Assimilating NOAA SST data into BSH operational circulation model for the North and Baltic Seas:

Inference about the data

Svetlana Losa[1], Jens Schröter[1], Sergey Danilov[1], Lars Nerger[1], Tijana Janjić[1] Silvia Massmann[2], Frank Janssen[2]

Alfred Wegener Institute for Polar and Marine Research (AWI), Bremerhaven, Germany
German Maritime and Hydrographic Agency (BSH), Hamburg, Germany

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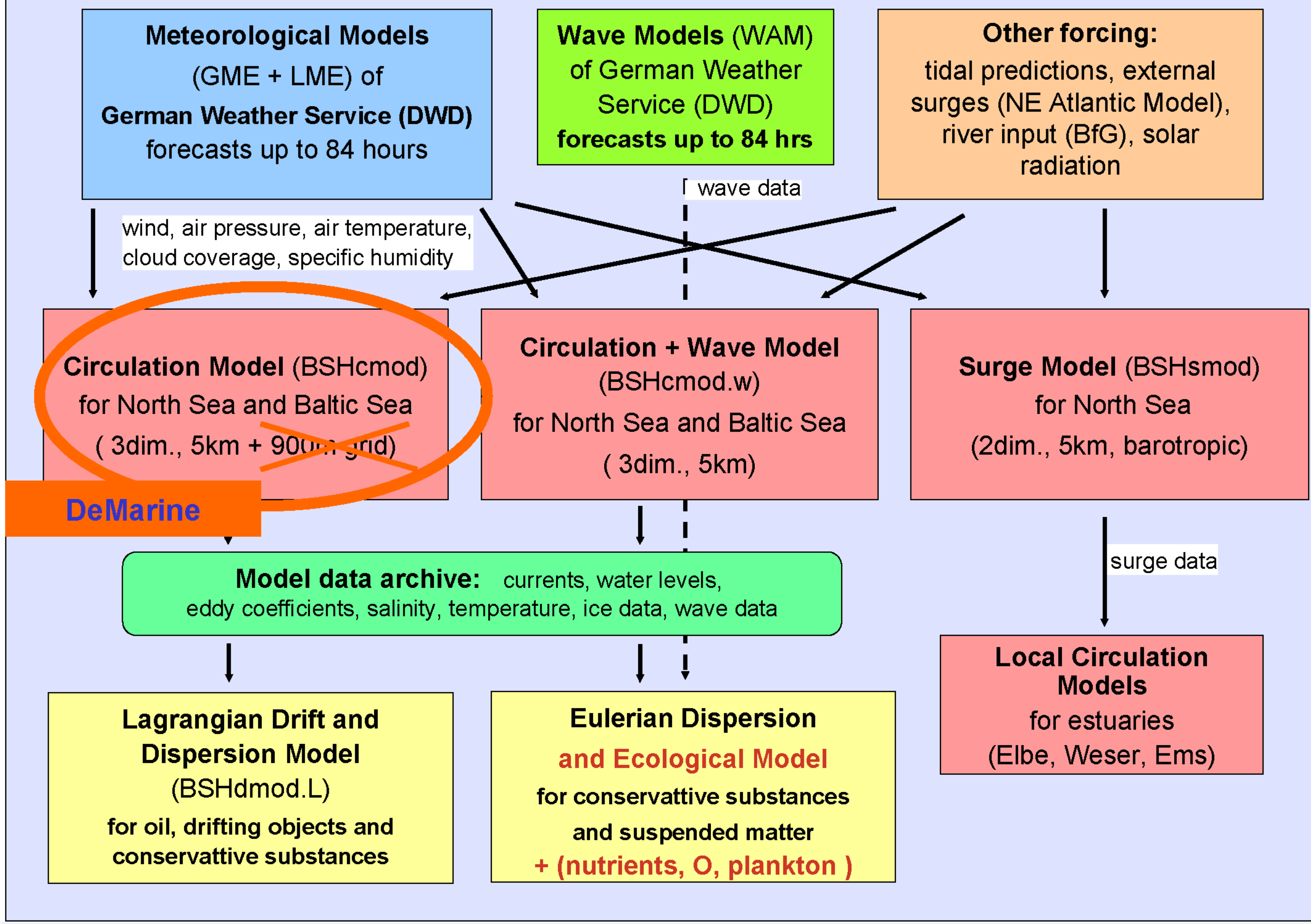
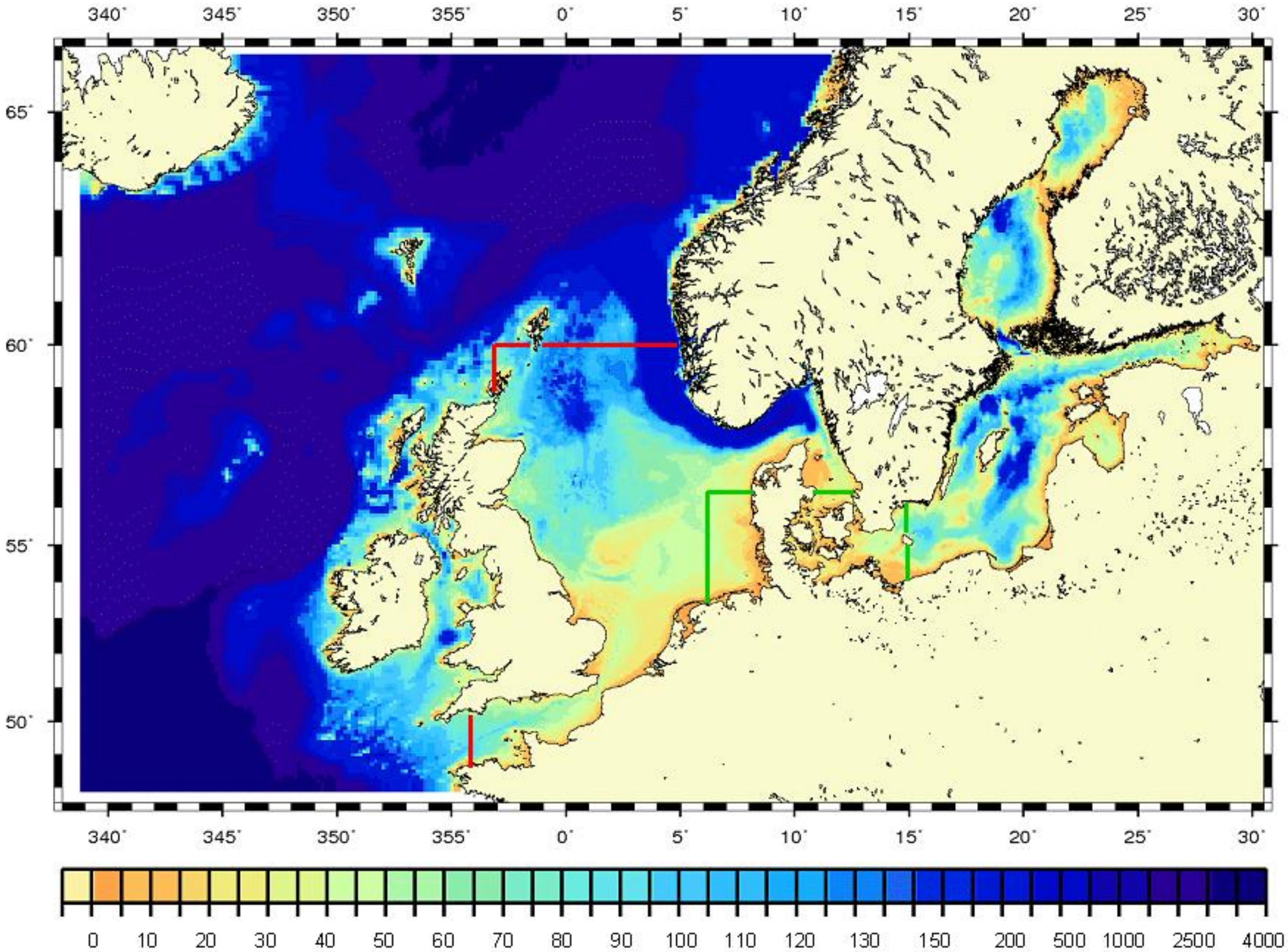
Operational Models of BSH (and DWD)



Operational BSH Model, Version 4



BSSC 2007, F. Janssen, S. Dick, E. Kleine

Grid nesting :

- **10 km grid**
- **5 km grid**
- **900 m grid**

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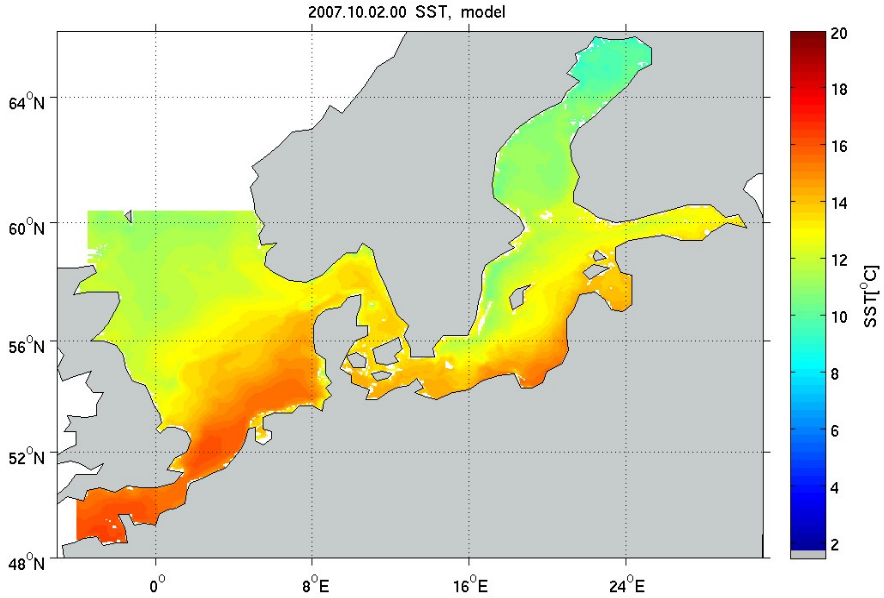
Data assimilation

