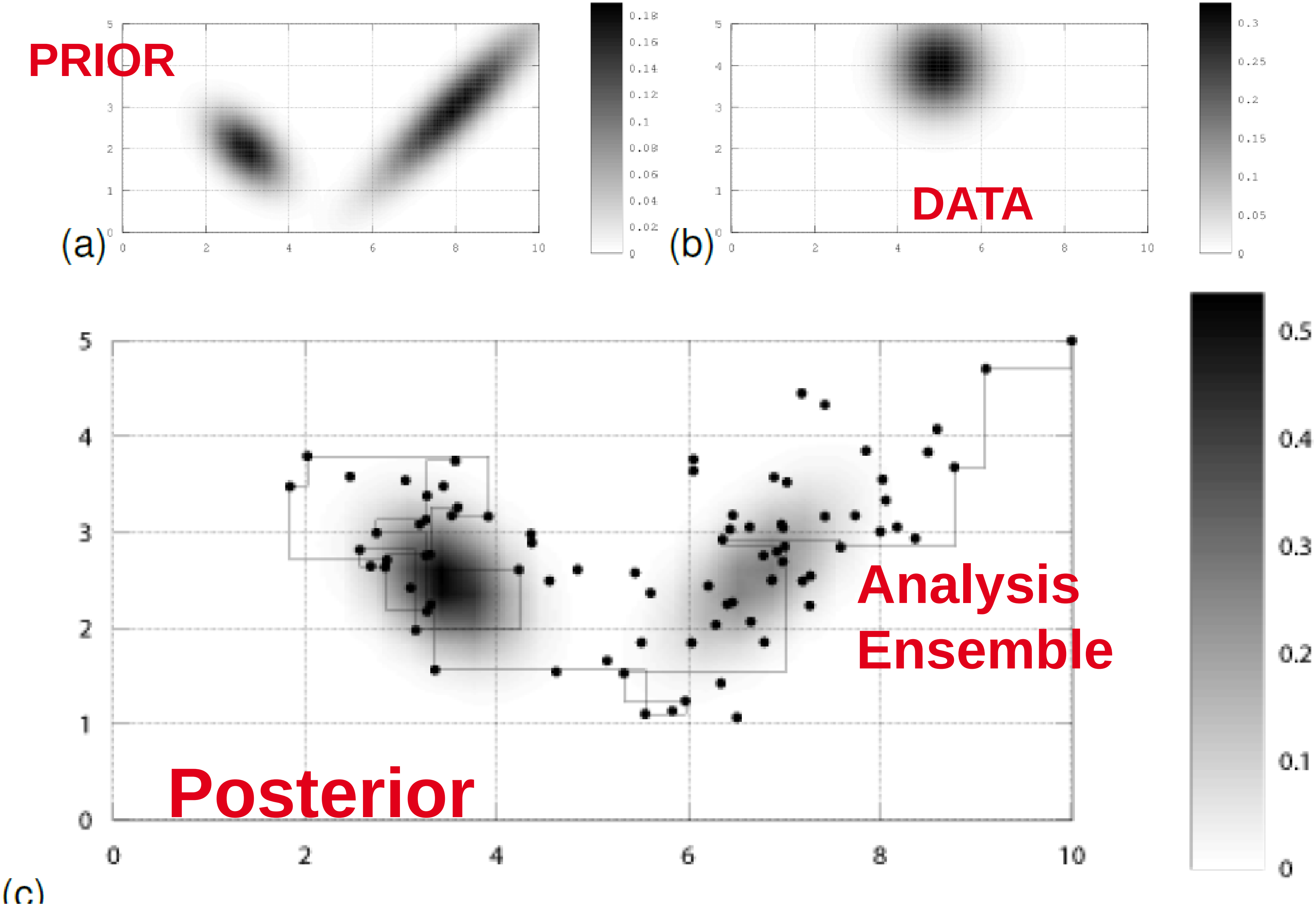
- Measurements define a **data distribution** p(y|x)

- **Bayes theorem** defines a posterior distribution by

$$p(x|y) = c\ p(x)\ \ p(y|x)$$

The core game is
how to get an **analysis ensemble** from p(x|y).

BAYES Data Assimilation



MCMC Methods

Let us start with some continuous transition probability $q(x', x)$ for the transition of x to x', which we use as a **proposal density** to suggest draws as candidates for our transition probability density $k(x', x)$, $x, x' \in \Omega$. The goal is to construct a correction $\alpha(x', x)$ such that have

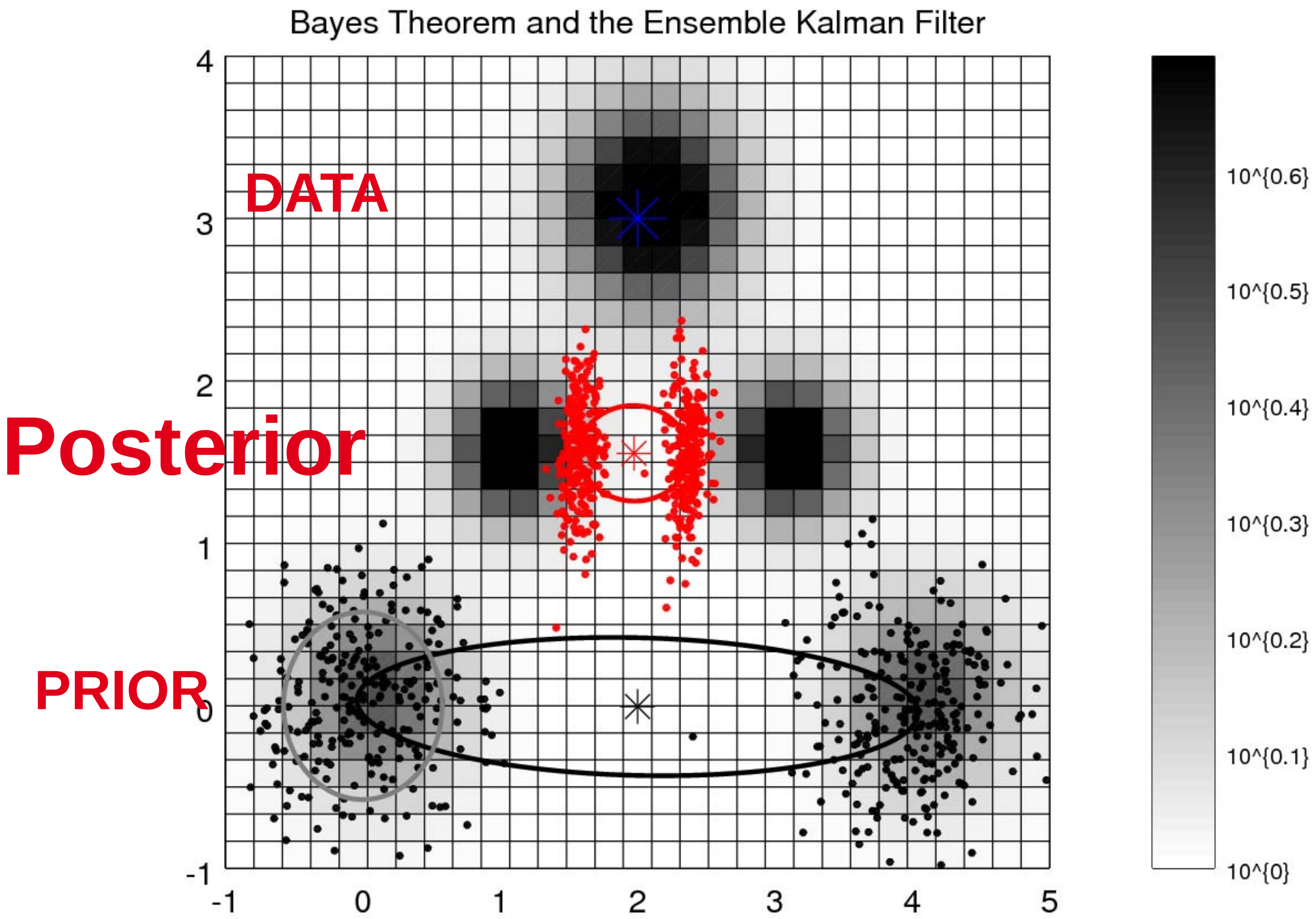
$$k(x', x) = \alpha(x', x)q(x', x), \quad x, x' \in \Omega, \tag{34}$$

is a transition kernel which satisfies the **detailed balance equation** (33). The choice

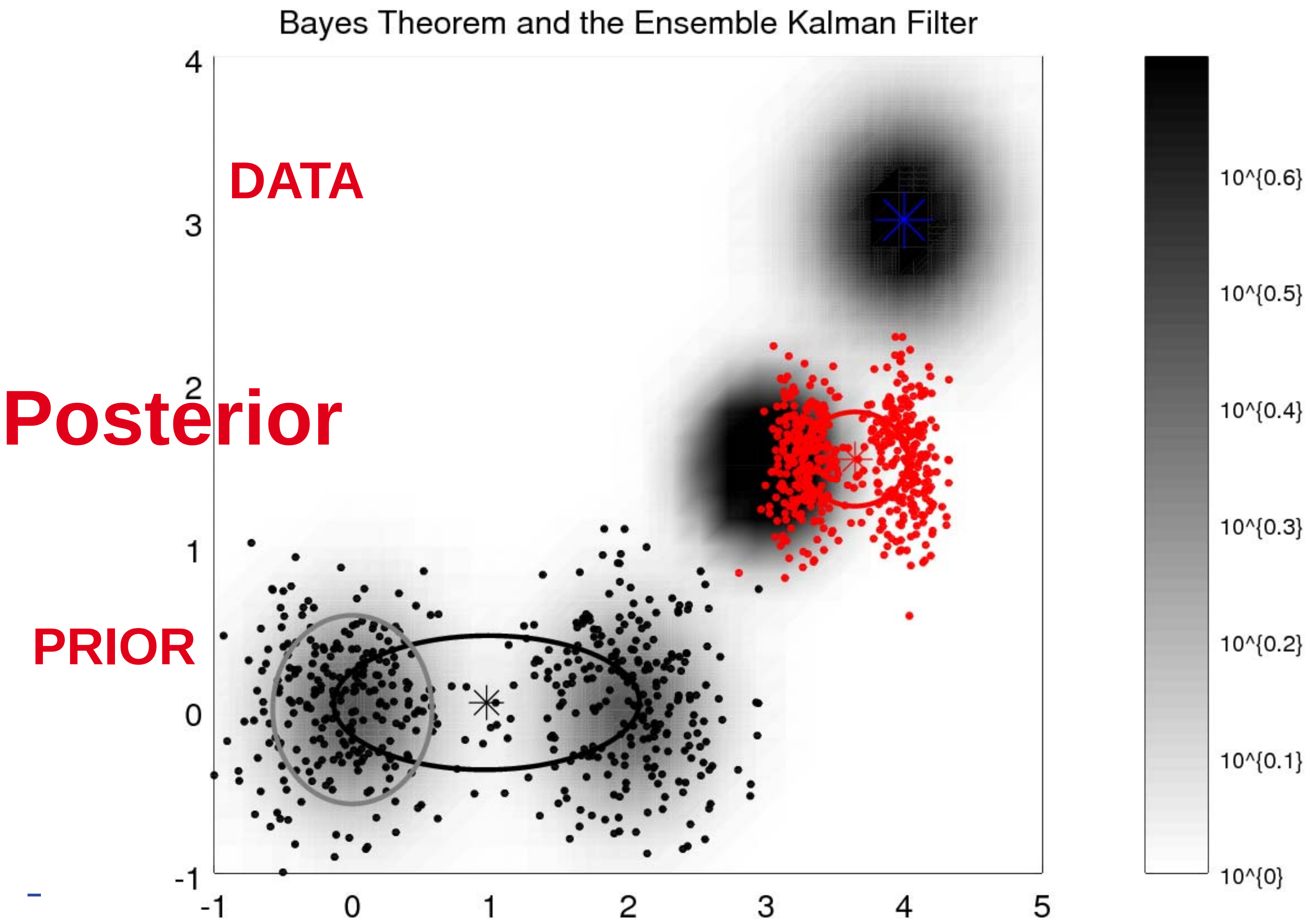
$$\alpha(x', x) := \min\left\{1, \frac{p(x')q(x, x')}{p(x)q(x', x)}\right\} \tag{35}$$

is known as **Metropolis-Hastings algorithm**.

