ECMWF Data Assimilation Training course

Land data assimilation and coupling

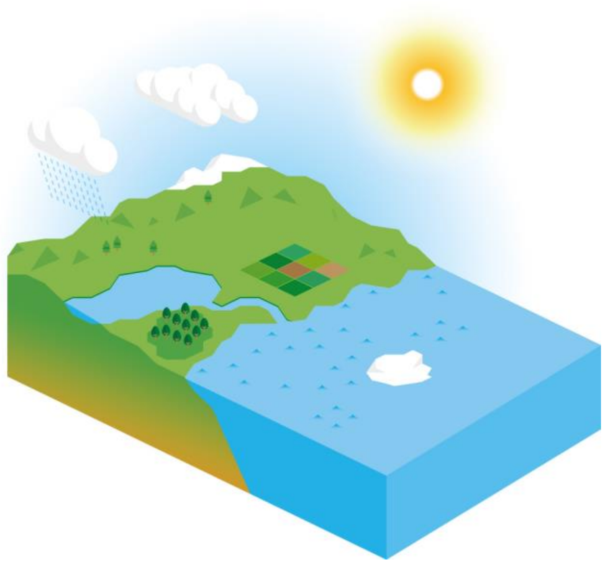
Patricia de Rosnay

20 Mars 2025

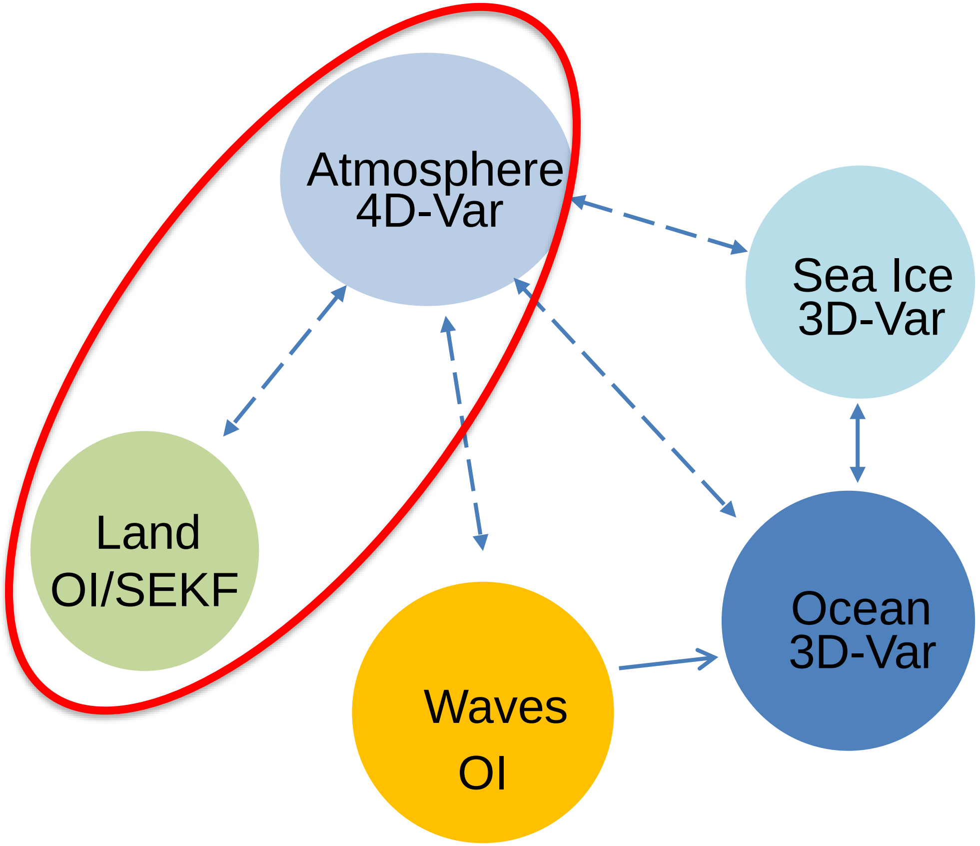
Outline

- **Introduction**
- Snow analysis
- Soil moisture analysis
- Summary

Earth system approach



Integrated Forecasting System (IFS)



Coupled surface-atmosphere data assimilation: Why?