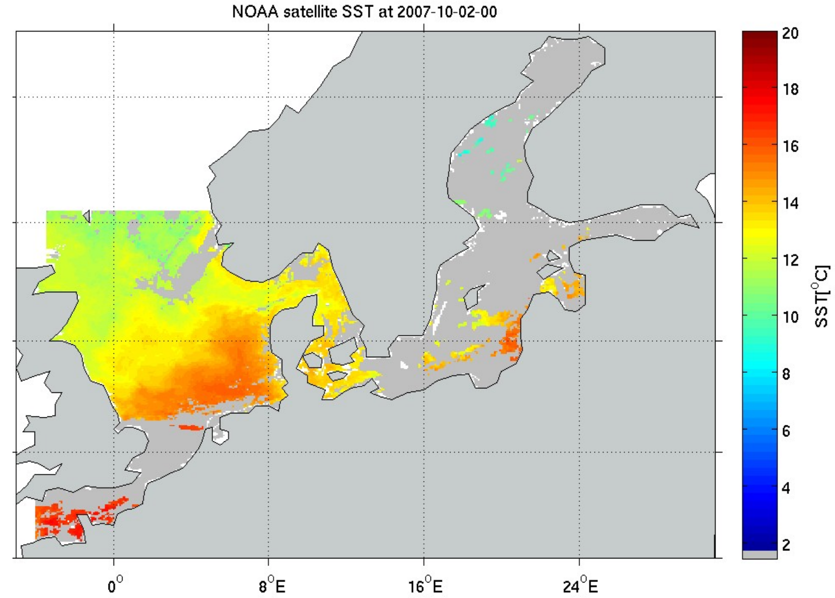
$$\rho_t^a(x(t_1|d_1)=C\rho_d(d_1|x(t_1)\rho_t^f(x(t_1))$$
$$\rho_t^f(x(t_1)=C\rho^f(x(t)|x(0))\rho_0(x(0))$$

BSHcmod

NOAA SST

12 hourly-around 00:00 and 12:00,- composites of SST measured by the Advanced Very High Resolution Radiometer (AVHRR) aboard polar orbiting satellites





Extraction and combination of the information from two different sources - the model and the data - in order to improve our understanding of both sources and, therefore, of reality itself

Improved SST fields are required for

- Monitoring the climate change
- Specification of oceanic boundary conditions for atmospheric models and initial conditions for ocean/sea circulation models
- Predicting sea-ice variables/conditions
- Primary productivity and water quality are also influenced by temperature either directly, through the dependence of the physiology and gas exchange proceses on it, or inderectly via changes in mixing conditions and stratification in the UML, in which phytoplankton grows.

!One has to consider the performance in simulating sea surface elevation, current velocities and salinity

Data assimilation algorithm

Ensemble based Singular Evolutive Interpolated Kalman filter (SEIK, Pham, 2001)

SEIK Filter is implemented locally (PDAF, Nerger et al., 2006) but with different formulations of data error correlation.

- Apply explicit low-rank approximation to model errors covariance matrix and generate ensemble model states
- Ensemble formulation:
  - improves ability to handle nonlinearity
  - leads to numerically very efficient algorithm
  - results in high parallel scalability
- Localization improves filter performance by increasing degrees of freedom for analysis

Localization introduces radius of data influence r_l, the degree of the influence can be weighted within the radius.

Tuning is needed with respect to the r_l and data weights.

Nerger, L., S. Danilov, W. Hiller, and J. Schröter. Using sea level data to constrain a finite-element primitive-equation model with a local SEIK filter. Ocean Dynamics 56 (2006) 634

Assimilation algorithm

$$x(t_n)^a = x(t_n)^f + K_n(d_n - H_n x(t_n)^f),$$

$x(t_n)^f$, $x(t_n)^a$ denote forecast and analysis of state vector consisting of temperature, salinity, SSH velocity components ot time t_n at all grid points

d_n- temperature satellite observation available at t_n

P_n^f- forecast error covariance matrix

R_n - observational error covariance matrix

$$K_n = P_n^f H_n^T (H_n P_n^f H_n^T + R_n)^{-1}$$

Implementation (model and data error statistics)

- We integrate the BSHcmod forced by atmospheric and river run-off data and assimilating NOAA SST over the period 1.10.2007 -- 30.09.2008. Real-time pre-operational results obtained for March 2011 are also presented.

- Initial model error covariance matrix is computed using three months (10-12.2007) output [T, S, SSH, u, v] from the BSH model run (12-hourly snapshots).
- First 8(16) EOFs are used to generate an ensemble of model states (temperature, salinity, current velocities, sea surface elevation).

- Assumptions on data errors

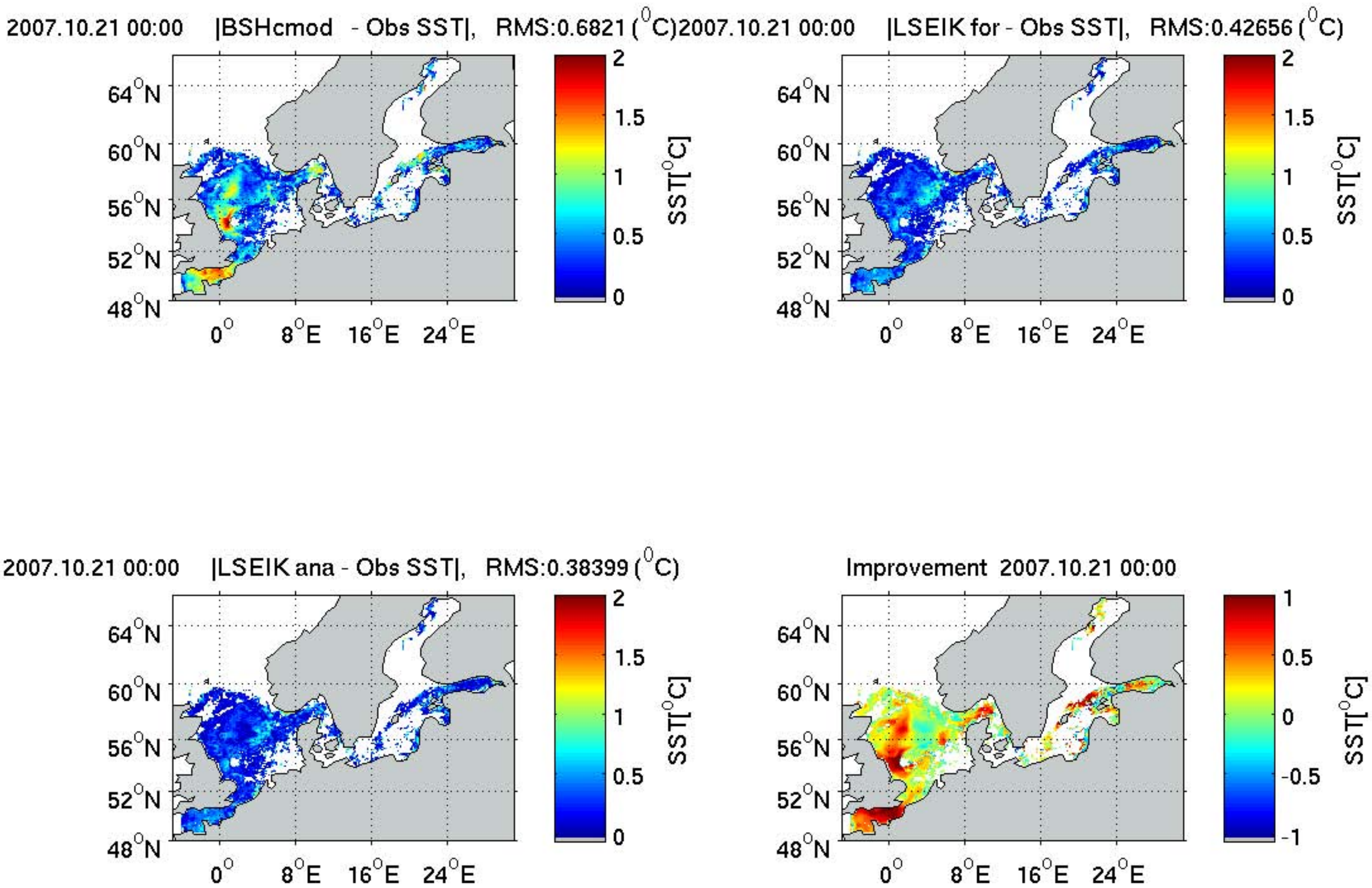
  σ_{sst}= {1.8°C, 0.8°C, 0.5°C}; data weighting implemented within

  r_l of 150 km, 100 km or 50 km assuming exponential, quasi Gaussian or uniform dependence of the weights on the distance from the analysed grid point.

- NOAA SST data are assimilated every 12(24) hours.

r_l– radius of assimilated data influence.