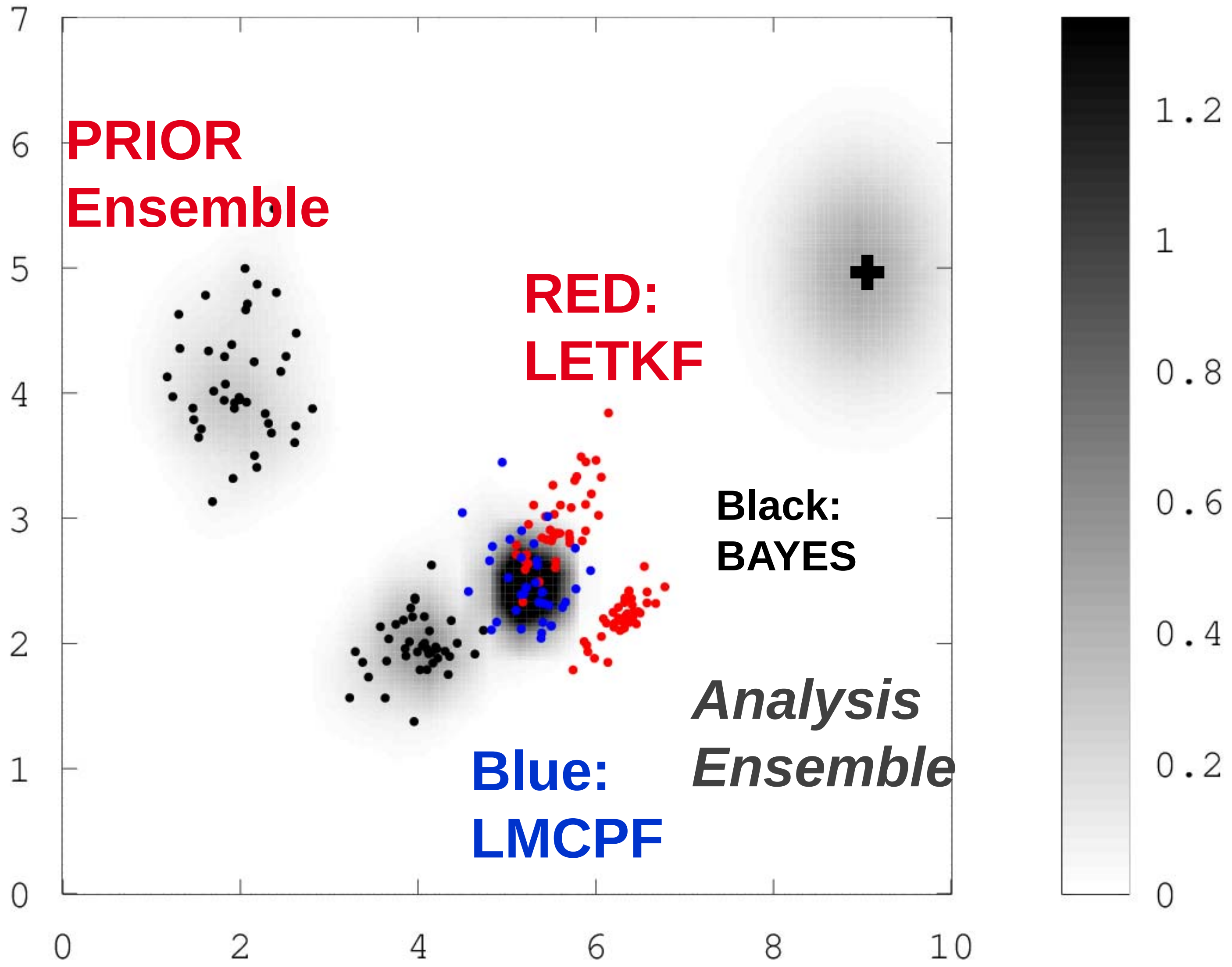
BAYES Data Assimilation

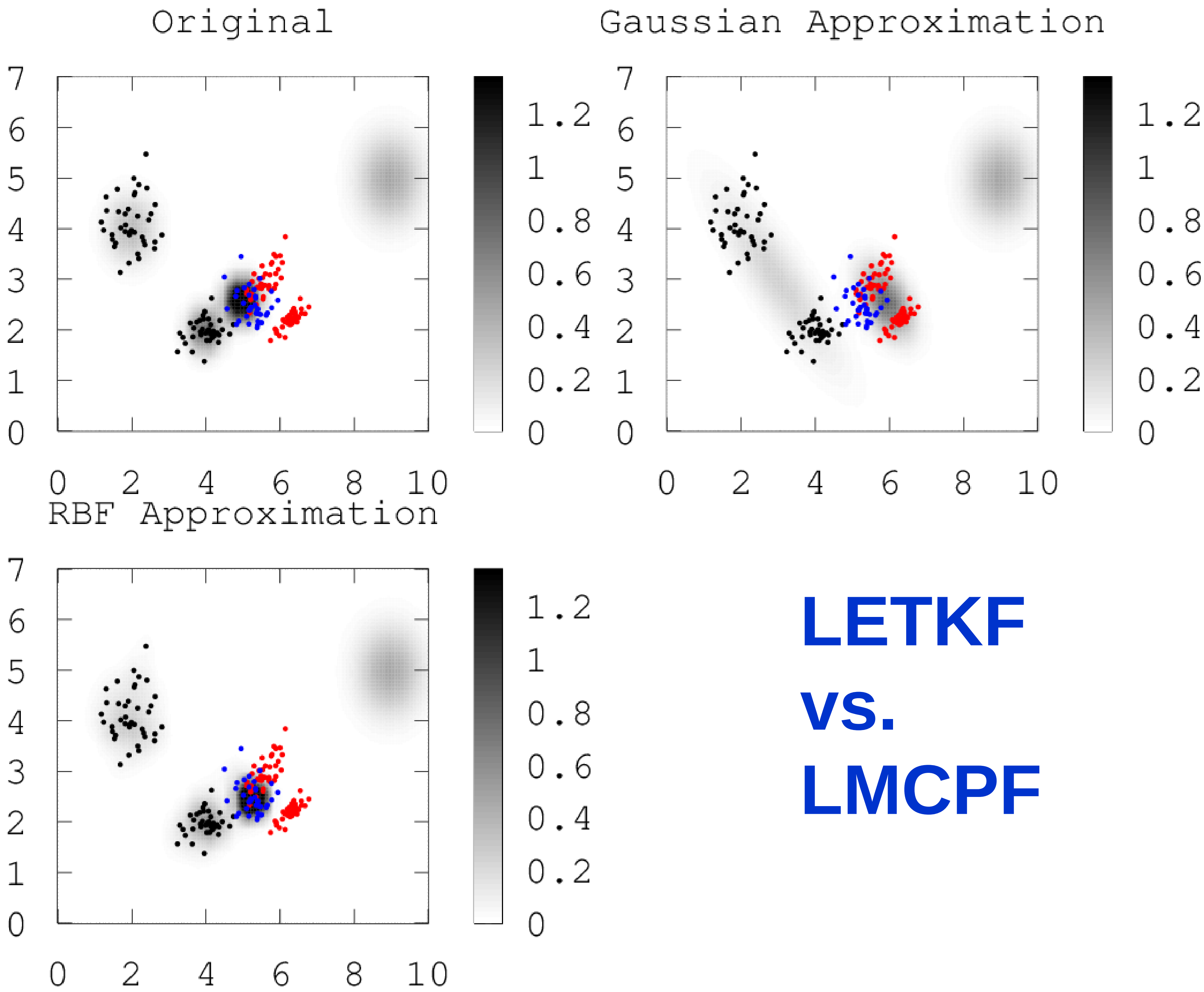


BAYES Data Assimilation



Particle Filter Example



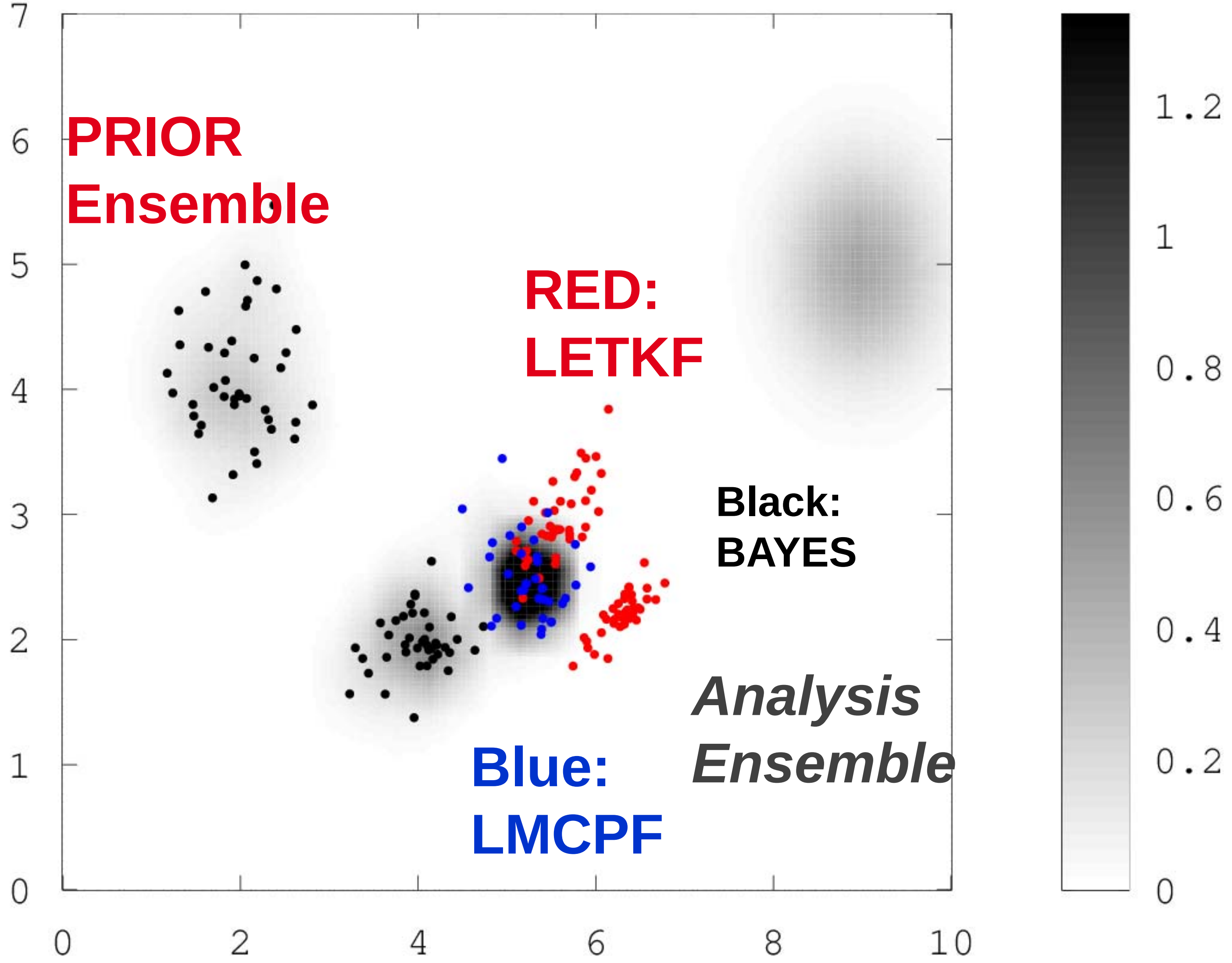


LETKF
vs.
LMCPF

The LMCPF Particle Filter

1. We carry out Bayes type data assimilation by creating an ensemble of states (the **particles** or **ensemble members**) $x^{(1)}, \ldots, x^{(L)}$ in step t_k for $k = 0$ according to some initial probability distribution $p[t_0](x)$.
2. The ensemble is propagated from t_k to t_{k+1}. It samples the background or *prior* probability distribution $p[t_{k+1}](x)$ at time t_{k+1}.
3. Given measurement data $y \in Y$ we employ Bayes Theorem to calculate the **posterior distribution** $p(x) := p^{(a)}(x) = cp^{(b)}(x)p(y|x)$. This needs the ability to calculate $p(x)$ for some given state x as well as $p(y|x)$ given y for some state x.
4. We use MCMC with **Metropolis-Hastings kernel** to draw $x^{(1)}, \ldots, x^{(L)}$ from $p(x)$. Then we proceed with Step 2.

Particle Filter Example



The LMCPF Particle Filter

- **Markov Chain Monte Carlo** Methods are a tool how to sample some given probability distribution p(x).
- We need the ability to calculate p(x) given some state x.
- Then we can employ MCMC, for example with Metropolis Hastings kernel.

- **Metropolis Hastings** is a particular way how to generate the posterior ensemble.
- The idea is to use a **proposal distribution q(x)**.
- For every proposal state a decision is made wether to take it or not.
- This depends on the Metropolis Hastings function α.

The LMCPF Particle Filter

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

- We can employ any **proposal distribution** q. In particular, we can use the result of the LETKF which brings us basically where we would like our particles to be - but with some wrong scaling in the directions of the LETKF-B-Matrix.
- Consequence: use a *relaxed* version of the LETKF to make sure we do not miss any states for our MCMC sampling! This is a form of **covariance inflation** for the LETKF which we have completely under our control.
- Our transition probability $q(x, x')$ can be independent of x, i.e. we can completely employ the **LETKF posterior probability distribution**! But we need the ability to calculate $p(x) = p^{(b,LETKF)}(x)$. This is no problem when we have the estimate for $B^{(b,LETKF)}$.

The LMCPF Particle Filter

- We work in the **ensemble space**

$$U = \mathrm{span}\{x^{(1)}, ..., x^{(L)}\}, \quad x = \sum_{\ell=1}^{L} \alpha_\ell x^{(\ell)} \tag{37}$$

  with the background ensemble propagated from the previous step.

- We might use a **localized** version of the space, i.e. we work around some point $p \in \mathbb{R}^3$.
- The term $p(y|x)$ can be calculated when we have observations in the same way as we do it for the LETKF.
- We need to calculate the **prior probability density** $p(x)$ for x given by (37) given the ensemble members $x^{(1)}, .., x^{(L)}$ many times in each analysis step of the LMCPF.

The LMCPF Particle Filter

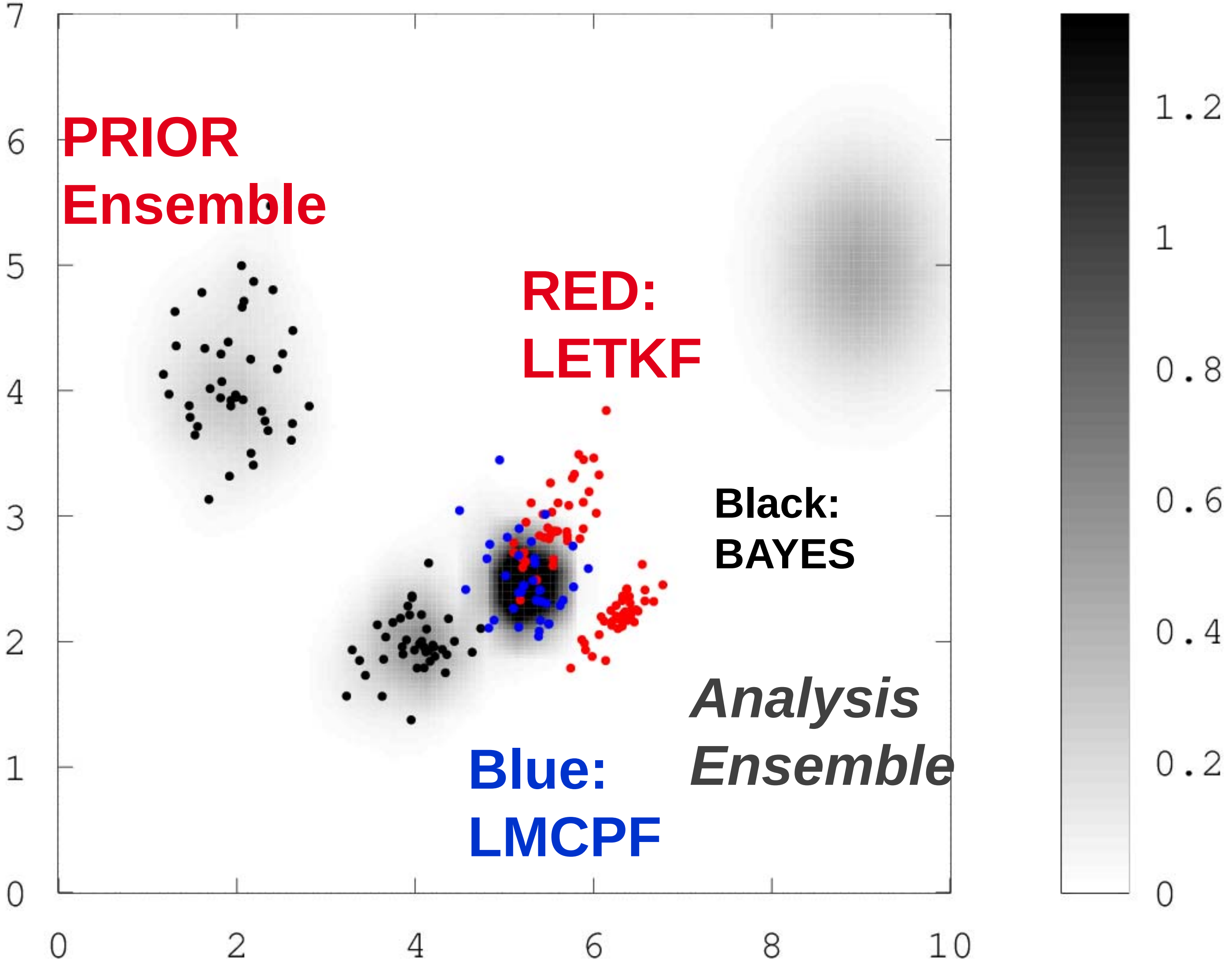
- To **approximate** $p(x)$ we can employ several methods. A very general approach is to attach a Gaussian to each ensemble member, i.e. to use

$$p(x) := \sum_{\ell=1}^{L} c_\ell e^{-\|x - x^{(\ell())}\| / b_\ell} \tag{38}$$

  with constants b_ℓ and c_ℓ. Here, c_ℓ is chosen in dependence of b_ℓ such that the integral is equal to 1 for each of the Gaussian ensembles. The constants b_ℓ are **tuning constants** to get a best approximation of $p(x)$ based on $x^{(\ell)}$.