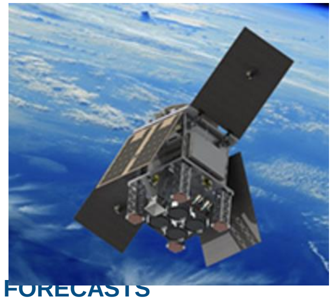
- ECMWF Earth system approach --> Earth system data assimilation
- Provide balanced initial conditions across the coupled forecast model components
- Enhance consistency of assimilation approaches and find optimal level of coupling between the various components of the Earth system
- Improve exploitation of satellite data sensitive to several Earth system components towards an "all surface" approach → Interface observations

ASCAT

SMOS

Sentinel-1

HydroGNSS

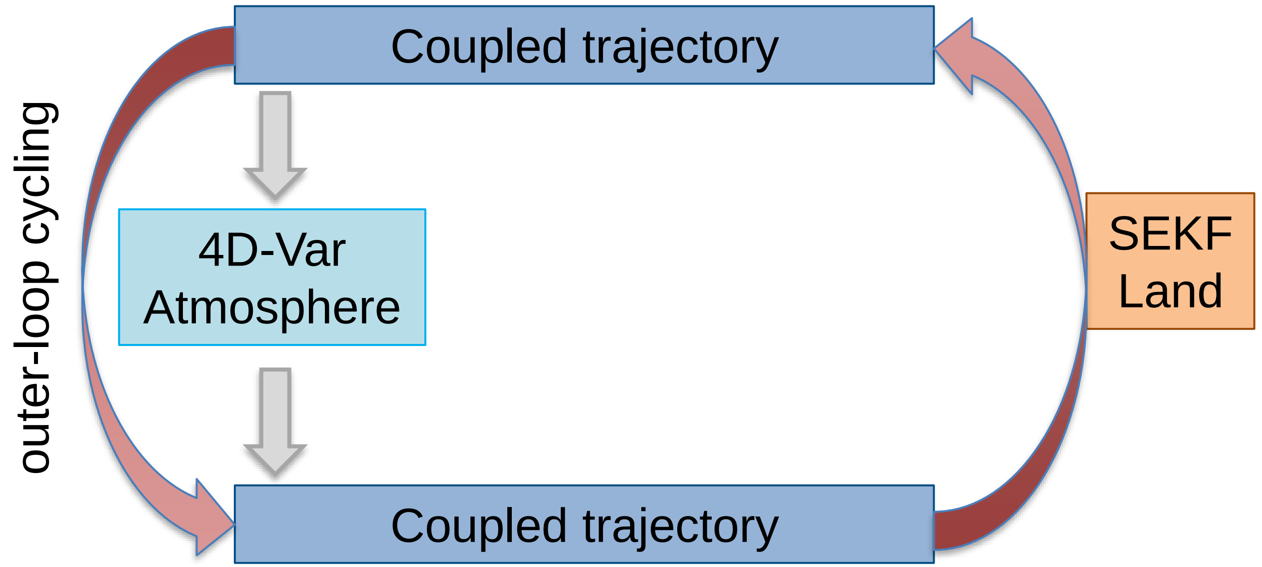


CRISTAL

LSTM

CIMR

Status of coupled land-atmosphere data assimilation for NWP at ECMWF

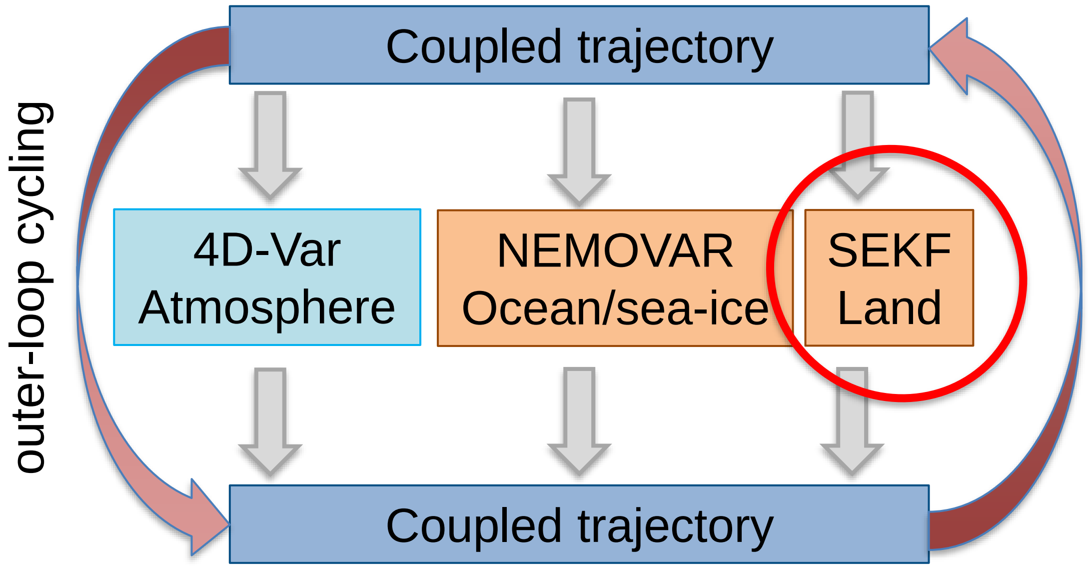


Current operational system:
Atmospheric and land data assimilation (DA) run in parallel to initialise the forecasts and the next 12h model background
→ Weakly coupled DA