Improvement of SST analysis and forecast



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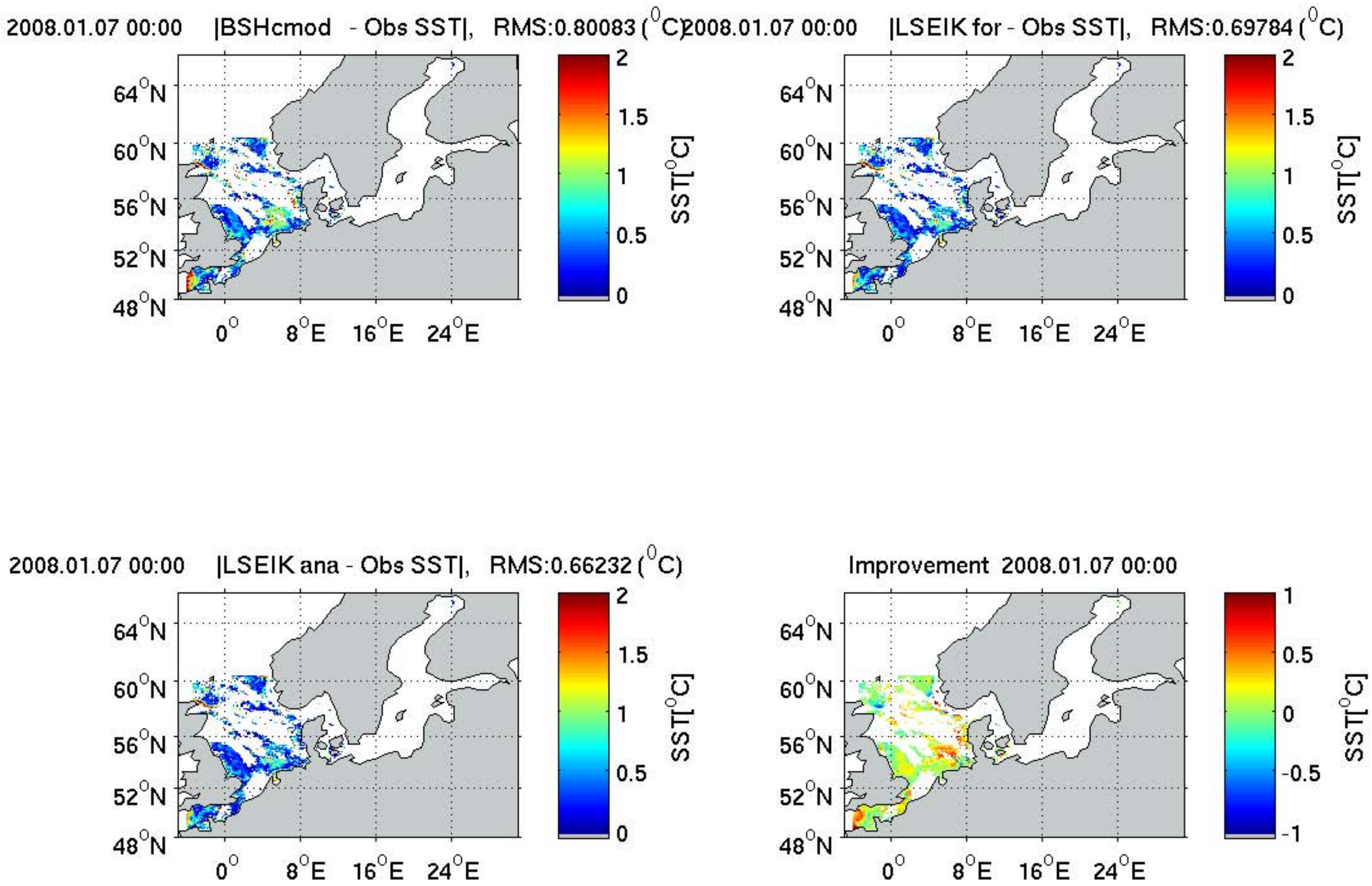
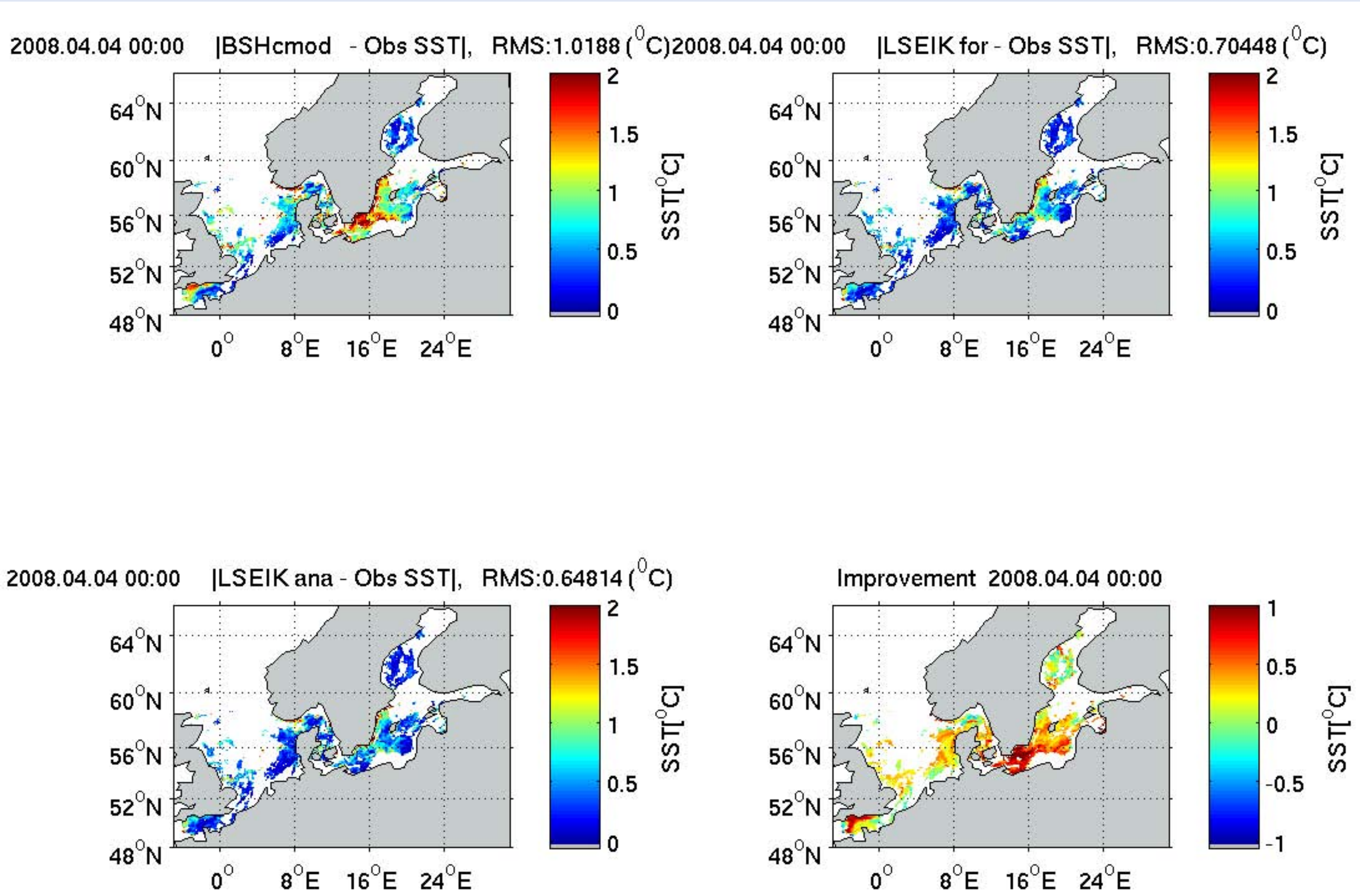
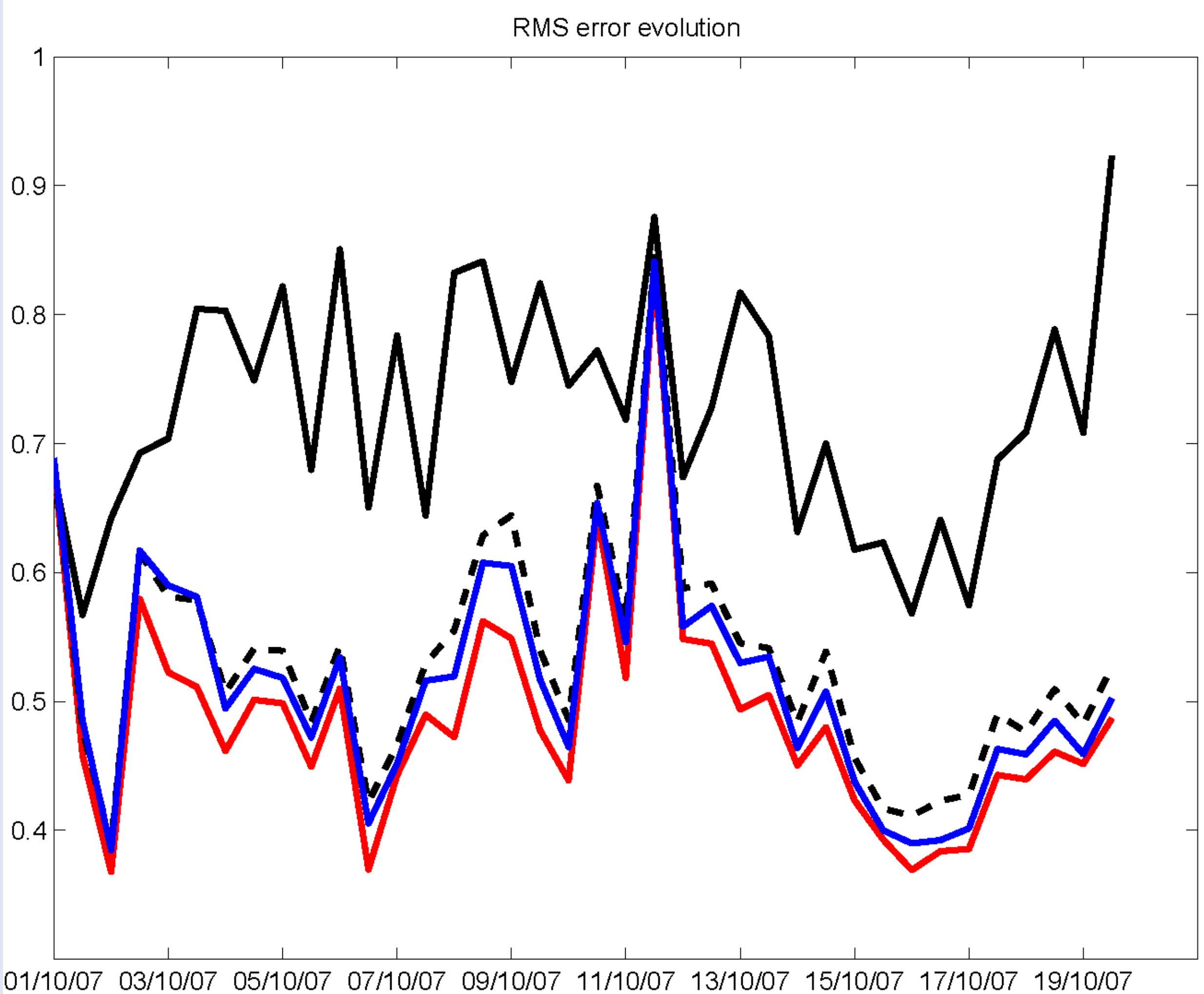
Improvement of SST analysis and forecast



Improvement of SST analysis and forecast



Sensitivity of the forecast quality to assumptions on data errors



—forecast without DA;

-- LSEIK filter forecast with σ_{sst}= 1.8°C, data are uniformly weighted within r_l=50 km;