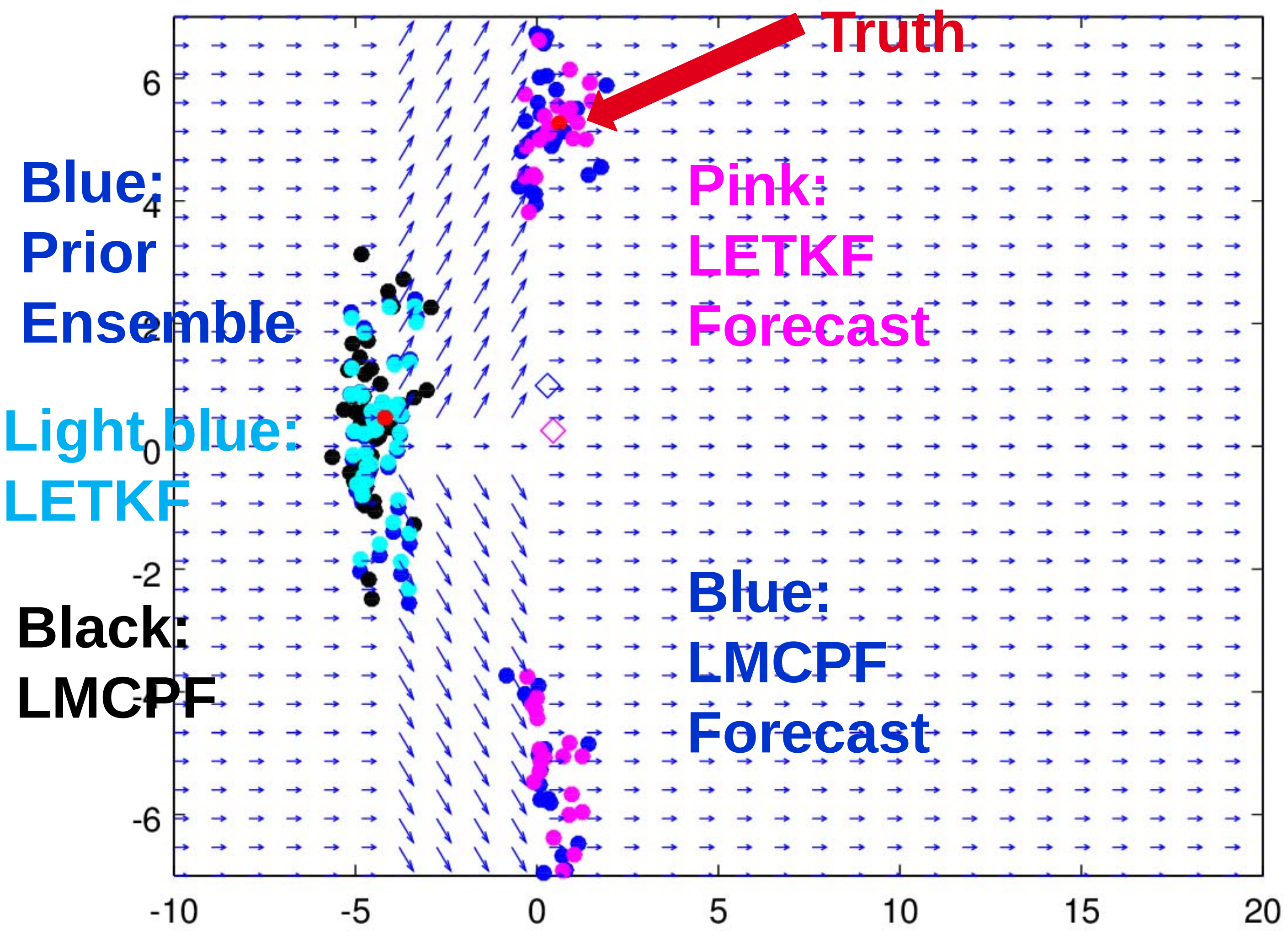
- *Some version of the* **Ensemble Kalman Filter** *can be obtained from the particular choice where we approximate $p(x)$ by a global Gaussian distribution!*

Particle Filter Example

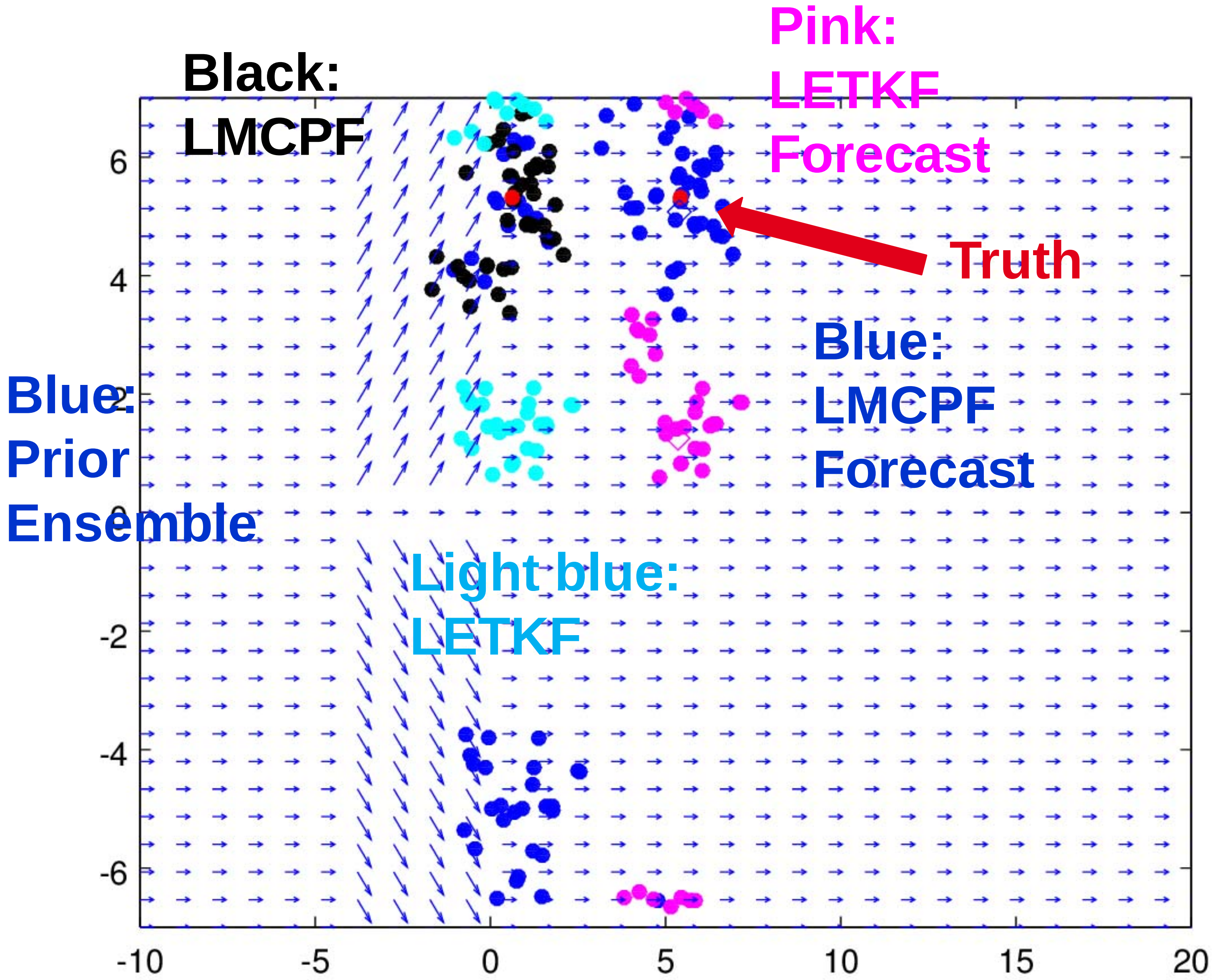


LMCPF Example: nonlinear gate

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

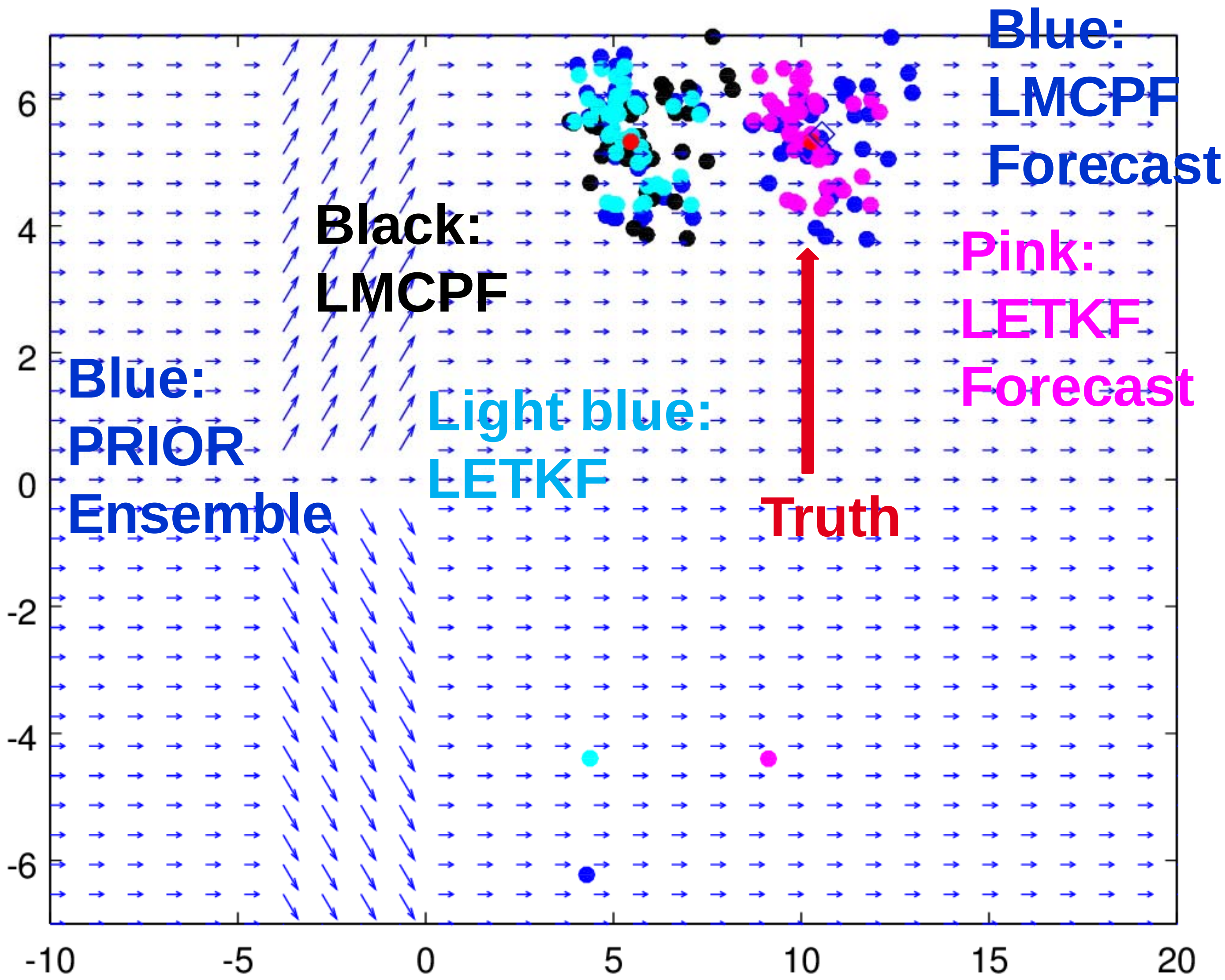


LMCPF Example: nonlinear gate



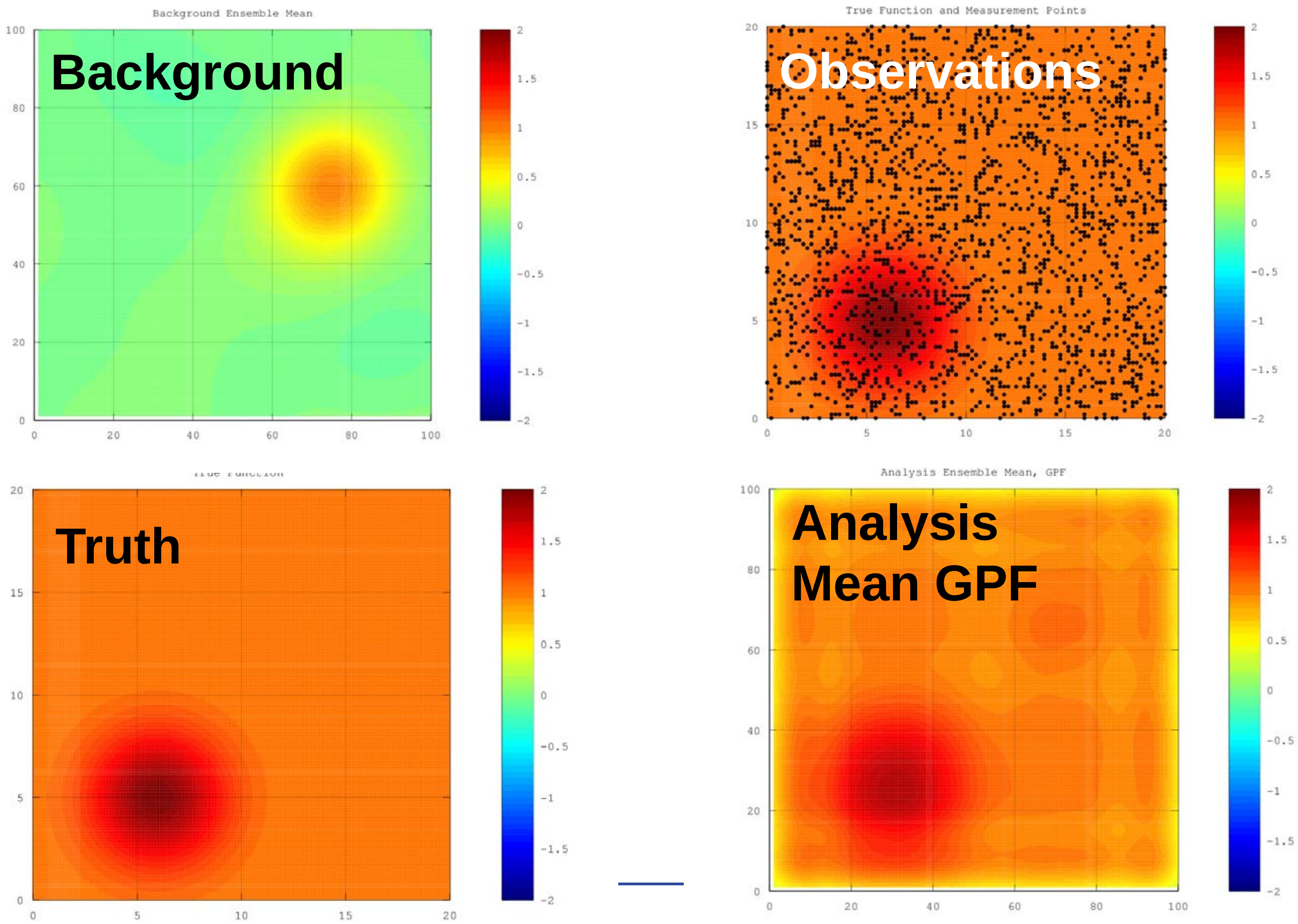
LMCPF Example: nonlinear gate

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



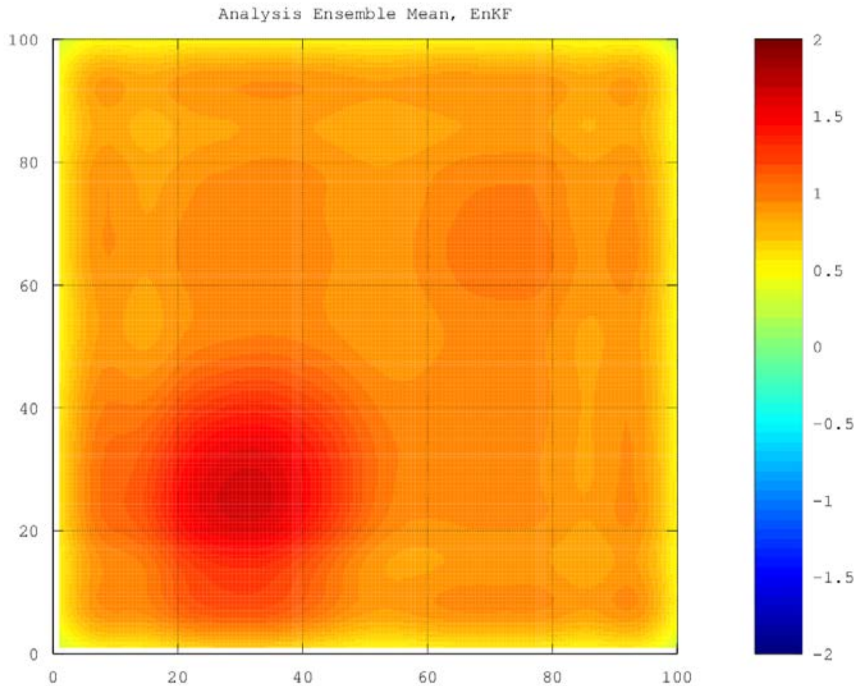
10.000 dimensional Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

