

Derivation of Structure Functions over the Copernicus Arctic Regional

Reanalysis (CARRA-2) Region

Swapan Mallick

Swedish Meteorological and Hydrological Institute (SMHI)

swapan.mallick@smhi.se

April 18, 2024 4th ACCORD All Staff Workshop



Introduction: Data Assimilation



Data Assimilation is the combination of information from a model and observations to produce a best estimate of the state of the atmosphere (the analysis).

Fundamental issues:

- Problem is under-determined: not enough observations to define the state.
- Forecast error covariances cannot be determined from observations.
- Large scale problem.
- Nonlinear system.

Methods:

- Variational (3D/4D-VAR)
- Extended Kalman Filter (EKF)
- Ensemble Kalman Filter (EnKF)
- Hybrid Method (3D/4D-VAR + EnKF)



Introduction: Observation



We are far from using all the observations.



- Observation quality dependent.
- Observing system dependent.
- NWP model resolution dependent.
- Assimilation method dependent.



Good observations only cover part of the model domain which provide incomplete model state at given locations. In addition, many observations are not NWP model variables.

Quality Control:

- Bad reporting practice check
- Probability Gross Error check (against some limits)
- Background check (short-range forecasts)
- Observation Thinning
- Analysis check: Var-QC

Introduction: 3D-Variational DA





Potential Problem:

Relies heavily on correct B matrix.

Typically no error estimate.

Copernicus Arctic Regional Reanalysis (CARRA-2)



Derivation and the importance of background error statistics (B-matrix) over the Copernicus Arctic Regional Reanalysis Second Generation (**CARRA2**) region.

CARRA2 is an reanalysis product that extends to a larger area (spatial resolution 2.5 km and 2880 x 2880 grid points) to provide pan-Arctic coverage.



Horizontal Resolution: **2.5 km**, Grid Points: **2880x2880** Vertical levels : **65**

Introduction: FESTAT



The background error statistics (BGE) also referred as a Structure Functions, are produced through the standalone FESTAT (Forecast Error Statistics) method.

The control variables encompass vorticity, divergence, specific humidity, surface pressure, and temperature.

$$VDF\left(\delta x
ight) = egin{pmatrix} \delta u \ \delta v \ \delta T \ \delta q \ \delta lnPs \end{pmatrix}$$

F: Horizontal 2-dim Fourier transformation from physical grid point space to spectral space.

D: Balance operator or statistical de-correlation operatore. **V:** Vertical transform utilizing the eigen-vectors of vertical covariance matrices.

The FESTAT manages multiple tasks related to the error statistics, including (1) converting variables from gridpoint space to spectral point space, (2) computing the balance operator, (3) generating horizontal variance density spectra for control variables, and (4) determining vertical correlations for the control variables.

HarmonieEPS Configuration:



BRAND:

B-matrix RANDom (BRAND) perturbations are generated as Gaussian (N(0,1)) random numbers in the entire control vector space and are projected to the physical space of the model state applying the square-root of background error covariance.

The covariance estimator is based on circular differences between 10-members.





Ensemble Prediction System (EPS): 9-member (mm1–mm9) and a control, mm0. IC/BCs: ERA5 EDA 10-ensemble members.

TEMPERATURE at LEVEL 65 (in Kelvin, 6HR FC)

256.00

49.02



| | Ten | nper | ature | diffe | rence | (in k |) from | Control | (CNTL |) and | each | ensei | mble I | member | |
|--------|--------|--------|--------|--------|--------|--------|--------|---------|-------|-------|------|-------|--------|--------|-------|
| 273.45 | 276.94 | 280.43 | 283.92 | 287.40 | 291.77 | -10.00 | -7.78 | -5.56 | -3.33 | 1 | 1.11 | 3.33 | 5.56 | 7.78 | 10.00 |

TEMPERATURE at LEVEL 65 (in Kelvin)





Time series of mean maximum and mean minimum temperature difference between control and each ensemble member (1-9) from 1 to 28 June 2022 and for each assimilation cycle (00, 06 12 and 18 UTC).







Data Assimilation 3D-VAR system

Assim OBS: (20220602 at 00-UTC) SYNOP AIRCRF BUOY TEMP PILOT

Assimilated Observation (20220602 at 00-UTC)







Cost Function Valid on 20230615 at 06 UTC



| Cases | Valid from | Season | Forecast hour | No. of files | LUNBC | Validated |
|-----------|----------------------|--------|------------------|-----------------|-------|----------------------|
| B1 | 20230101 to 20230215 | Winter | 6 HR | 999 | FALSE | 20140701 to 20140715 |
| B2 | 20230601 to 20230715 | Summer | 6 HR | 999 | FALSE | 20140701 to 20140715 |
| B3 | 20230601 to 20230715 | Summer | 12 HR | 999 | FALSE | 20140701 to 20140715 |
| B4 | 20230601 to 20230715 | Summer | 6 HR | 999 | TRUE | 20140701 to 20140715 |

LUNBC: Upper Nested Boundary Conditions (Switch : TRUE/ FALSE)

B-Matrix:

WINTER (B1)

SUMMER (B2)

Percentage of the variance of temperature that is explained by balanced geopotential as a function of height and wave number.

B-Matrix:

Percentage of the variance of specific humidity that is explained by Tu as a function of height and wave number.

SMHI

Average vertical cross-covariance matrix between specific humidity and unbalanced divergence (kg kg -1 s -1).

B-Matrix:

Average vertical cross-covariance matrix between specific humidity and vorticity-balanced geopotential (kg kg -1 J).

WINTER

SMHI

Background error standard deviations for humidity.

B-Matrix:

SMHI

Percentages of humidity background variances error explained by vorticity, unbalanced divergence and unbalanced temperature and surface pressure function of horizontal as а wavelength.

B-Matrix:

Level 10 spectral density at different horizontal wavelength (km).

Validation:

Cost Function Valid on 20150716 at 18 UTC

Validation:

Validate on 20150716 at 18 UTC

Temperature DIFF L45 (B2 - B4) in K Temperature Cross-section DIFF (B2 - B4) in K - (0.0E,64.5N) and (21.5E, 67.0N)

B2 : LUNBC=FALSE B4: LUNBC=TRUE

Validate on 201507

SMHI

Validate on 201507

Date

SMHI

No cases

1. The results are presently being integrated into a draft of the paper.

2. An Approach Leveraging Machine Learning. Uncertainty Estimation in Ensembles Across the CARRA Domain:

Super-Resolution Convolutional Neural Networks (SRCNN):

3. Variational Quality control (VAR-QC) over CARRA2.