Status of coupled land-atmosphere data assimilation research at ECMWF

Funded by the European Union

Outer loop coupling based on incremental 4D-Var cycling



de Rosnay P. et al QJRMS 2022 → Coupled DA strategy
Herbert et al. in prep 2025 → land-atmosphere outer loop coupling
Browne et al. → ocean-atmosphere coupling

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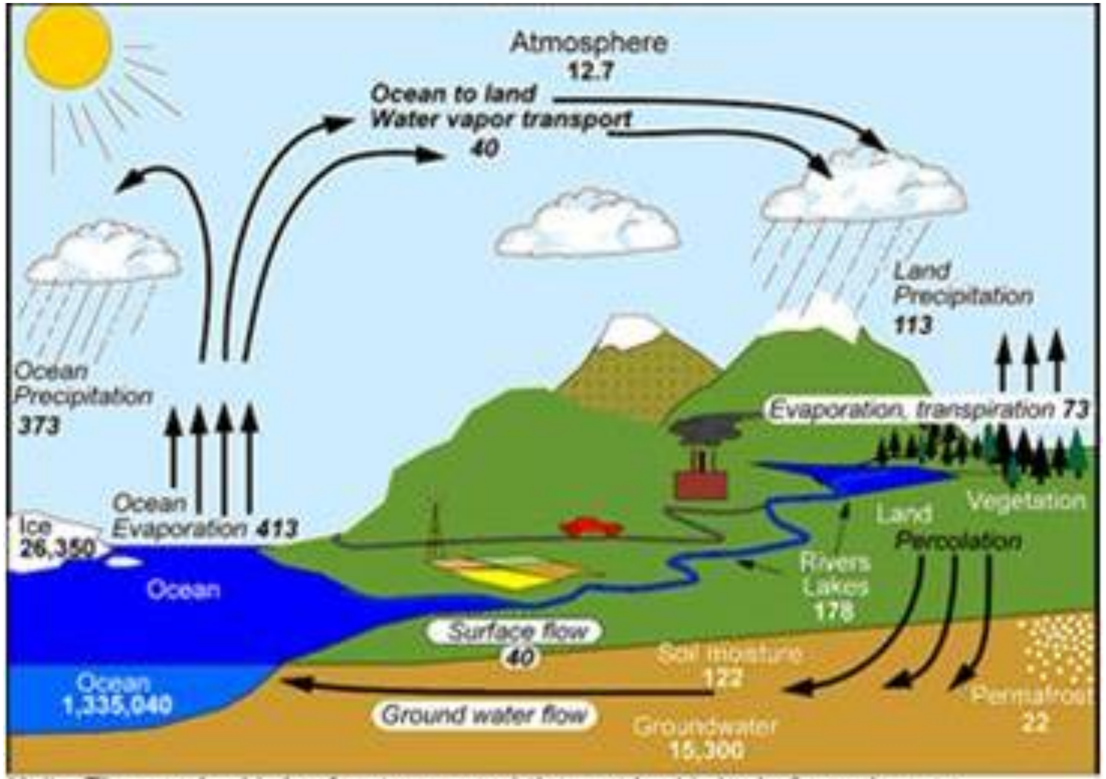
Land Surface Data Assimilation (LDAS) for NWP

Image: Trenberth et al J. Hydrometeorol. 2007



Units: Thousand cubic km for storage, and *thousand cubic km/yr* for exchanges

- Vertical correlations dominate land surface processes. Each grid point is analysed independently. Land data assimilation is a 2D problem, whereas atmospheric DA is a 4D problem → Separate Land & atmospheric DA systems.
- Flexibility to run offline land analysis without the expensive 4D-Var component

Land Surface Data Assimilation (LDAS) for NWP

Snow depth

- Methods: **2D Optimal Interpolation (2D-OI)** (ECMWF operational, ERA5, & future ERA6)
- Conventional Observations: *in situ* snow depth
- Satellite data: NOAA/NESDIS IMS Snow Cover Extent (ECMWF), H-SAF snow cover (UKMO)