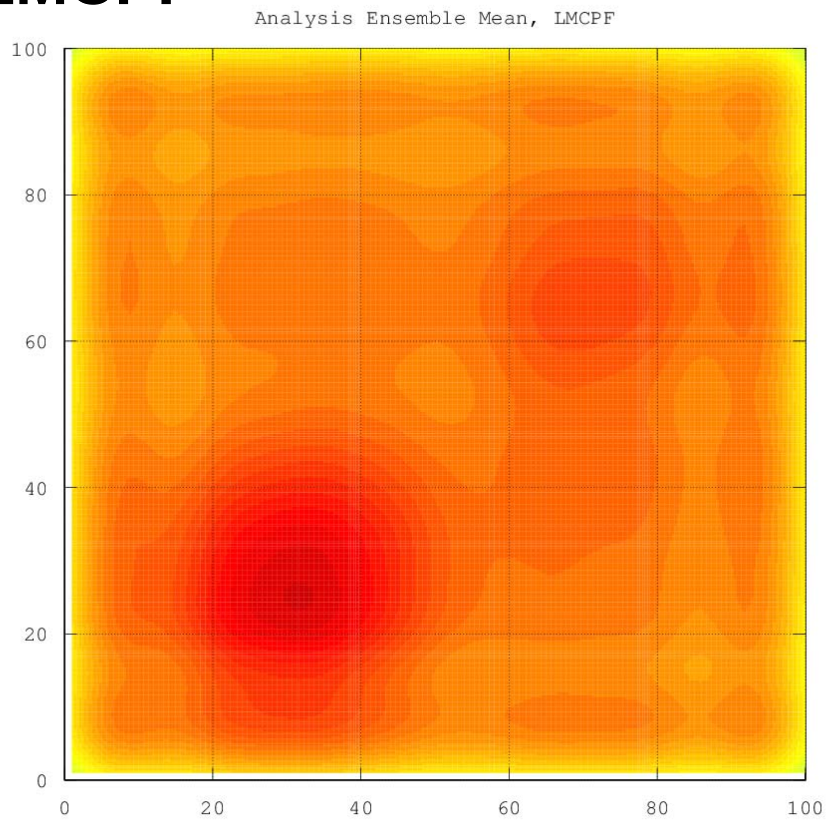


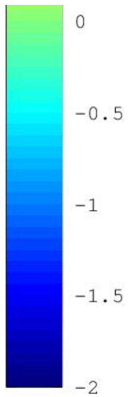
10.000 dimensional Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



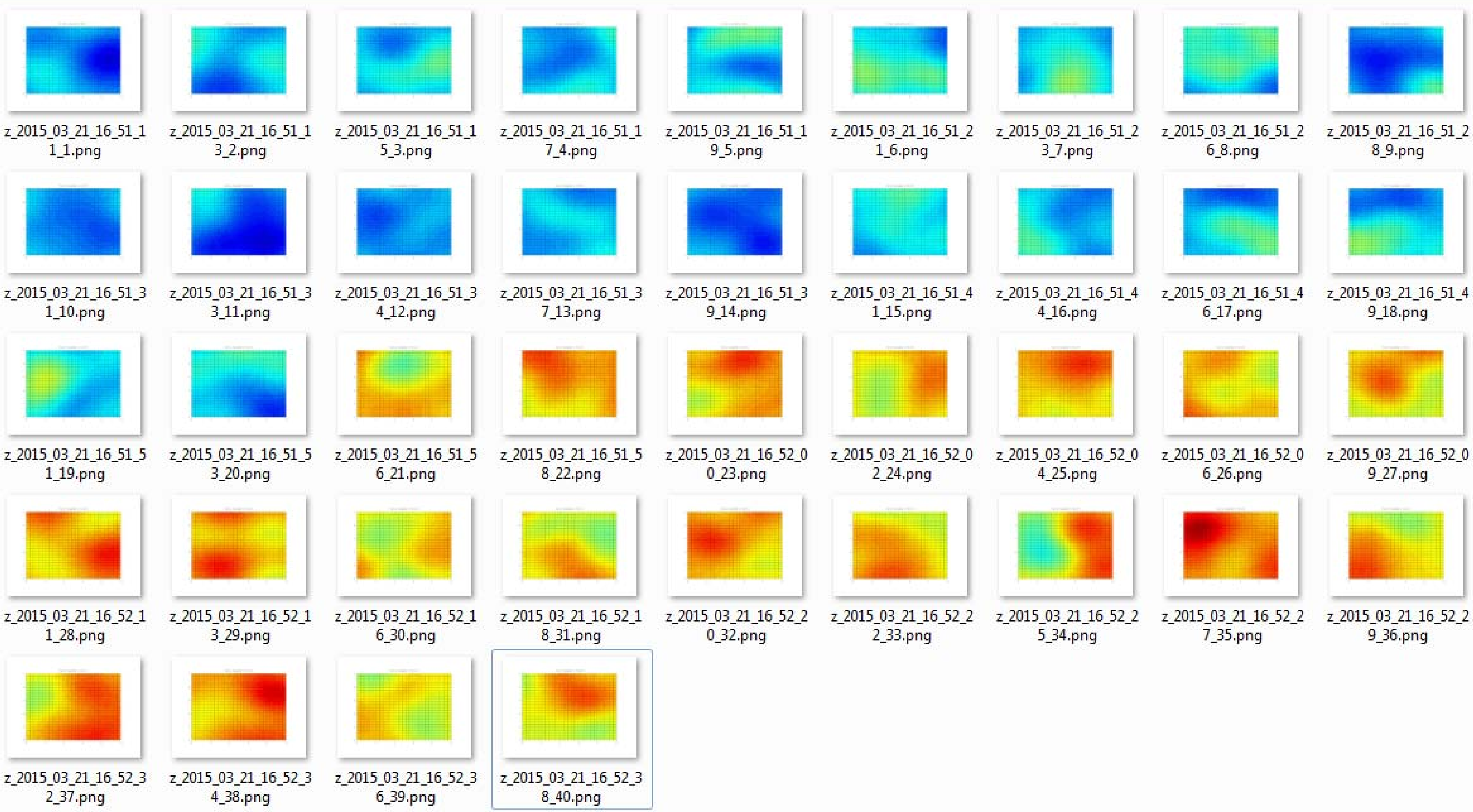
Analysis Mean LMCPF





Analysis Mean EnKF/LETKF

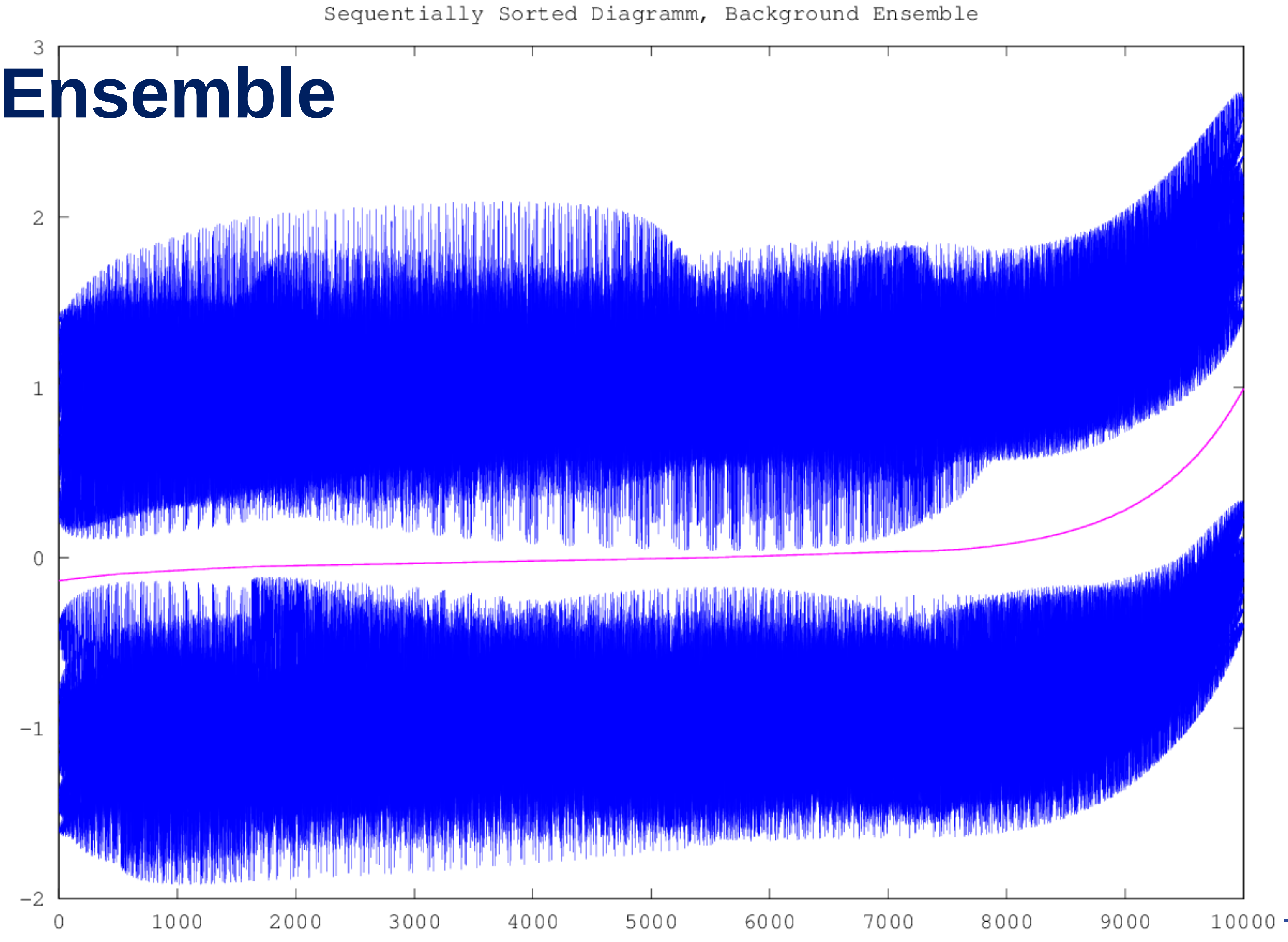
Prior Ensemble – Bi-Modal



10.000 dimensional Example

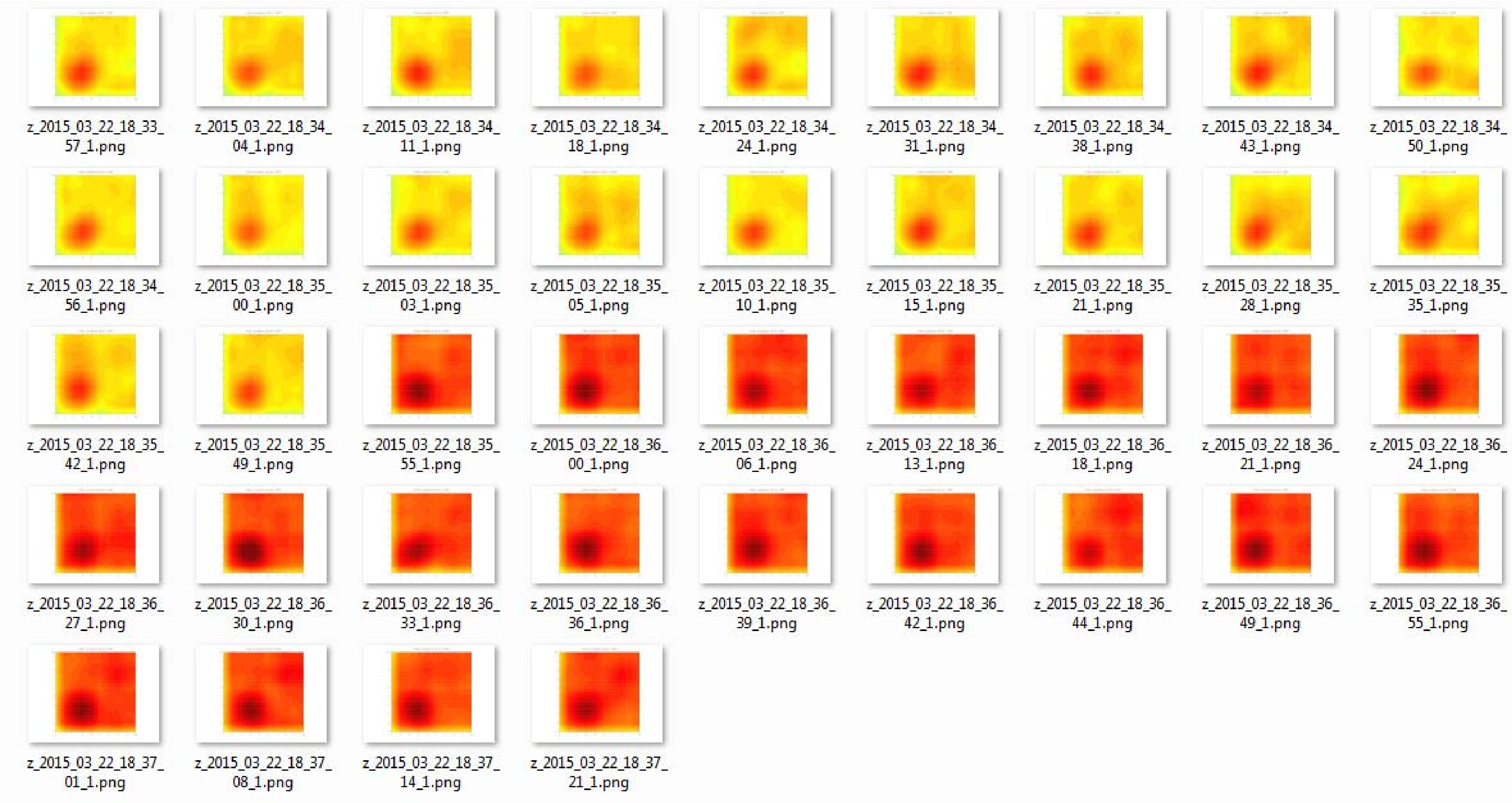
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Prior Ensemble