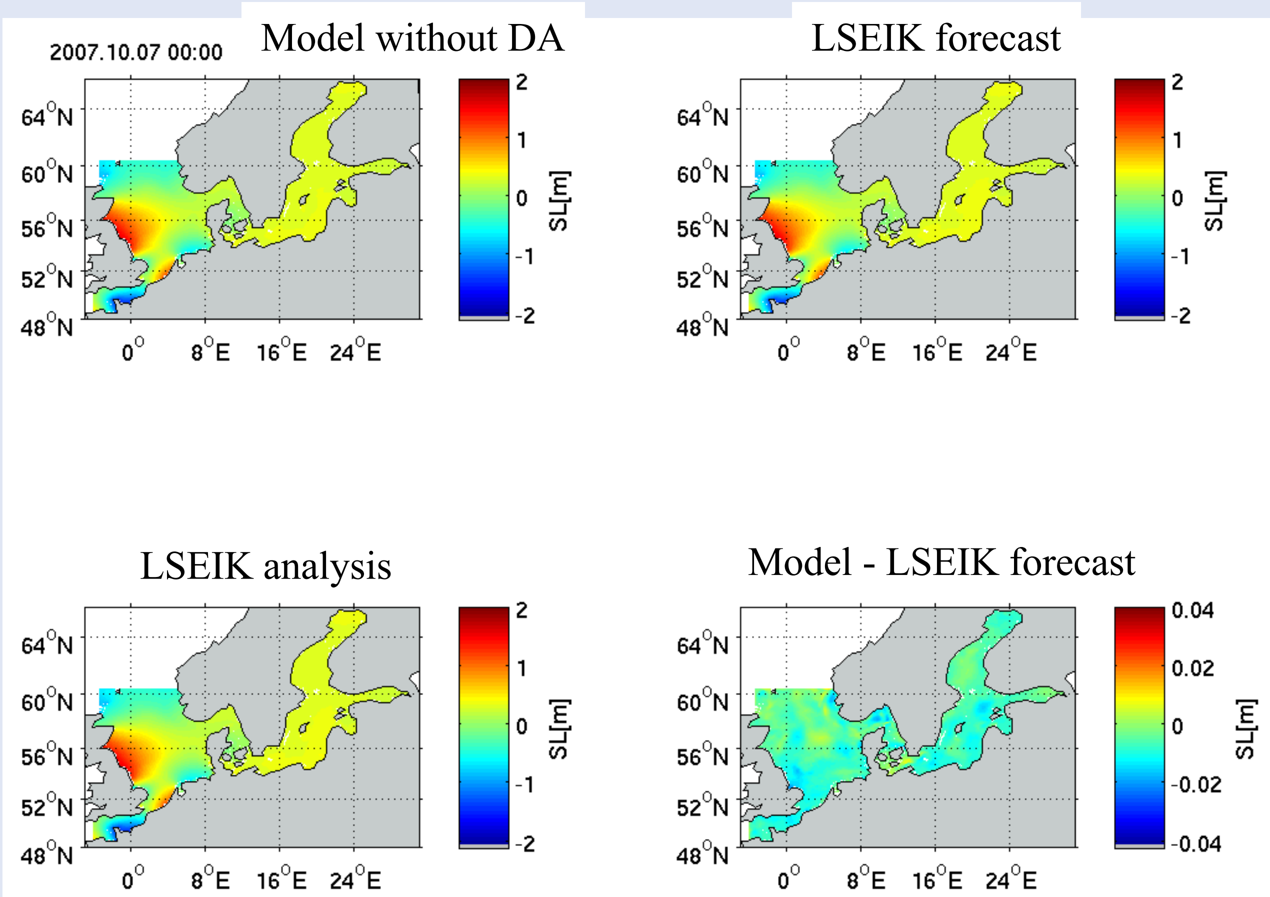
LSEIK forecast with σ_{sst}=0.8°C, uniform data weighting within r_l=50 km;

LSEIK forecast with σ_{sst}=0.8°C LR=100km, and exponential data weighting within r_l=100 km.

Temporal evolution of RMS estimates of the forecast deviation from observations in the North and Baltic Seas over the period 1.10.2007 - 21.10.2007.

SSH simulation

- is not destroyed by SST data assimilation



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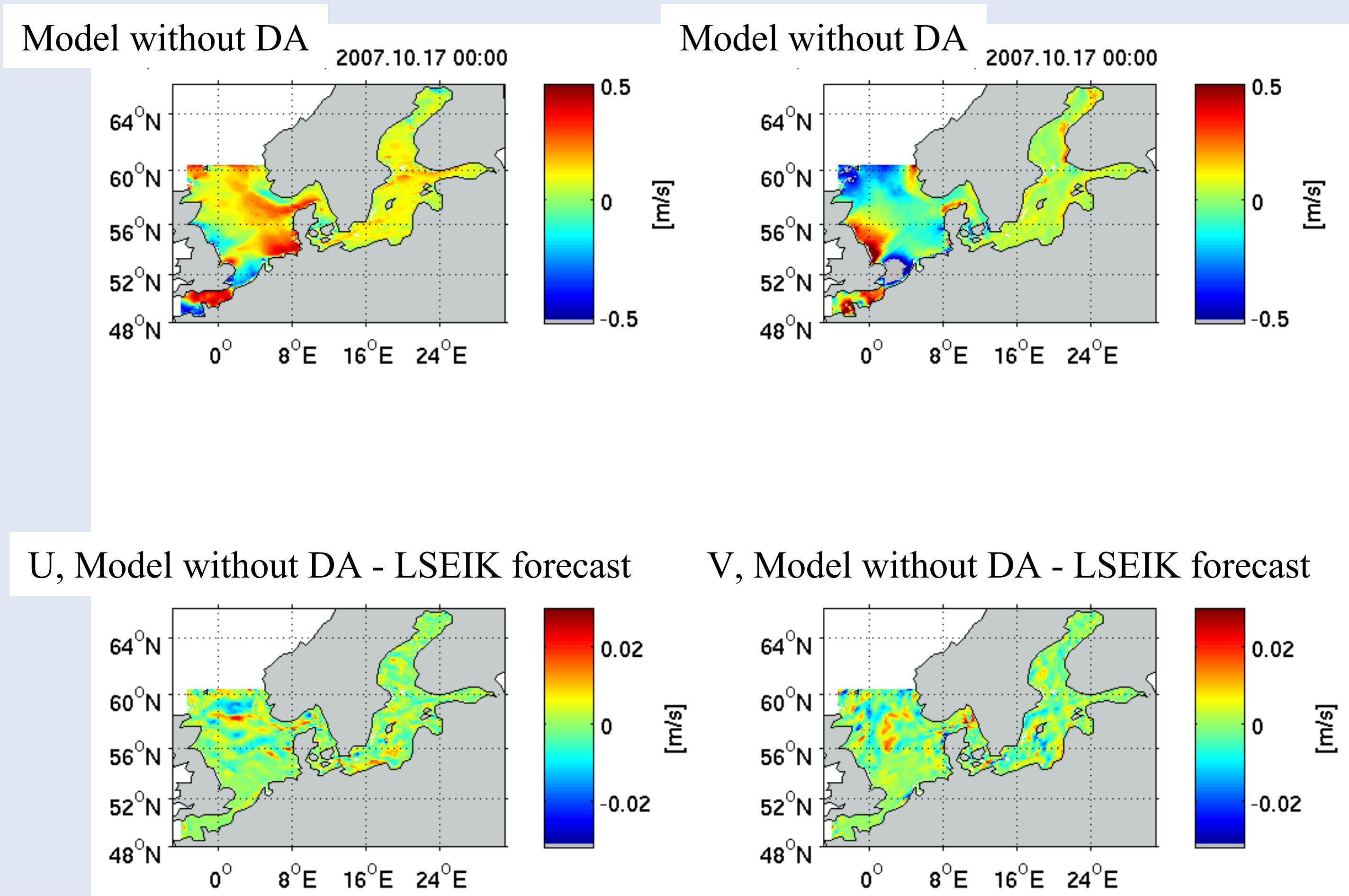
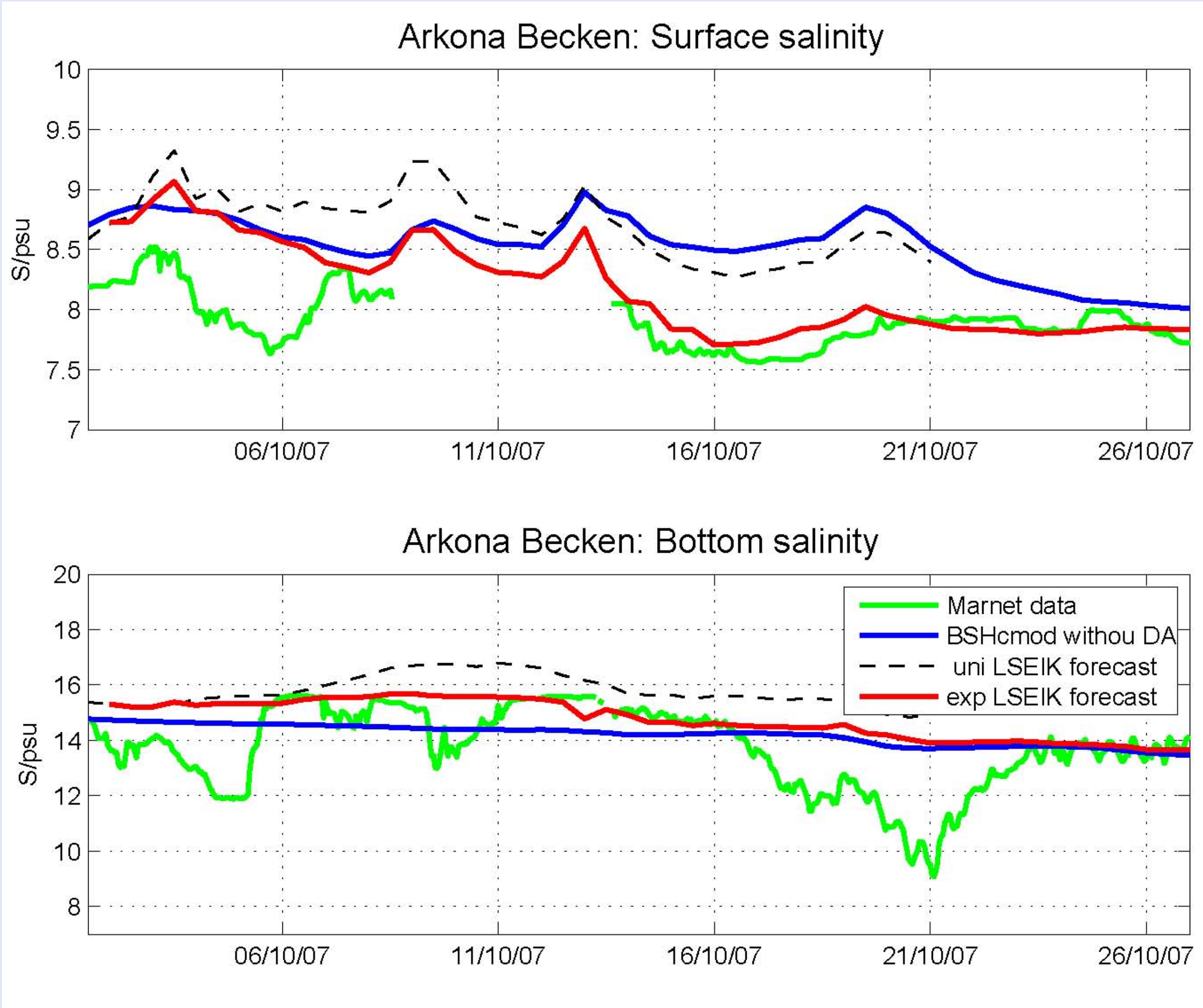
Current velocity simulation

