

Validating an Ensemble based Forecasting System of the North and Baltic Seas

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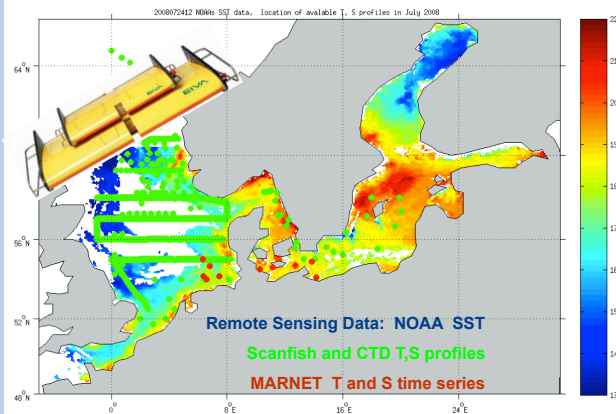
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Abstract

The quality of the forecast provided by the German Maritime and Hydrographic Agency (BSH) for the North and Baltic Seas had been previously improved by assimilating satellite sea surface temperature SST (project *DeMarine*, Losa et al., 2012). We investigate possible further improvements using *in situ* observational temperature and salinity data: MARNET time series and CTD and ScanFish measurements. To assimilate the data, we implement the Singular Evolutive Interpolated Kalman (SEIK) filter (Pham et al., 1998). The SEIK analysis is performed locally (Nerger et al. 2006) accounting for/assimilating the data within a certain radius. In order to determine suitable localisation conditions for MARNET data assimilation, the BSHmod error statistics have been analysed based on LSEIK filtering every 12 hours over a one year period (September 2007 – October 2008) given a 12-hourly composites of NOAA's SST and with the prior error statistics assessed with an entropy approach (Kivman et al., 2001). The principle of Maximum Entropy is used as an additional criterion of plausibility of the augmented system performance.

Assimilated Data



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Principle of Maximum Entropy

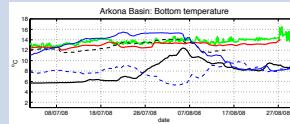
general formulation, Kivman et al., 2001

From a probabilistic point of view, the problem of data assimilation into dynamical models is formulated as estimating $\rho(x|y)$, the probability density function (PDF) of model trajectories realisations x given the data y . This conditional (analysis) PDF should maximize the entropy $S(\rho) = -\int \rho(x|y) \ln \rho(x|y) dx$, where $\mu(x)$ is the lowest information about x . The maximum probable x or mean with respect to $\rho(x|y)$ is $x^* = M_m x_m + M_d x_d$, x_m and x_d are any system states satisfying the model equations $L(x) = f$ and data $H(x) = y$, respectively. Here, L is the model operator, f is external forcing, H is an observational operator. Kivman et al. (2001) show that the operators M_m and M_d depend on both L and H and on our assumptions on the prior error statistics. M_m and M_d are nonnegative, self-adjoint and $M_m + M_d = I$. Assessing the assumptions on the model and data errors, we search for the prior which generates the operator-valued measure M with the highest entropy $S(M) = -\text{trace}(M_d \ln M_d + M_m \ln M_m) = -\sum_i [\lambda_i \ln \lambda_i + (1 - \lambda_i) \ln(1 - \lambda_i)]$.

In Kalman type Filtering

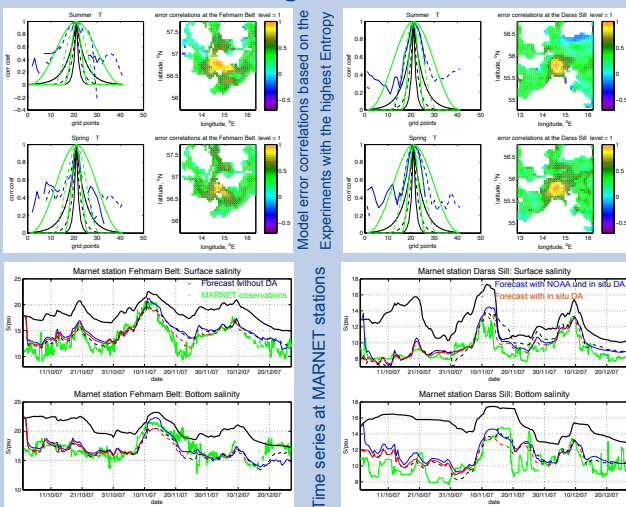
The maximum probable x or state vector analysis x^a is $x(t_n)^a = x(t_n)^f + K_n (d_n - Hx(t_n)^f)$, where $x(t_n)^a$ and $x(t_n)^f$ denote analysis and forecast of the model state at certain time t_n , y_n is observations available at t_n , K is the Kalman gain $K_n = P_n^f H (HP_n^f H^T + R)^{-1}$.

Here, following Pham (1998), P_n^f is the forecast error covariance matrix, H is the observation operator and R is the observational error covariance matrix. The operator-valued measure M is determined by Kalman gains. To calculate the entropy $S(M)$, we just need to know λ_i of the Kalman gain matrix (using SVD decomposition). Such a matrix could be constructed by collecting and considering $K_n H$, for instance, globally over a certain period of time or locally.



Temporal evolution of the bottom temperature forecast at the MARNET station "Arkona Basin" produced with BSHmod without DA (black); with LSEIK analysis of the model and NOAA's SST DA under statistical conditions corresponding to the $\lambda = 4.86$ for the period 25 June – 8 August 2008 (blue solid); based on NOAA's SST LSEIK analysis under error statistics with $\lambda = 2.71$ for the same period (blue dashed); assimilating satellite SST and *in situ* T, S data including MARNET (black dashed); assimilating only *in situ* data (red). The green curve depicts MARNET observations.

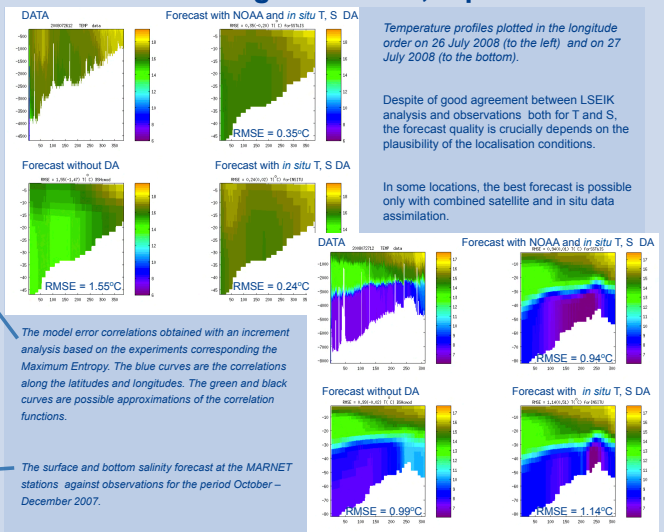
Assimilating MARNET data



Pham, D. T., J. Verron and L. Gourdeau (1998). Singular evolutive Kalman filters for data assimilation in oceanography, *C. R. Acad. Sci. Paris, Earth and Planetary Sciences*, 326, 255–260.

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Assimilating Scanfish T, S profiles



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