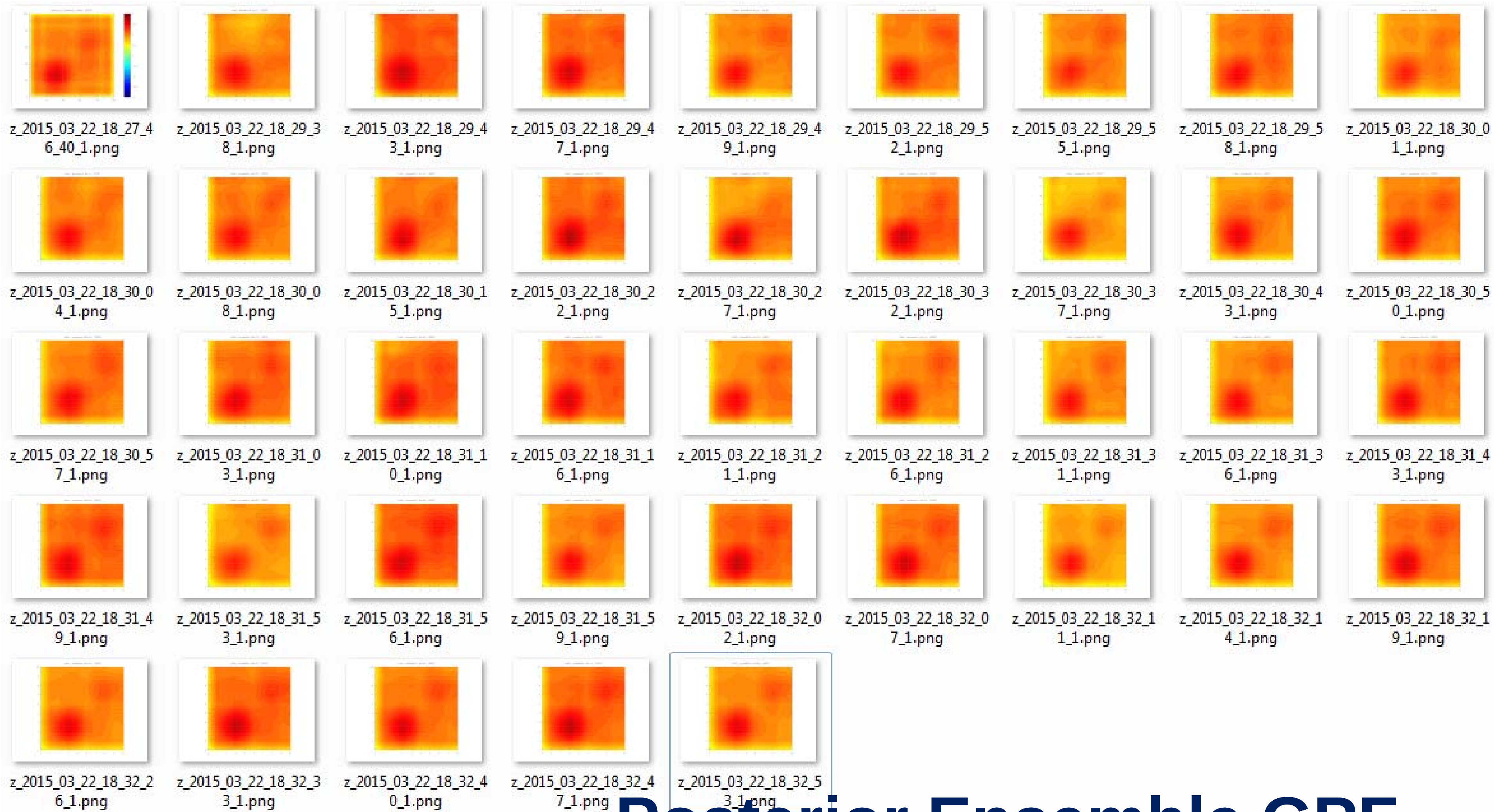
10.000 dimensional Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand



Posterior Ensemble EnKF

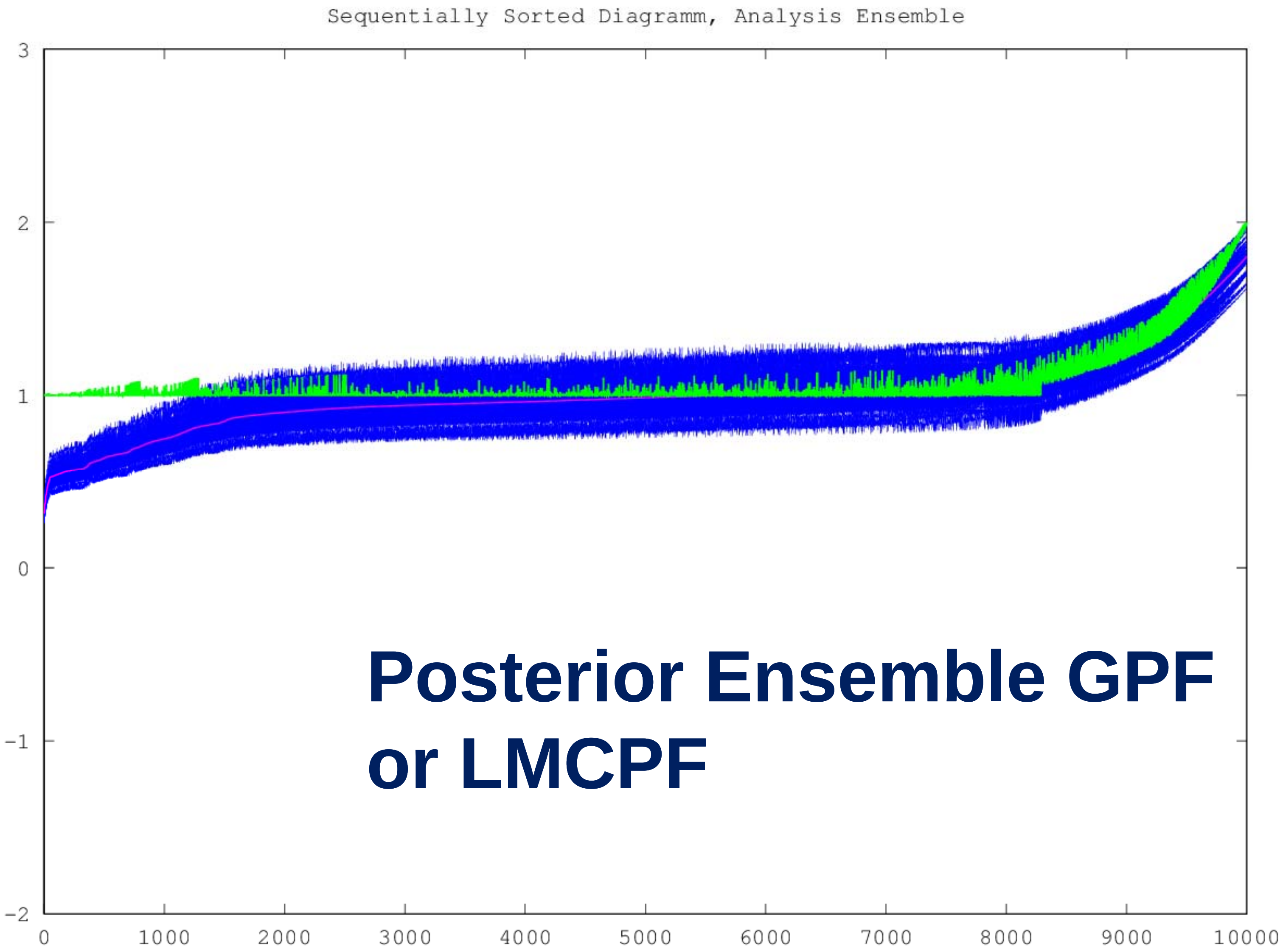
10.000 dimensional Example



Posterior Ensemble GPF

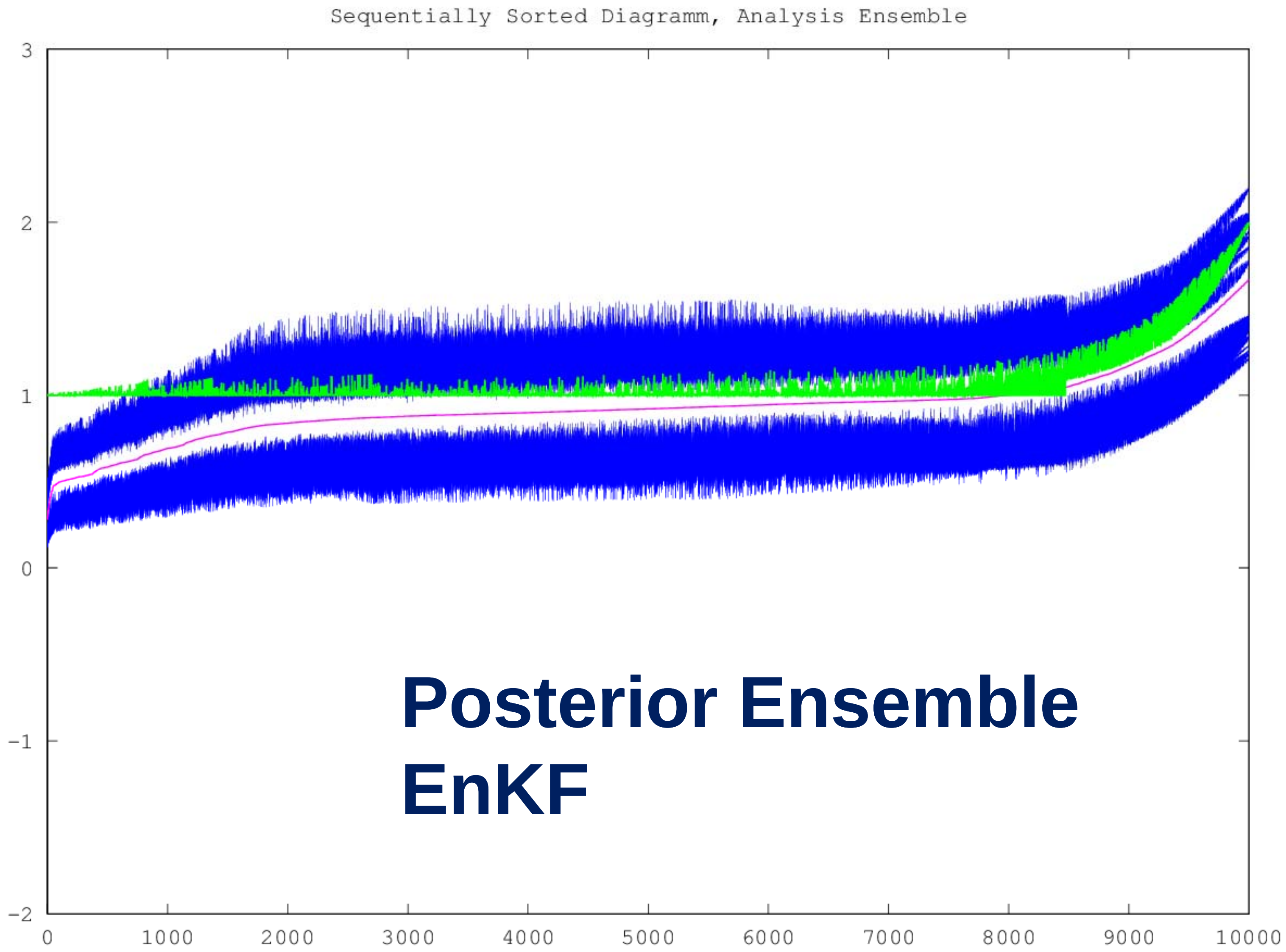
10.000 dimensional Example

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

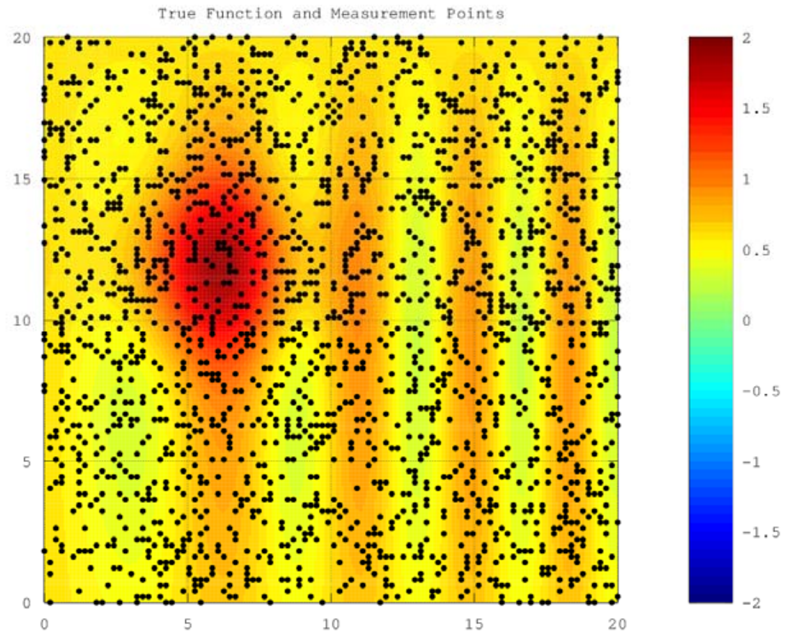


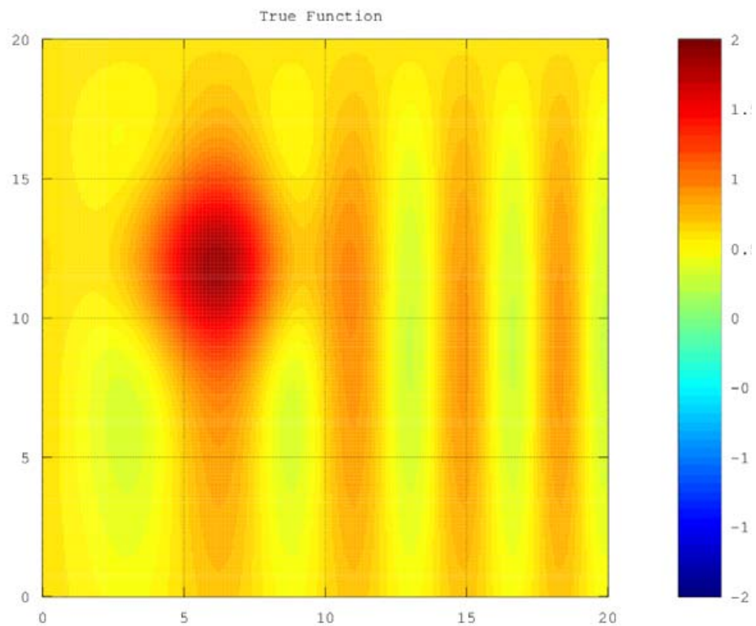
Posterior Ensemble GPF or LMCPF

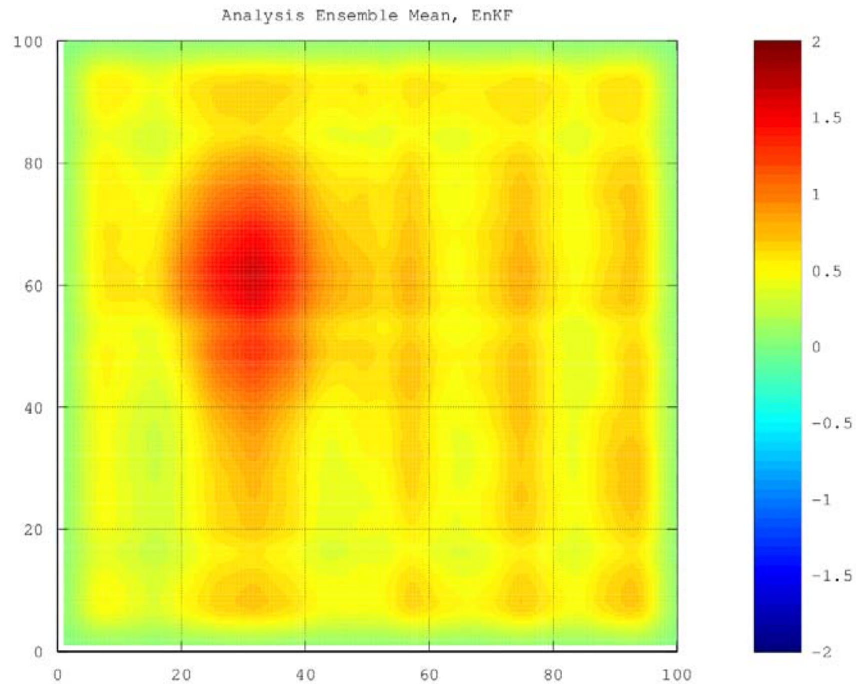
10.000 dimensional Example



Higher Modes

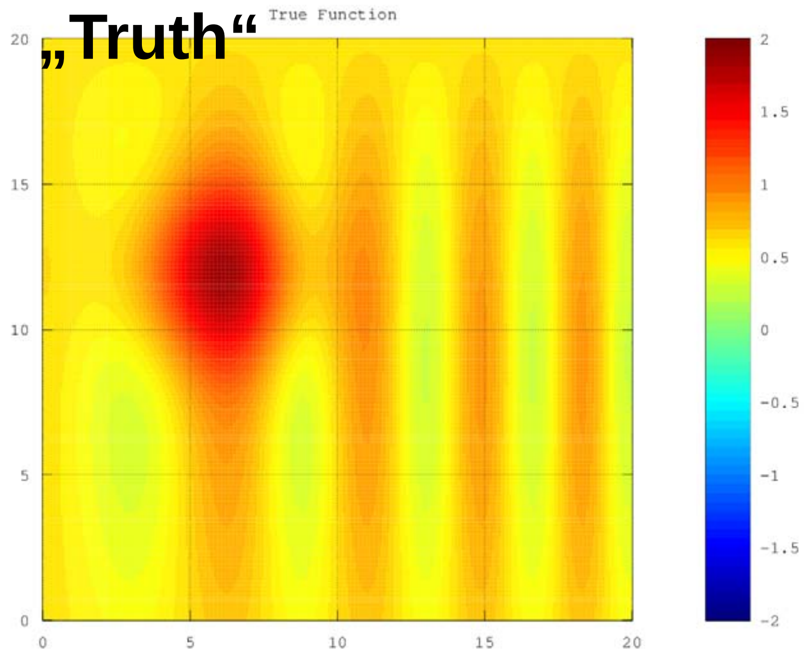


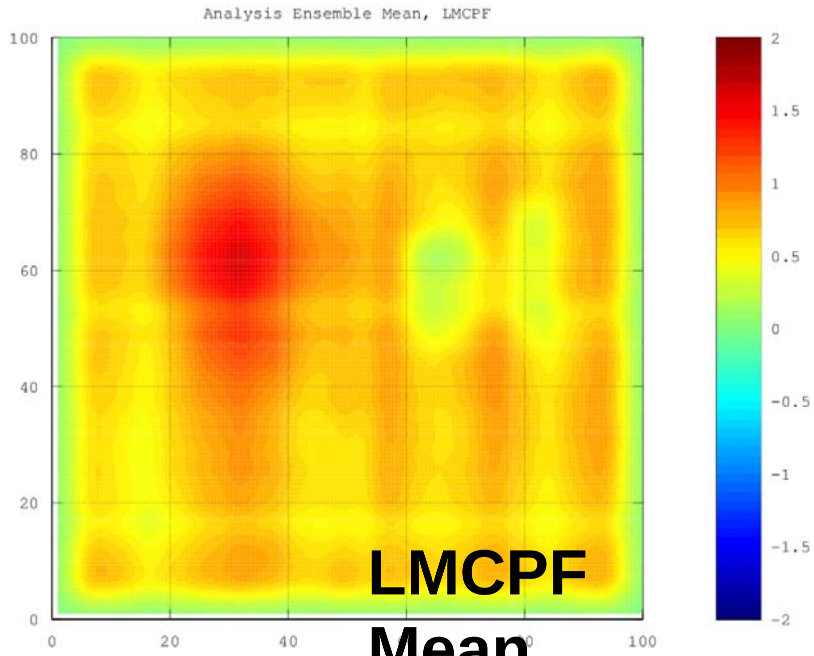




Higher Modes LMCPF

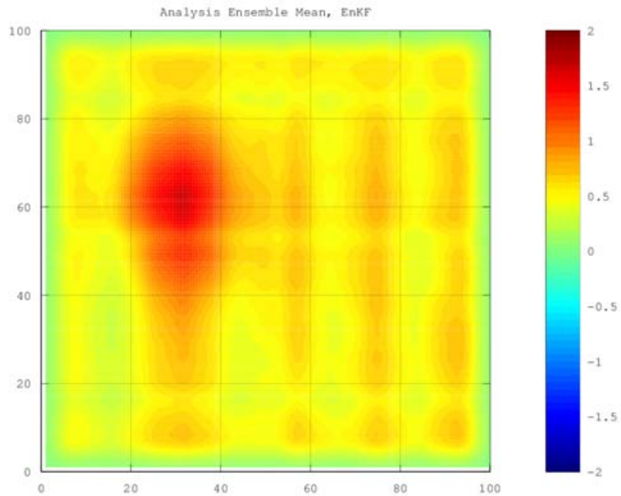
„Truth“





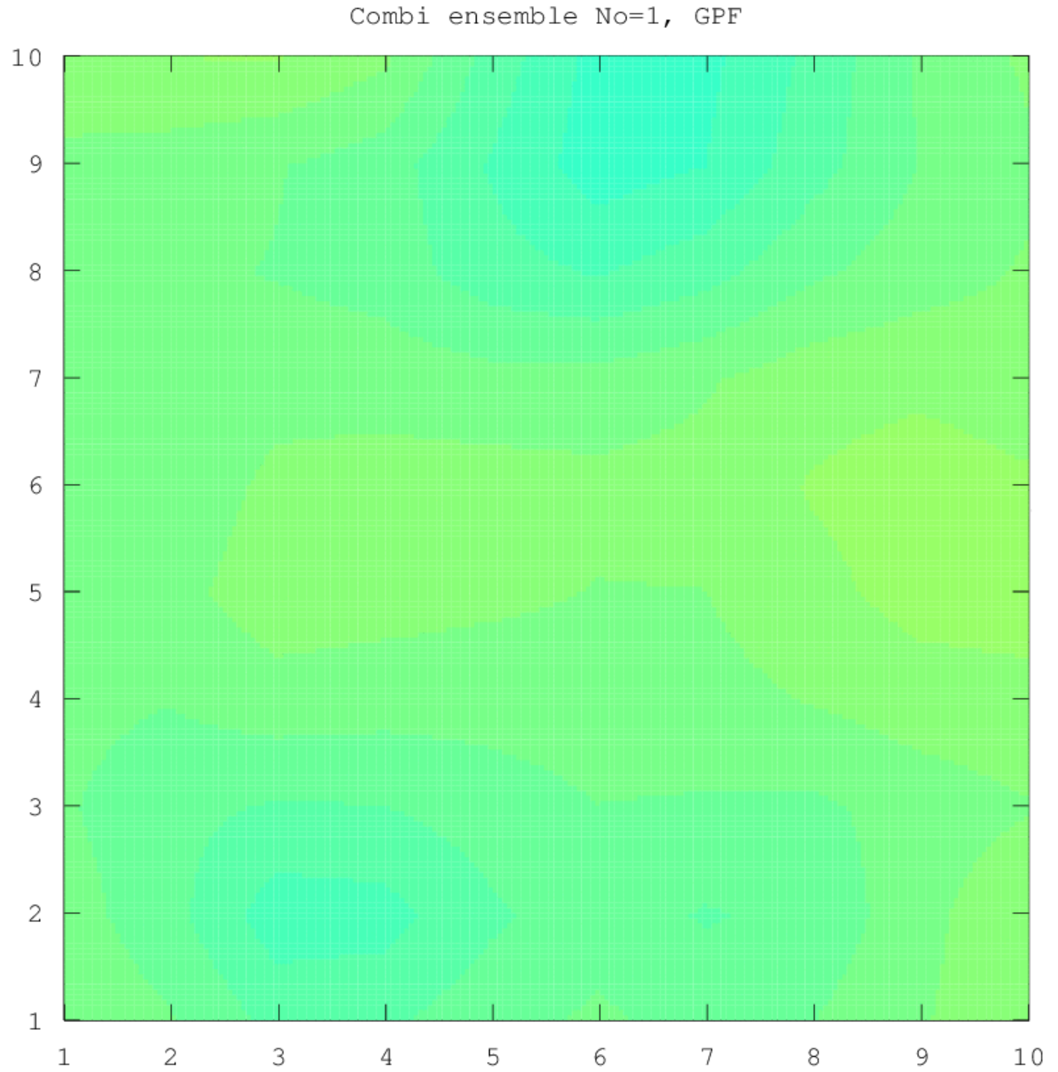
LMCPF
Mean

EnKF
Mean

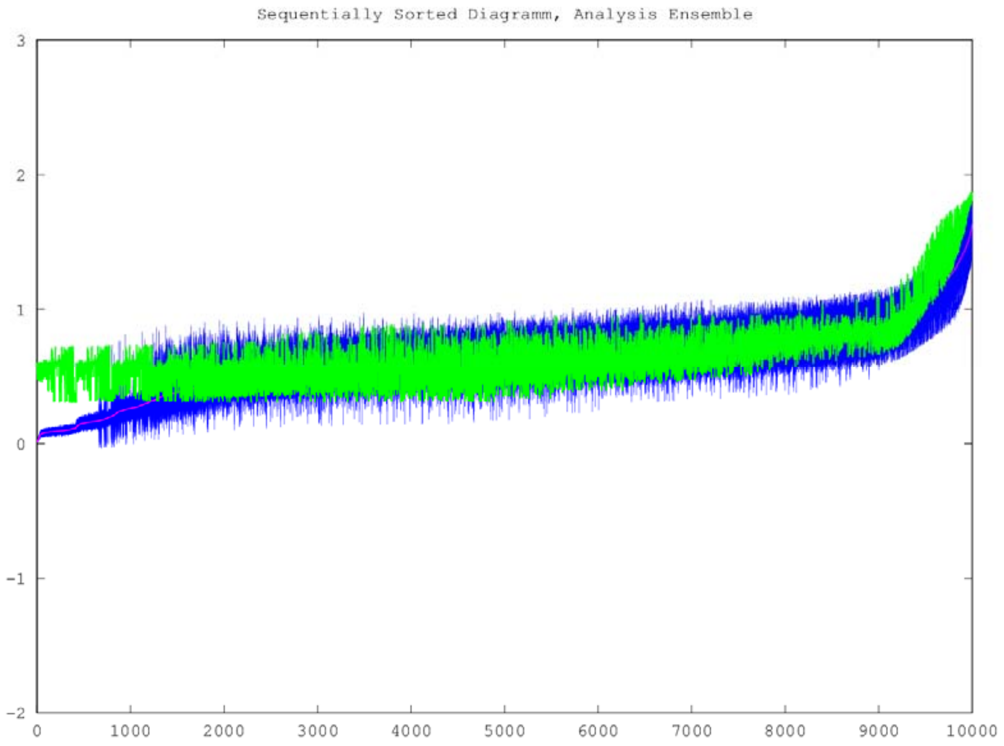


GPF Difference Ensemble

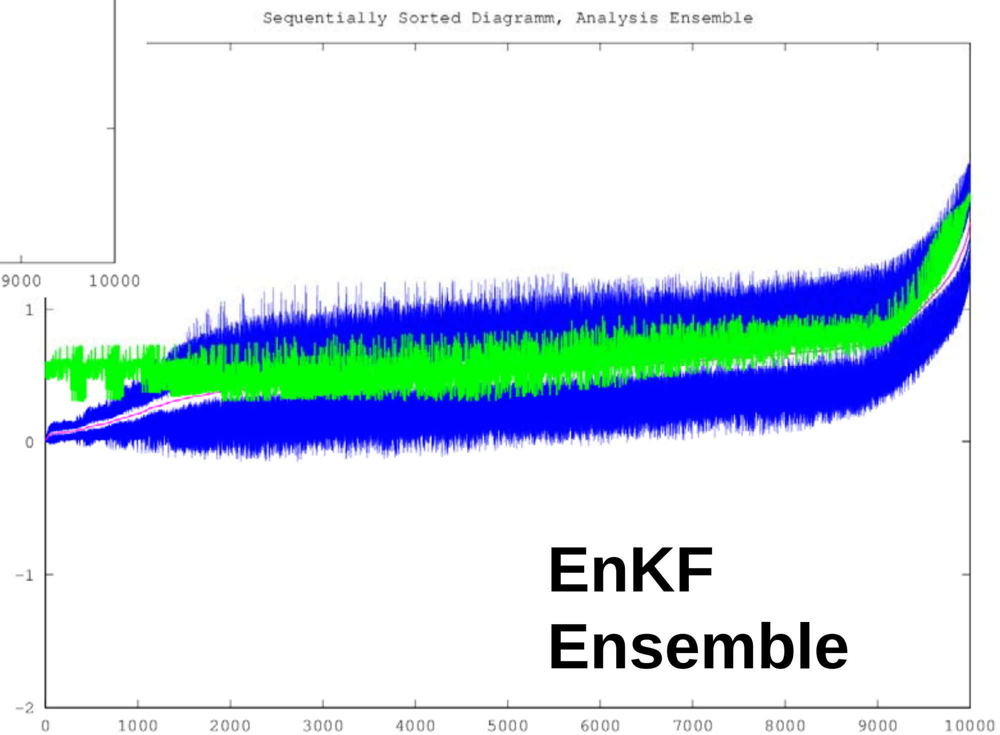
Deutscher Wetterdienst
Wetter und Klima aus einer Hand