Soil Moisture

- Methods:
  - 1D Optimal Interpolation (e.g. operational at Météo-France)
  - 1D-EnKF (Env. Canada CC)
  - **Simplified Extended Kalman Filter (EKF)** (DWD, ECMWF, UKMO)
- Conventional observations: Analysed 2m air relative humidity (RH2m) and temperature (T2m), from 2D OI screen level parameters analysis (using SYNOP observations)
- Satellite data : ASCAT soil moisture (UKMO, ECMWF, KMA), SMOS (ECMWF, ECCC), SMAP (ECCC)

Soil Temperature and Snow temperature

- **1D OI** for the first layer of soil and snow temperature (ECMWF, Météo-France)
- 1D-EnKF (ECCC) using AIRS, CrIS and IASI
- **SEKF** (ECMWF from IFS cycle 50r1 in 2025, and ERA6)

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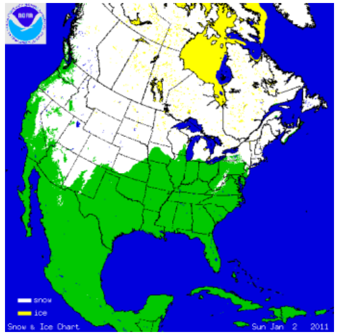
Snow in the ECMWF IFS for NWP

Snow Model: Component of H-TESSEL **(Dutra et al., JHM 2010, Balsamo et al JHM 2009)**
- Single layer snowpack until 2023 (Dutra et al, JHM 2010, used in ERA5
- Multi-layer snowpack from June 2023 (Arduini et al., James 2019, for NWP & ERA6)

- Snow water equivalent SWE (m)
- Snow Density ρ_s

$\}$ **Prognostic variables**

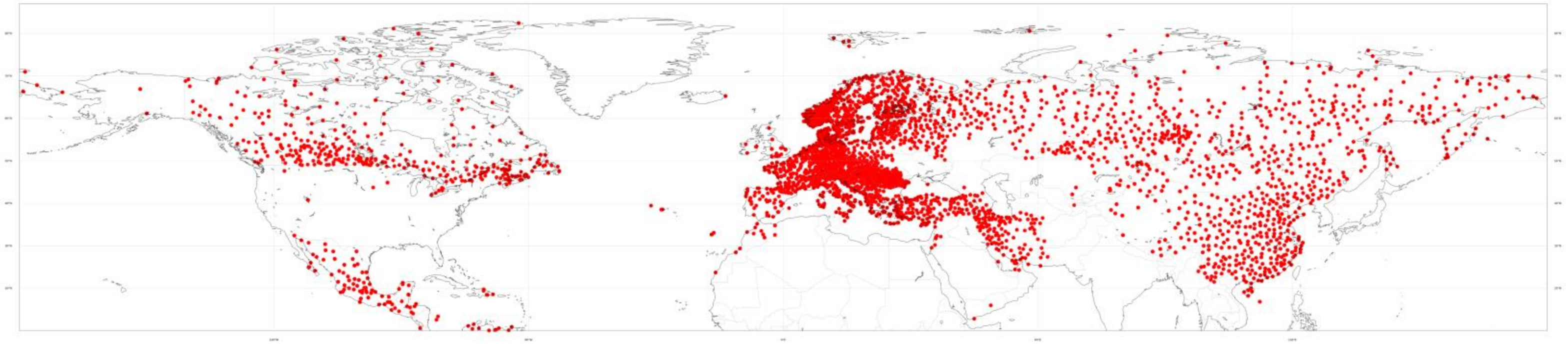
Observations: **de Rosnay et al ECMWF Newsletter 2015**
- Conventional snow depth data: SYNOP and National networks
- Snow cover extent: NOAA NESDIS/IMS daily product (4km)