- U und V components



Comparison against independent salinity data



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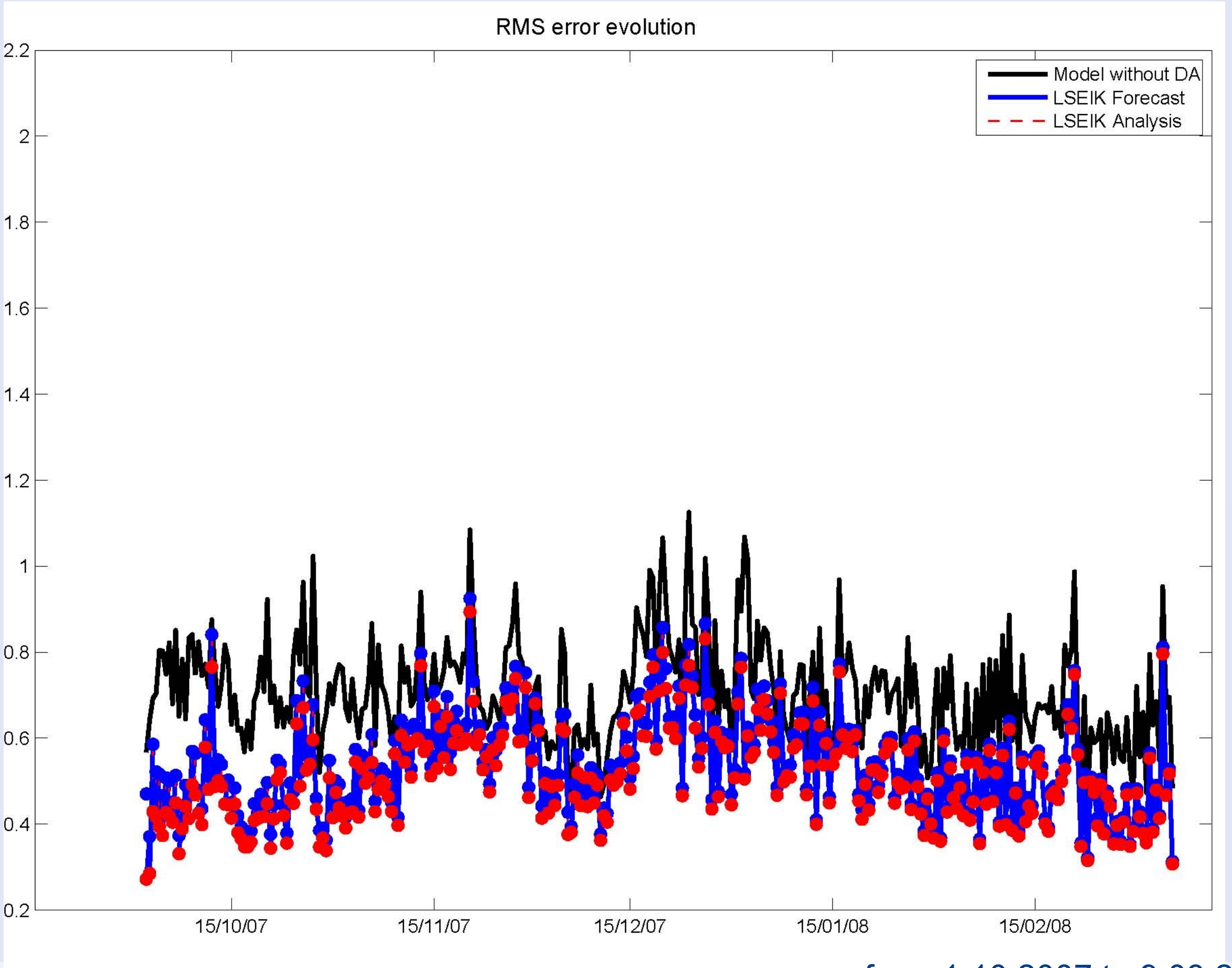
Assessing SST forecast

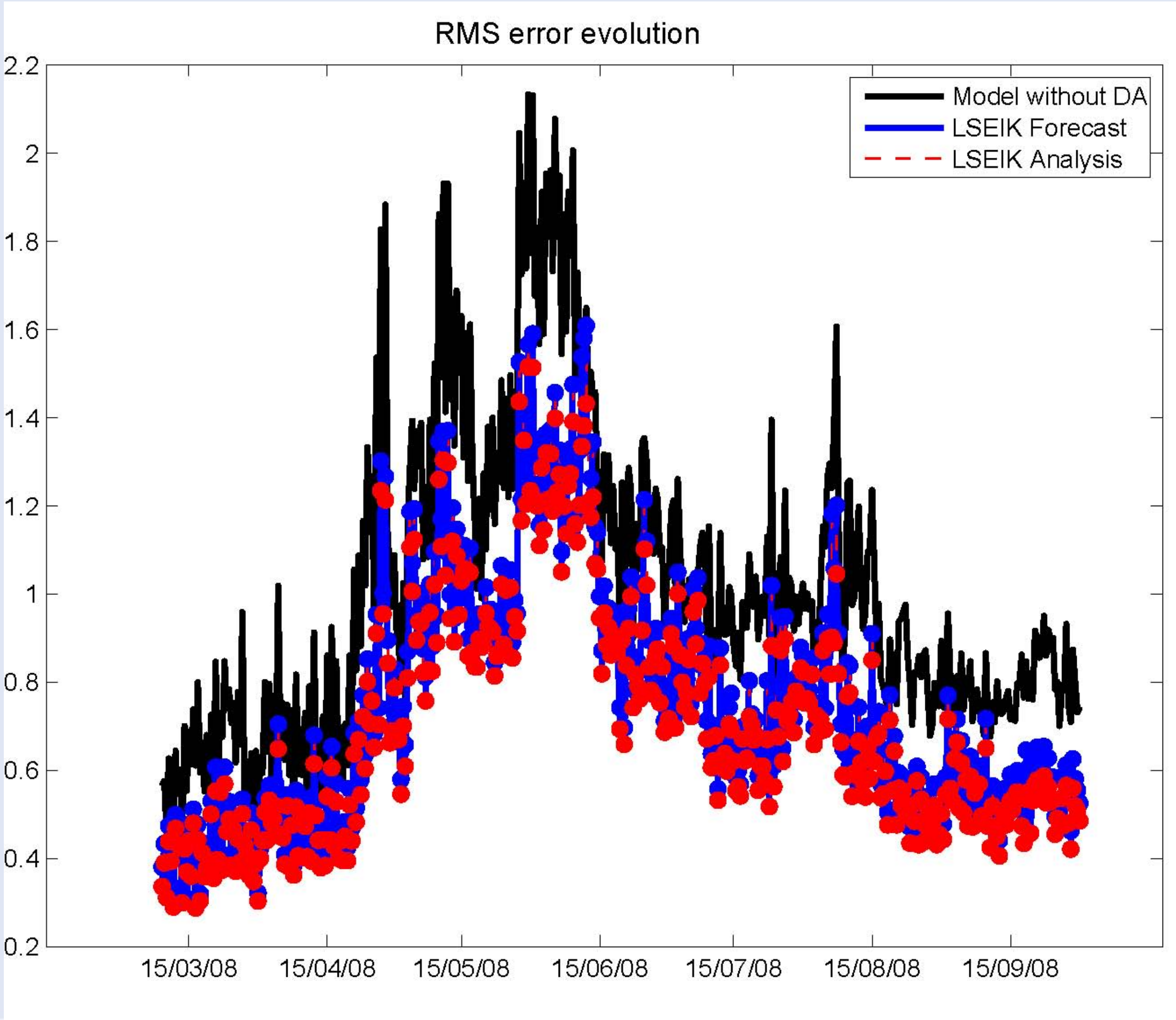
Temporal evolution of SST RMS error for BSHcmod forecast