LMCPF versus EnKF



LMCPF Ensemble



EnKF Ensemble

Next Steps

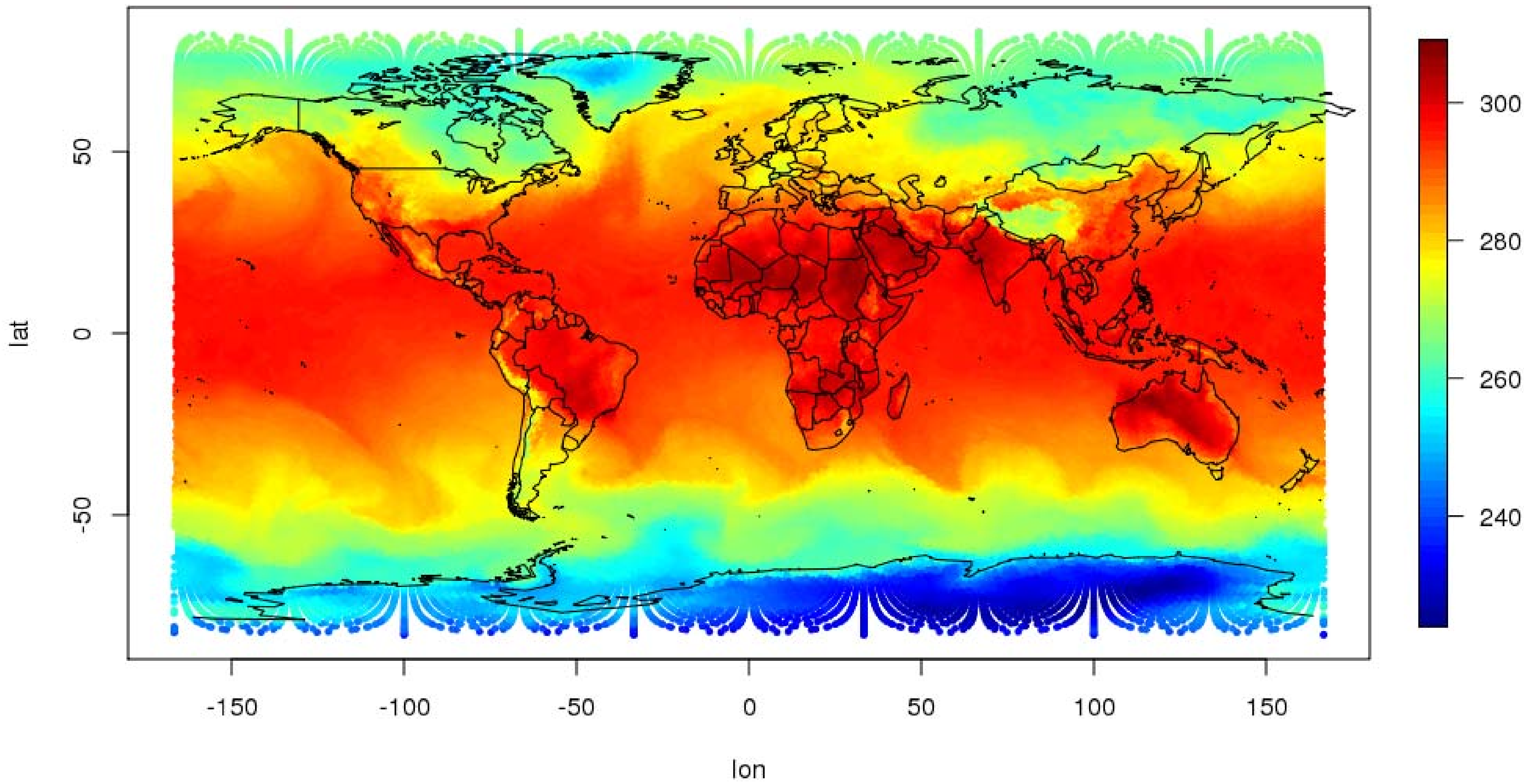
Deutscher Wetterdienst
Wetter und Klima aus einer Hand

- Ongoing LMCPF and Ensemble Kalman Particle Filter Implementations for Numerical Wether Prediction (270 Mio DoF)

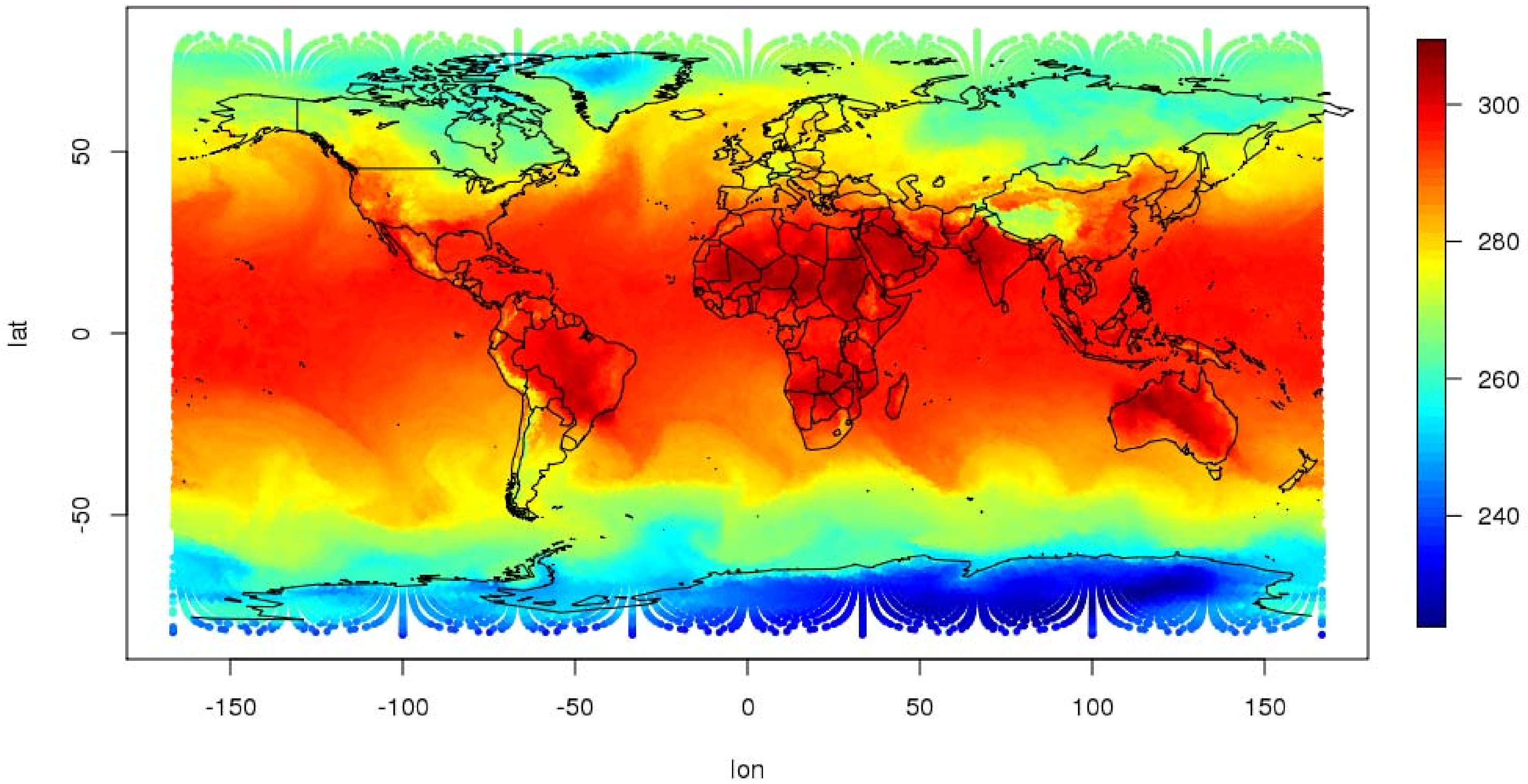
- Further diagnostics on nonlinear dynamics and the behaviour of particle filters (simple statistics are not sufficient)

- Test different localization schemes

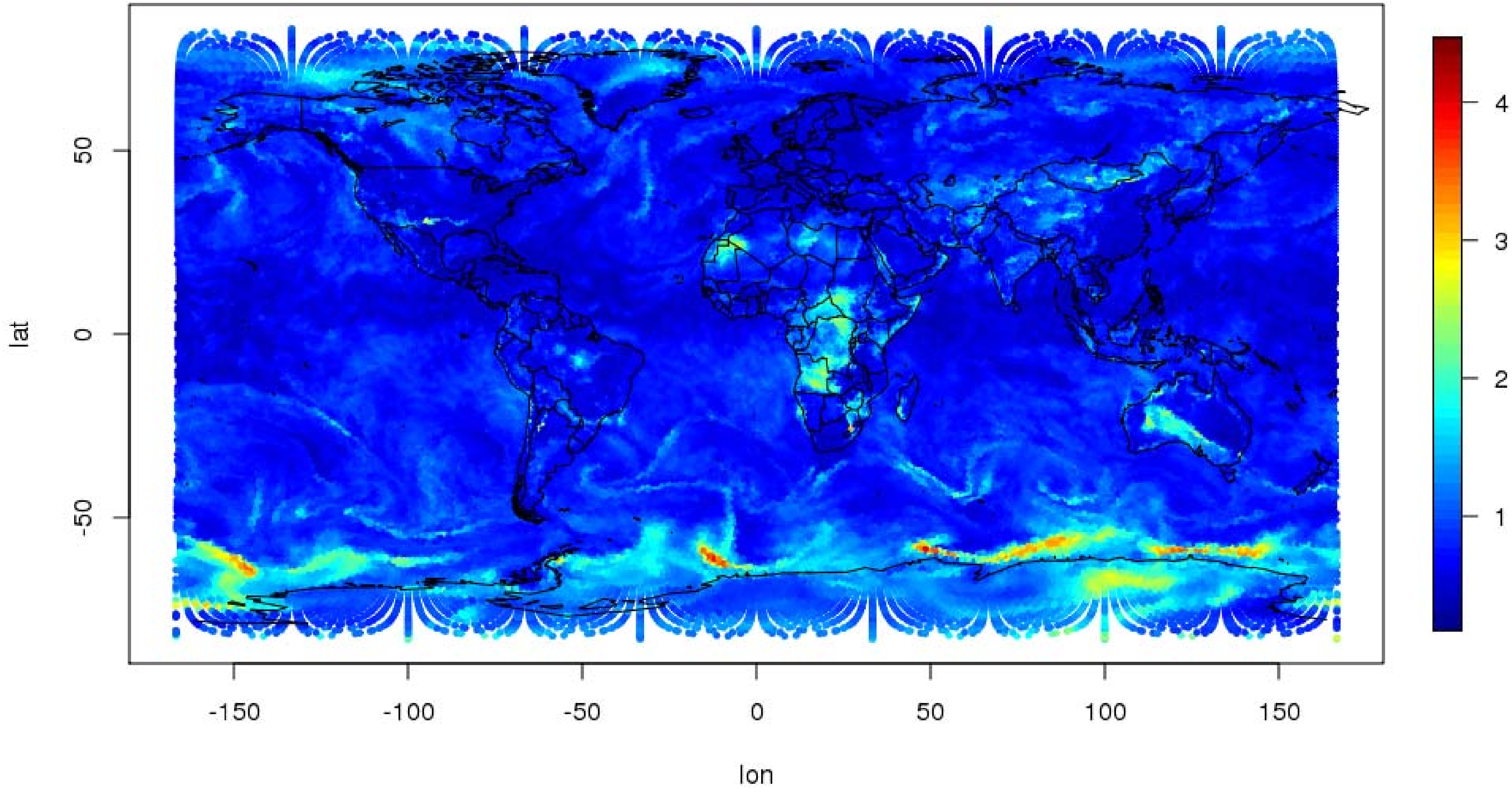
- Extensive testing for large-scale NWP systems.