from 1.10.2007 to 9.03.2008

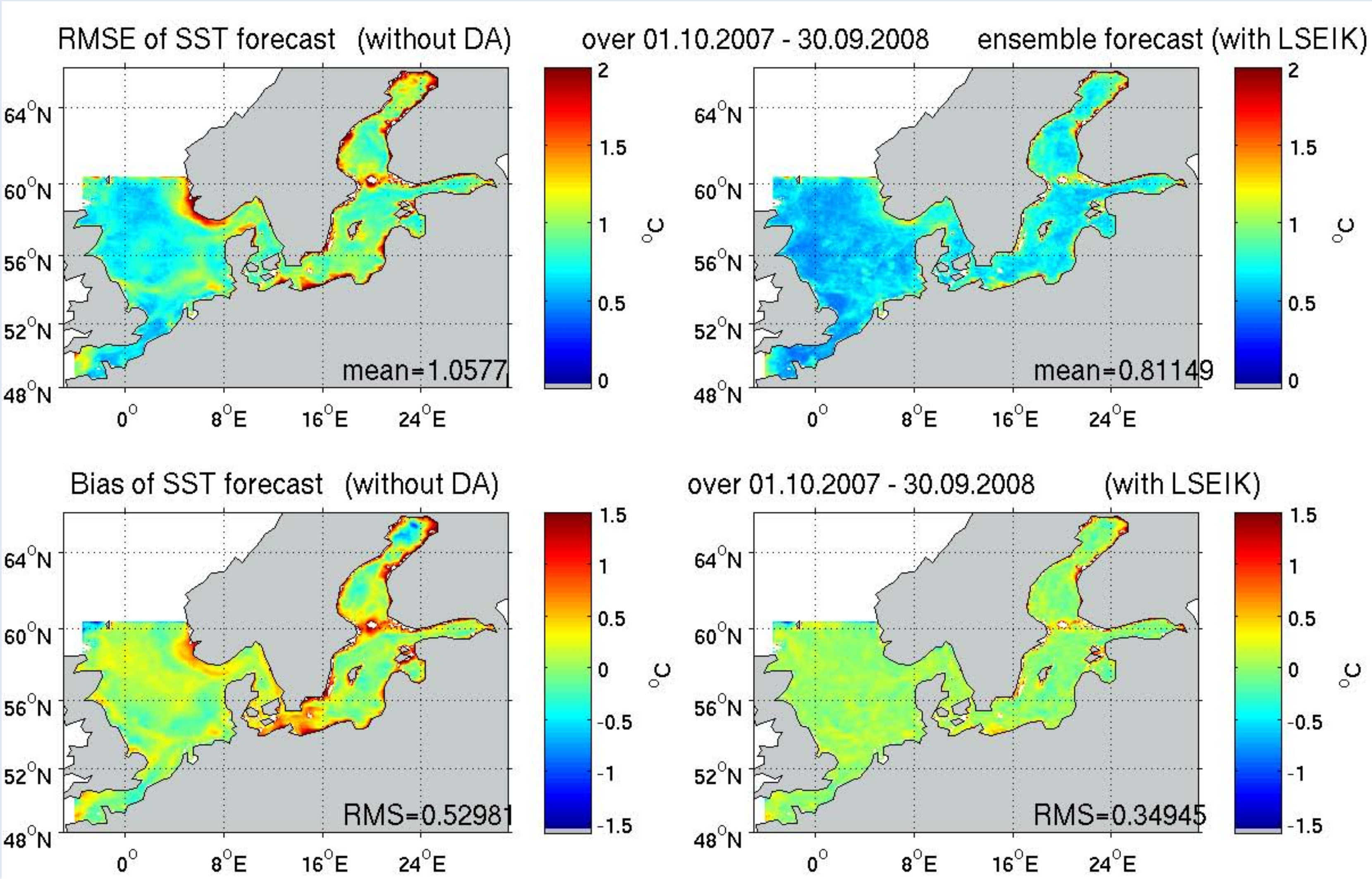
Assessing SST forecast

Temporal evolution of SST RMS error for BSHcmod forecast



Improvement of SST forecast in the North and Baltic Seas

without DA | with LSEIK filter



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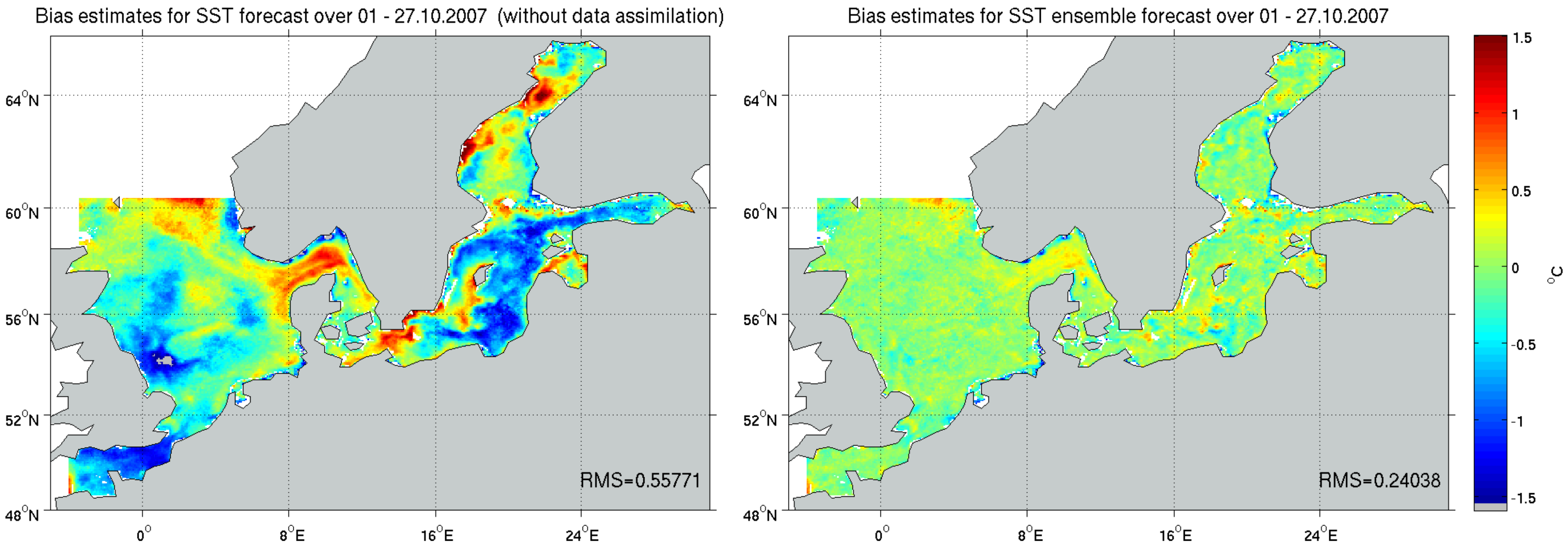
Improvement of SST forecast in the North and the Baltic Seas when sequentially assimilating satellite data

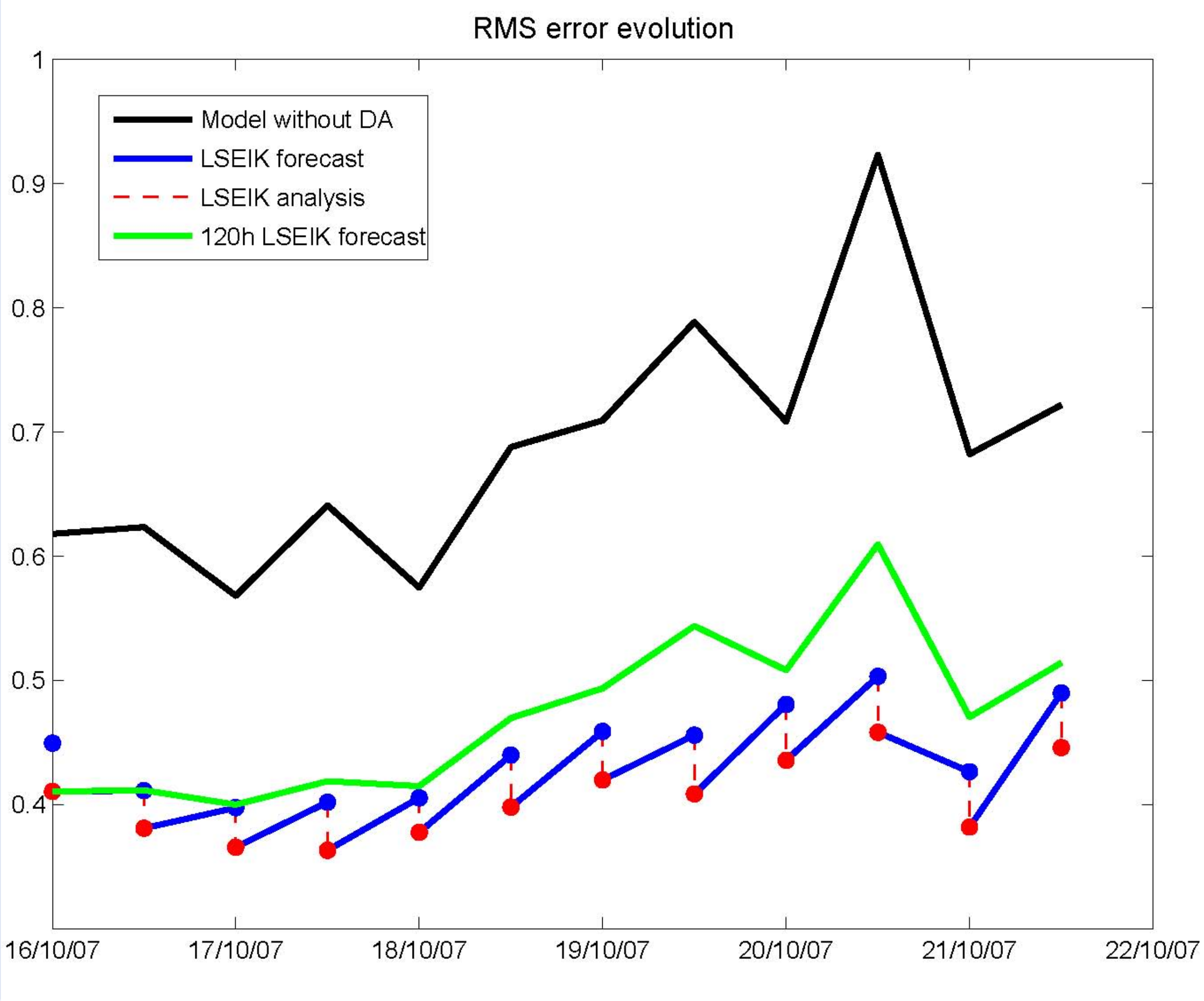
- Bias   without DA   with LSEIK filter



Bias reduction

Long forecast (~ 120 hours)

Temporal evolution of SST RMS error for BSHcmod forecast



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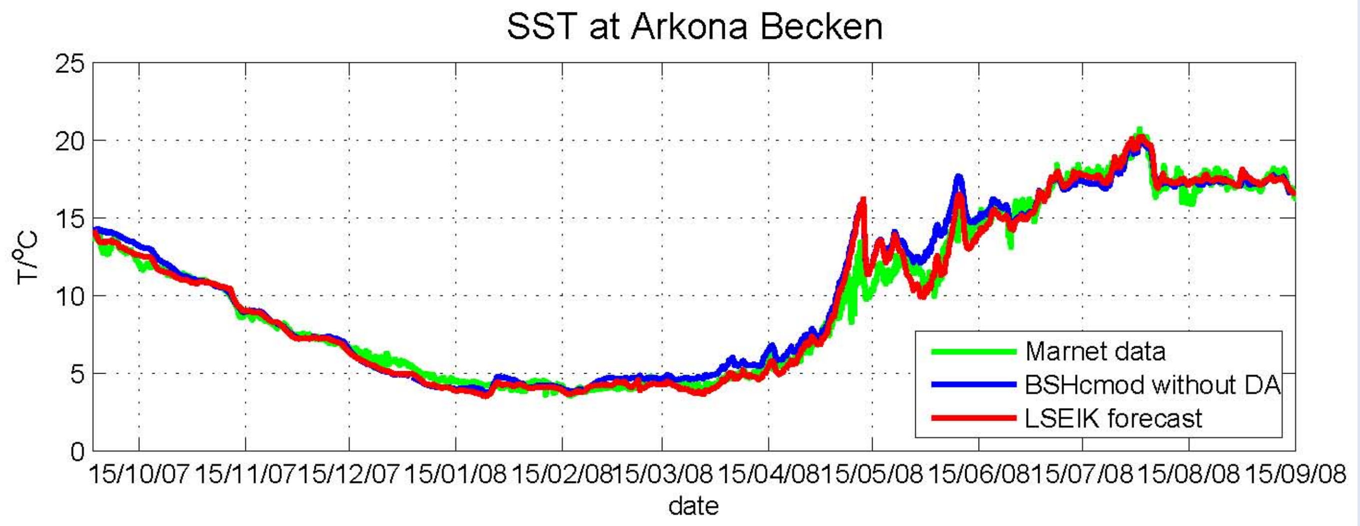
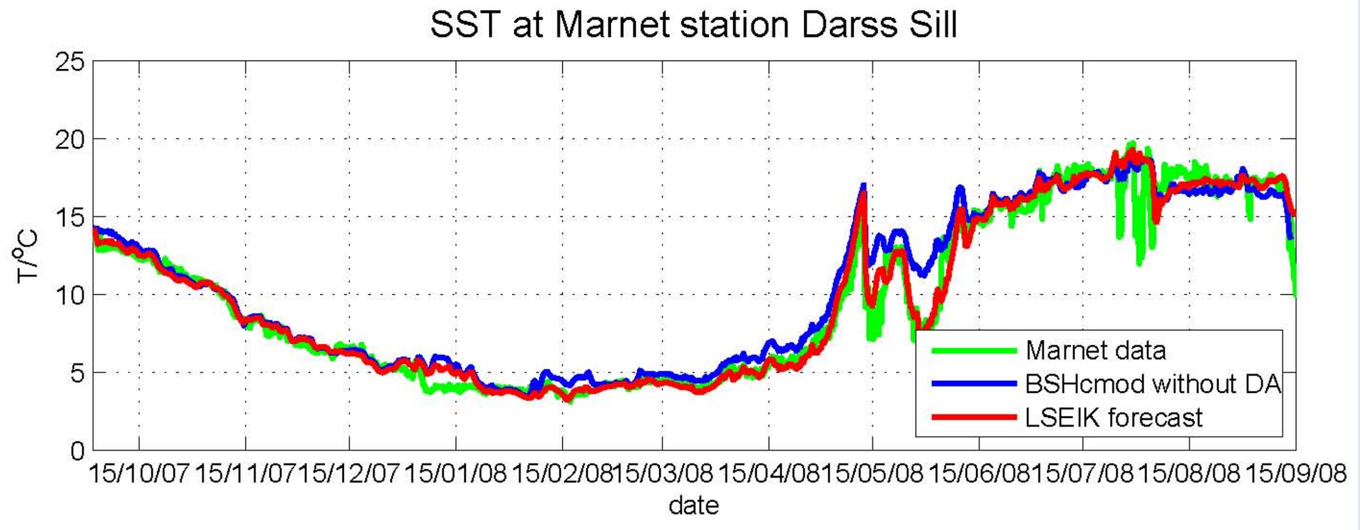
Comparison with independent MARNET data