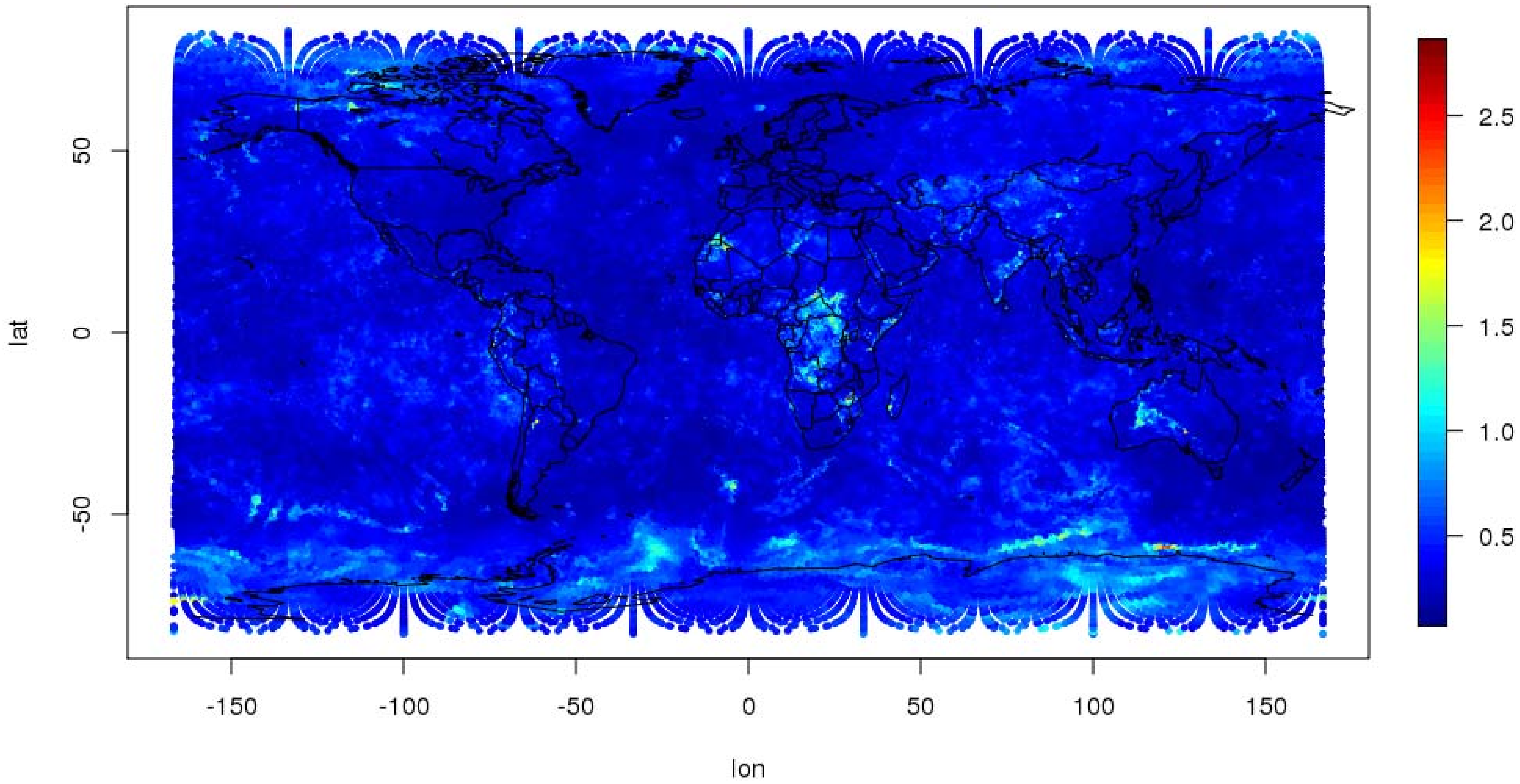
EnKF T on level 85



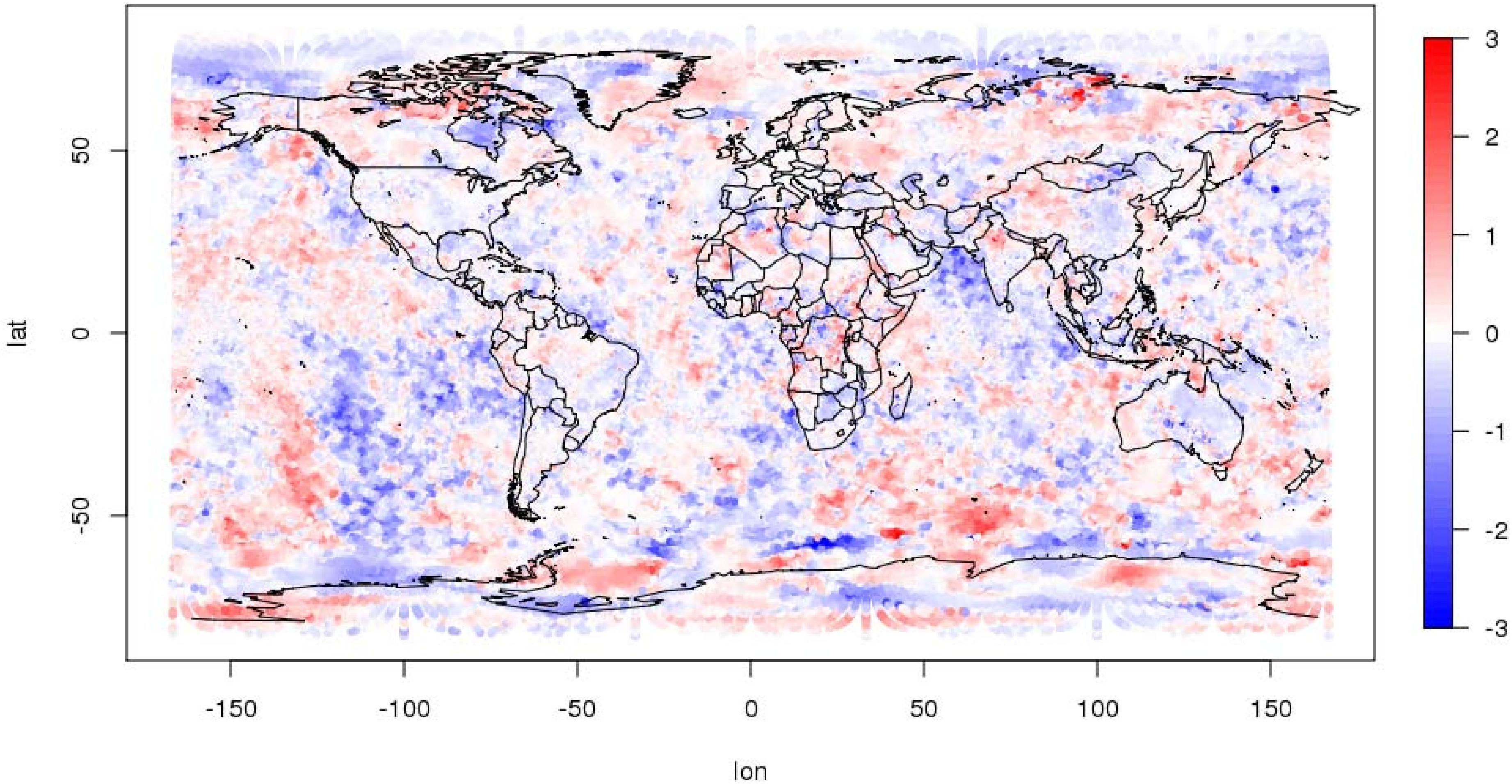
PF T on level 85



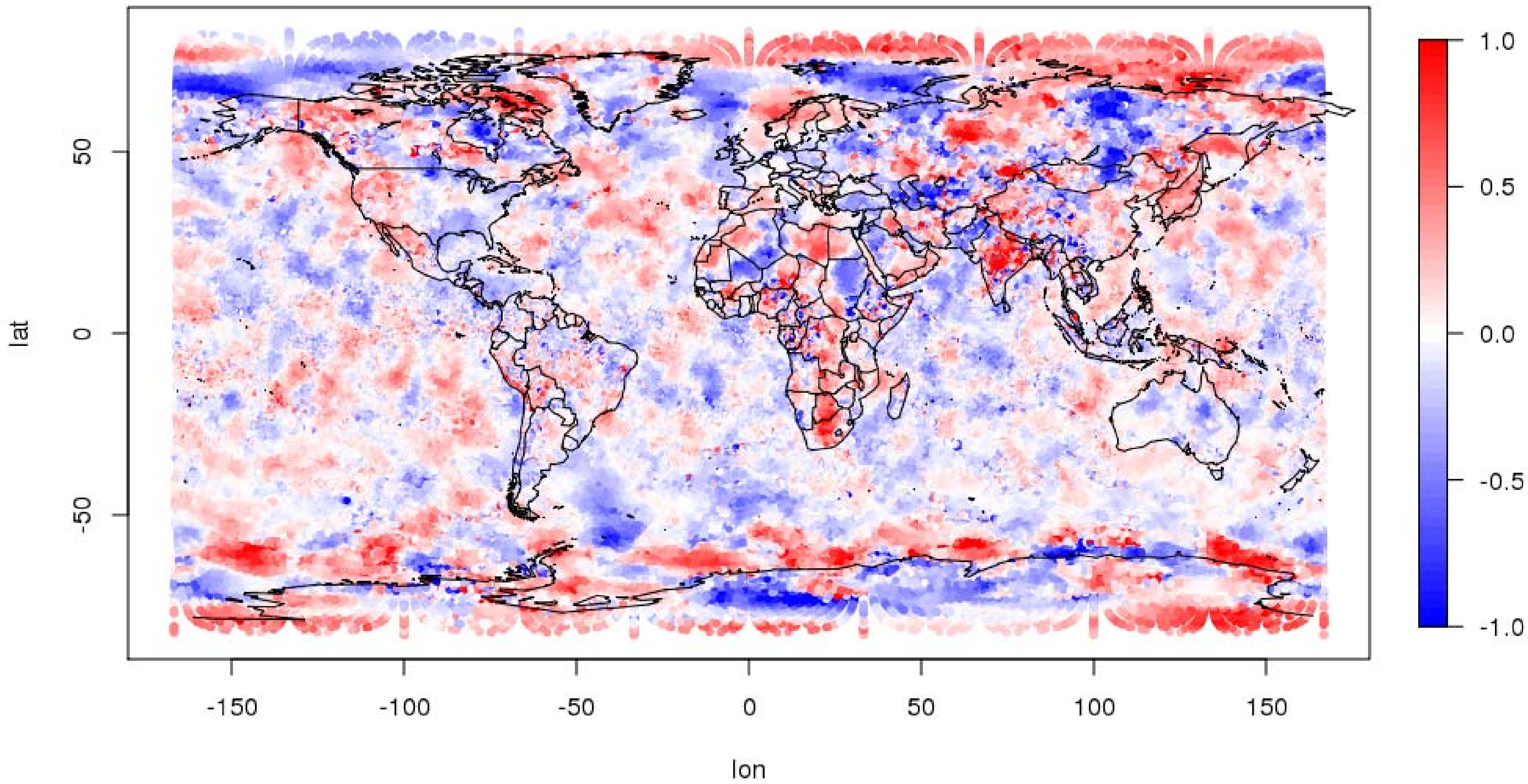
Spread EnKF T on level 85



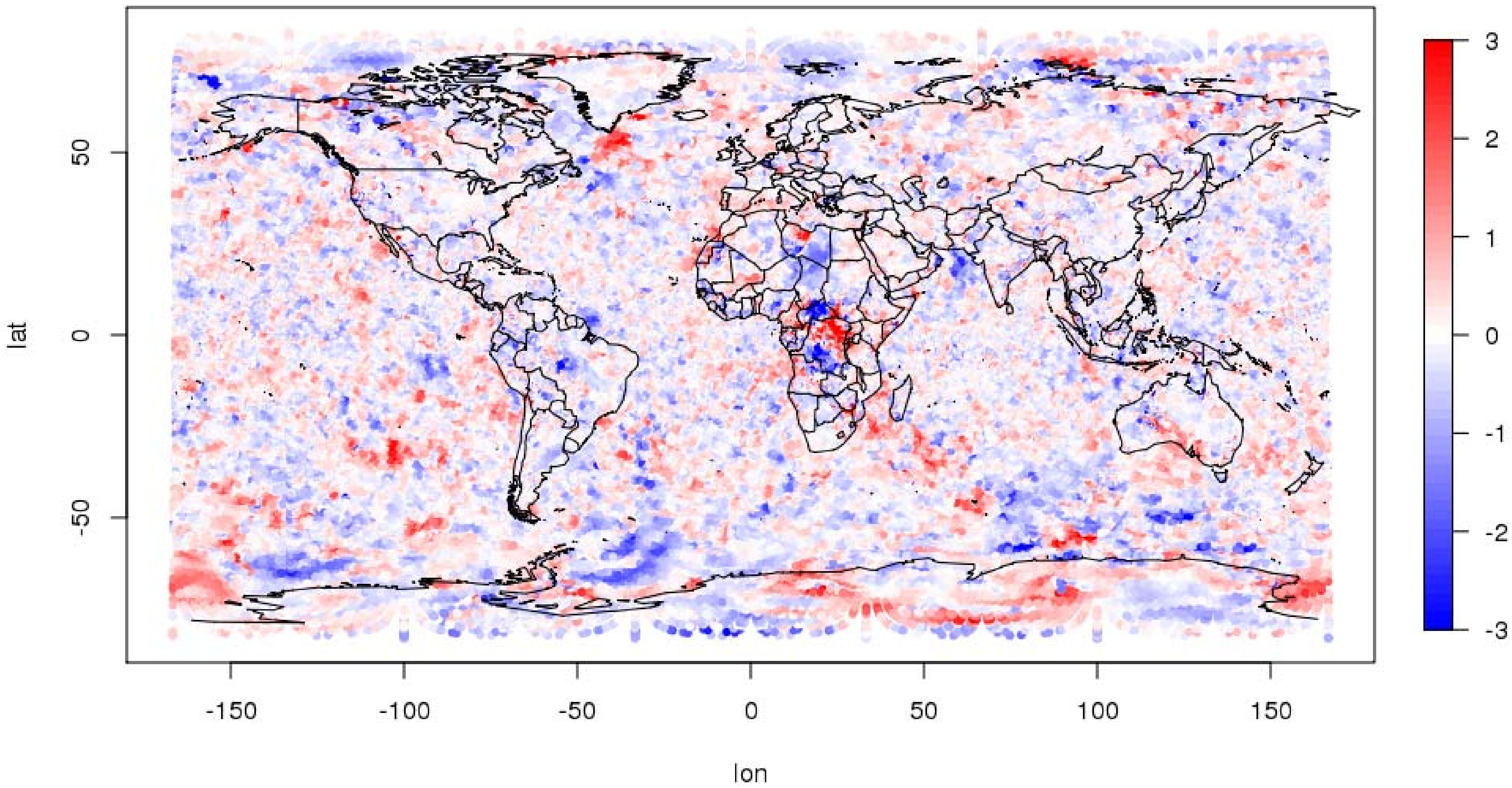
Spread PF T on level 85



Ens 01-Mean, PF T 90

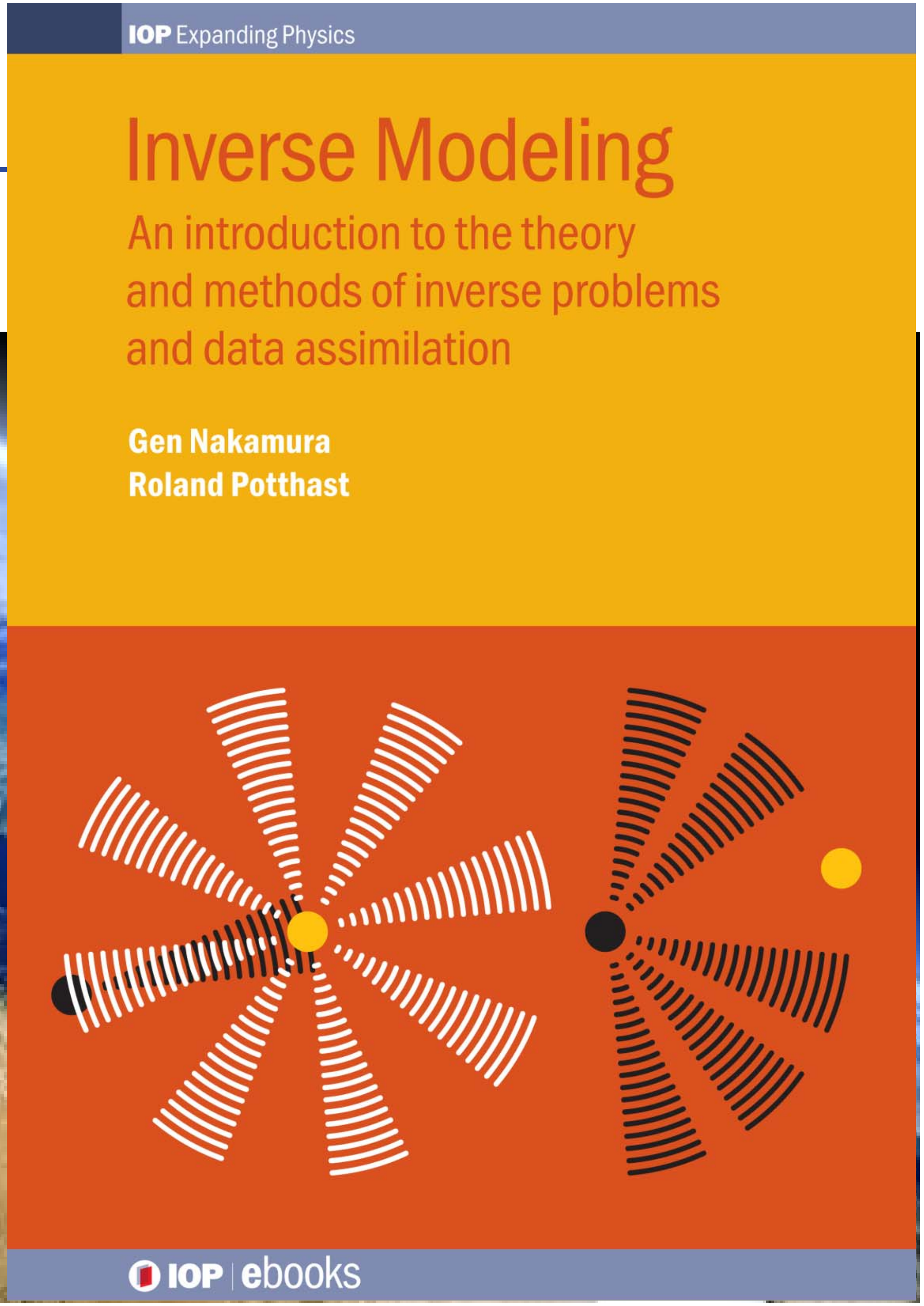


Ens 01-Mean, EKF T 90



Ens 01- Ens 01, PF1 vs PF2   T 90

Many Thanks!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