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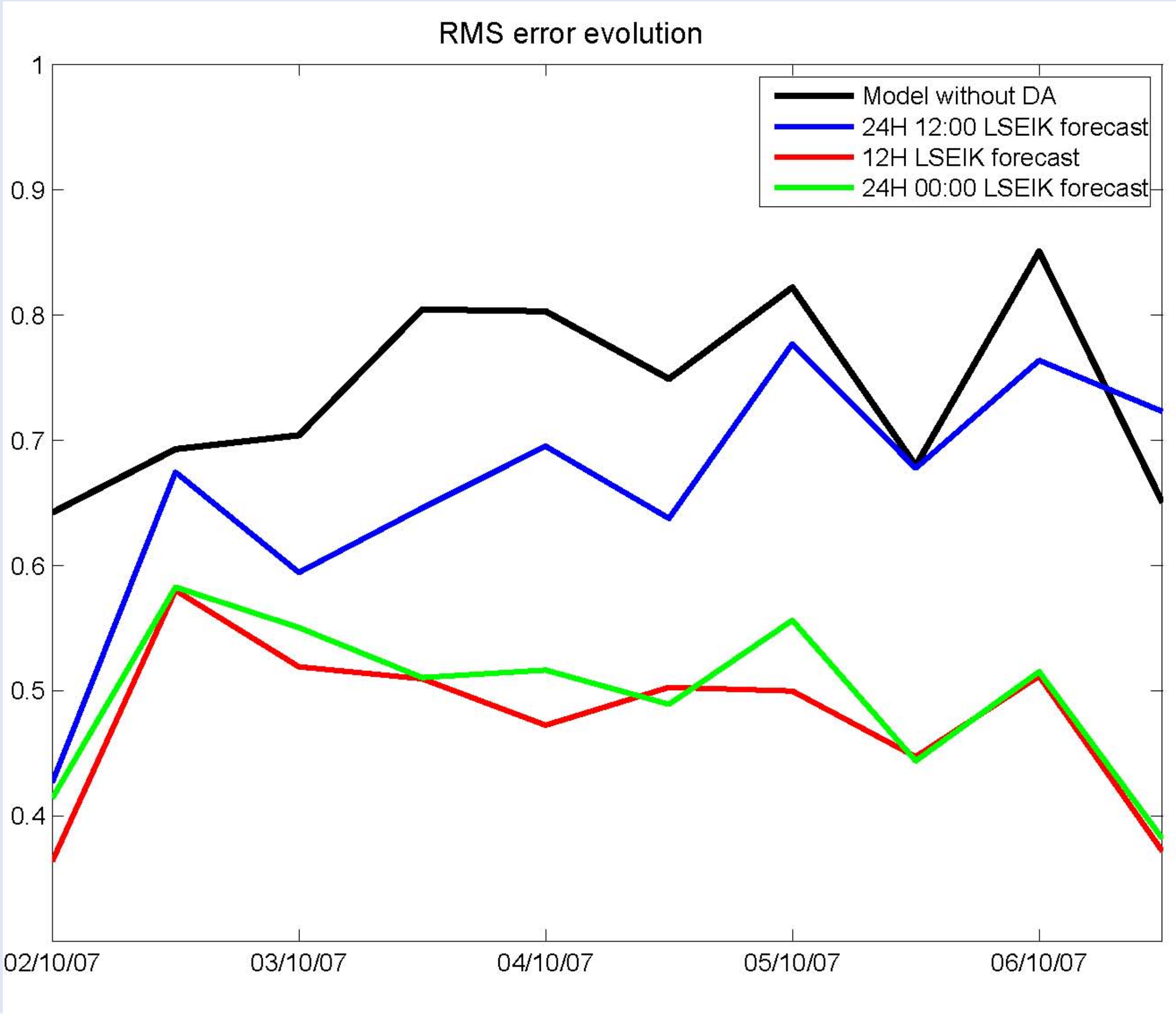
Validation with independent data

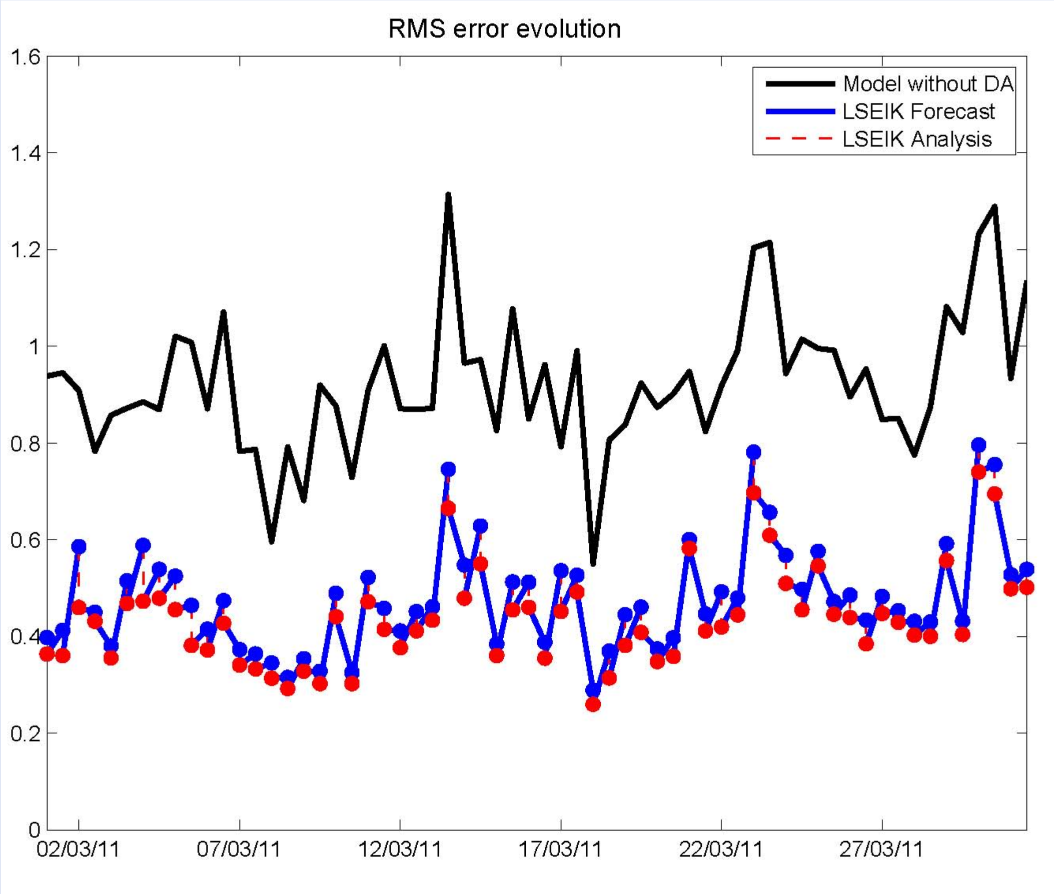
- Deviation from MARNET SST Daten

Station	RMS (^oC)			Bias (^oC)		
	Model	LSEIK	NOAA	Model	LSEIK	NOAA
Arkona	0.88	0.58	0.61	-0.29	0.	0.04
Darβ	1.27	0.81	0.69	-0.55	-0.17	0.01
Kiel	0.79	0.49	0.61	-0.13	0.07	0.08
Fehm	0.63	0.43	0.56	-0.16	0.03	0.16
Ems	0.67	0.45	0.49	0.33	0.2	0.17
Dbucht	0.97	0.53	0.57	-0.34	-0.03	0.27
nsb			0.73			

Different timing and period of LSEIK analysis/forecast

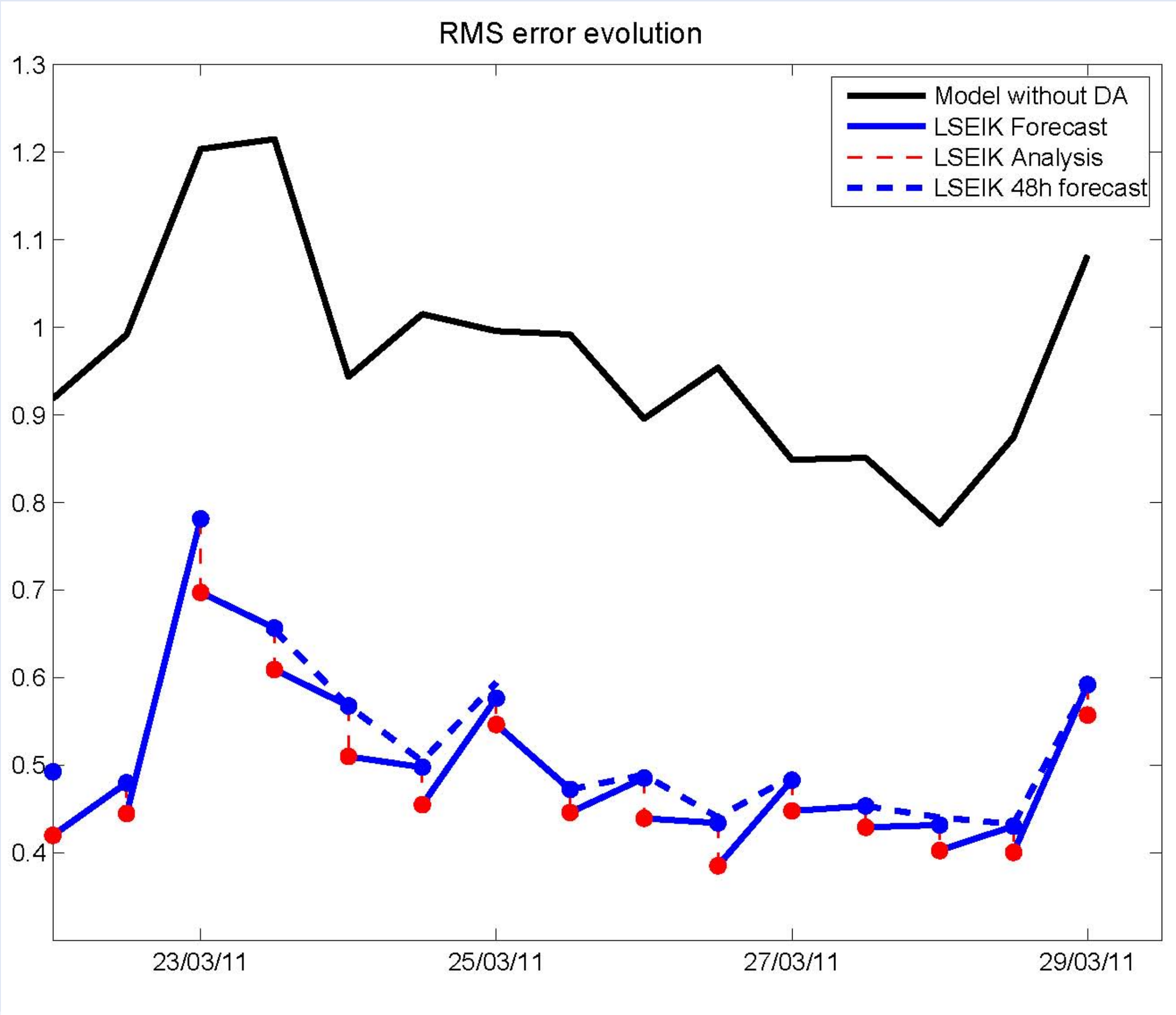


Assessing real-time SST forecast (March 2011)

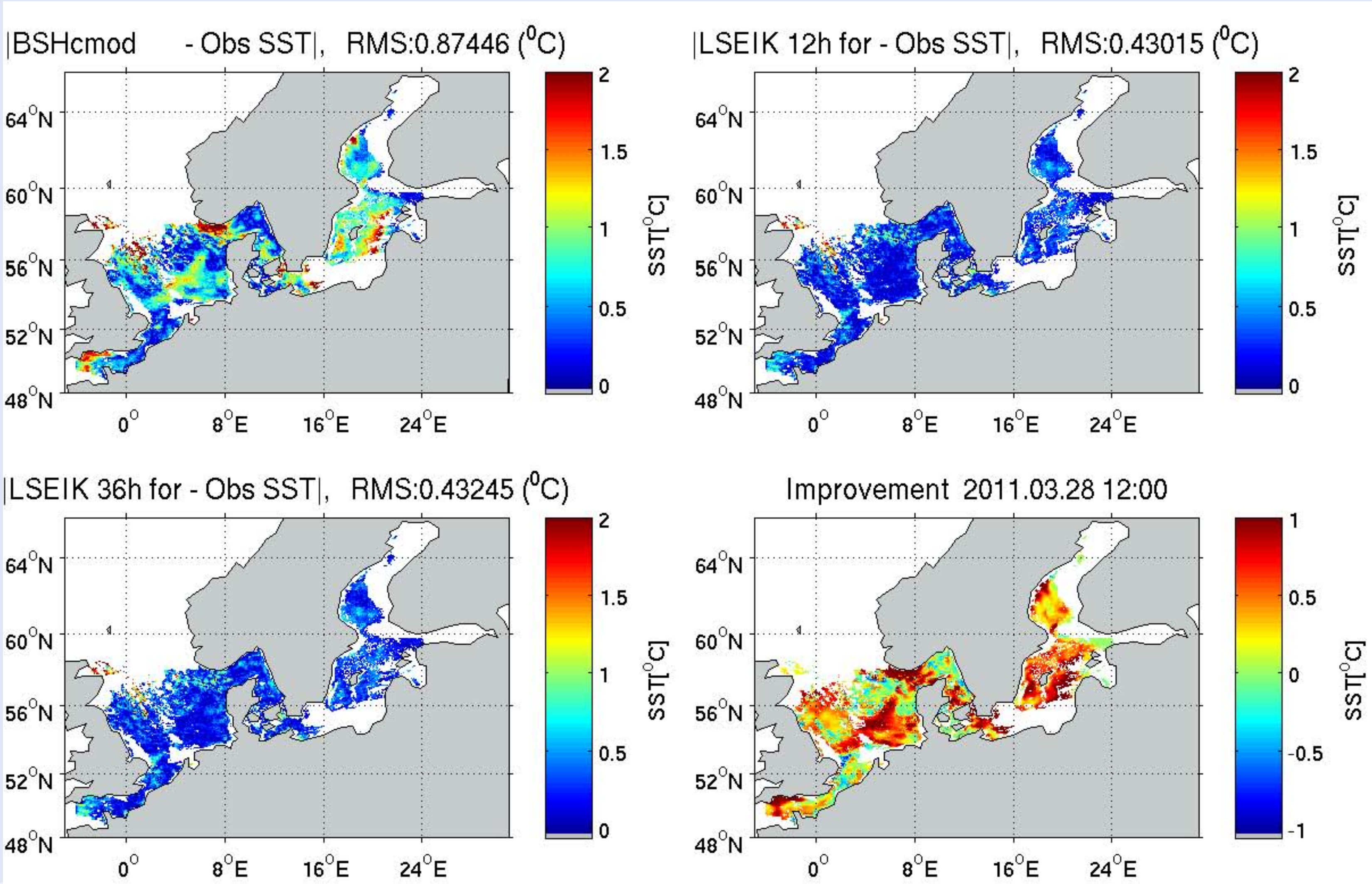


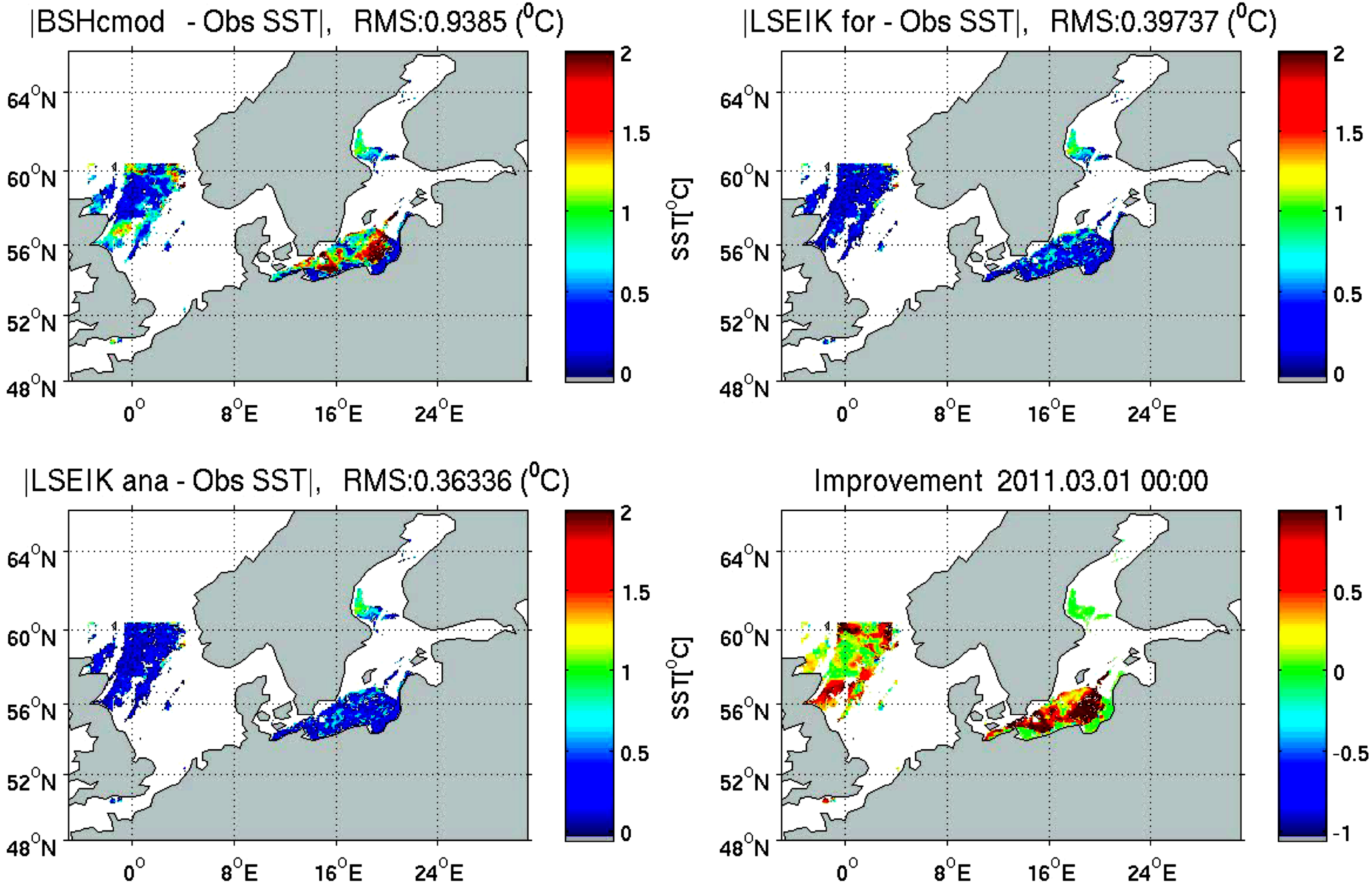
37% of the error reduction

Long forecast



Assimilating NOAA SST data into BSHcmod: pre-oprerational




|BSHcmod - Obs SST|, RMS:0.9385 (0C)
|LSEIK for - Obs SST|, RMS:0.39737 (0C)
|LSEIK ana - Obs SST|, RMS:0.36336 (0C)
Improvement 2011.03.01 00:00
SST[0C]
64°N
60°N
56°N
52°N
48°N
0°
8°E
16°E
24°E
2
1.5
1
0.5
0
-0.5
-1

Conclusions

- LSEIK Filter has been implemented for NOAA SST data assimilation into operational BSHcmod. 27% of SST forecast error reduction has been achieved over the period of 01.10.2007-30.09.2008.
- Pilot real-time data assimilative pre-operational runs manifest much higher quality of the SST forecast in March 2011 in comparison with the regular BSH forecast without DA. On average, over that period, RMS error has been decreased from 0.8^{o}C to 0.5^{o}C.
- The experiments conducted with different timing and frequency of data assimilation and variable forecasting periods show that the data assimilation system enables one to correct the systematic model uncertainties and,
- due to memory on the corrections, better predict over periods of up to 5 days;
- Our results also apparently illustrate the bias in AVHRR daytime product, but, however, reveal low informative influence of the data on the forecasting system when daytime SSTs are assimilated additionally to 'midnight' observations.
- Extending the DA system by including other types of observations

  ICES, sea ice, MARNET

  DA in ecosystem modelling