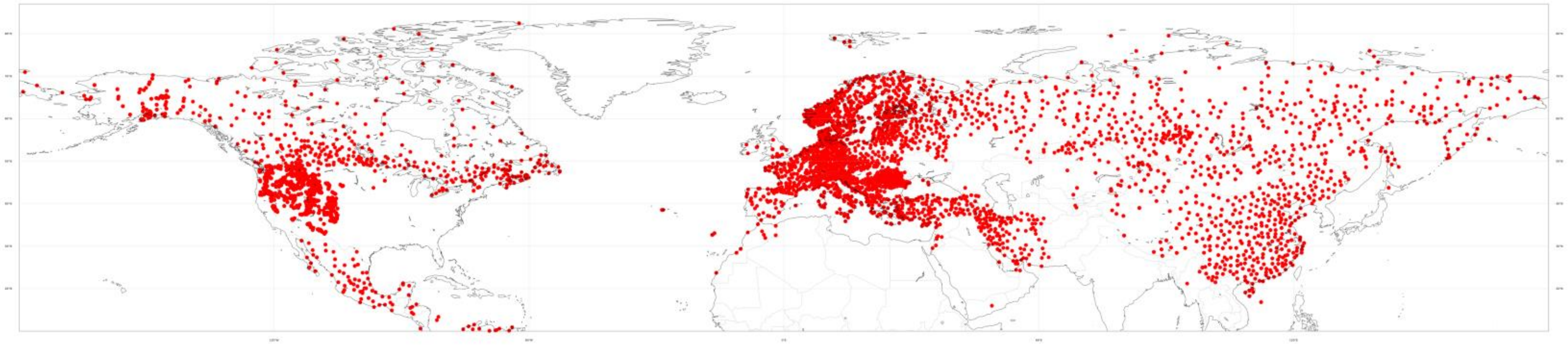
Data Assimilation: **de Rosnay et al SG 2014**
- Optimal Interpolation (OI) is used to optimally combine the model first guess, in situ snow depth and IMS snow cover
- Analysis of SWE and snow density
  → used to initialize NWP.

Land observing system: the example of in situ snow depth

Near-Real-Time access to observations



Prior 29 March 2023



From 29 March 2023

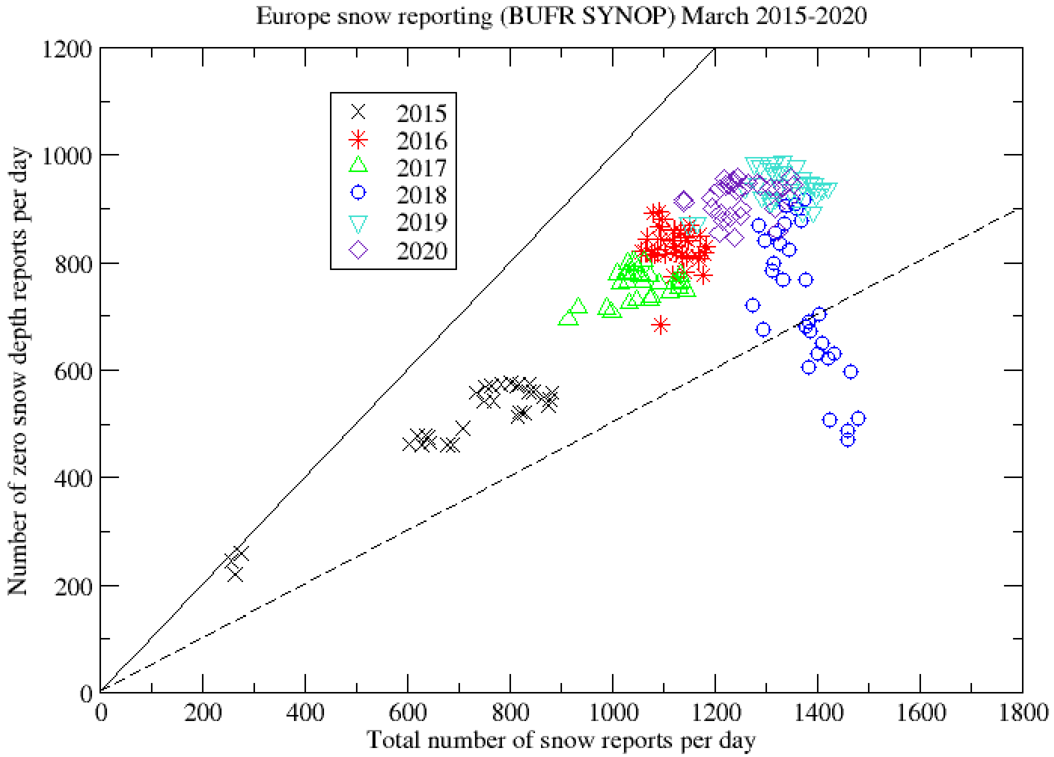
Snow depth availability on the Global Telecommunication System (GTS)

WIGOS (WMO Integrated Global Observing System) Newsletter April 2023
https://community.wmo.int/en/news/wigos_newletters

Importance of data exchange and WMO

- Several Groups and Teams at WMO
  - Global Cryosphere Watch (GCW)
  - Expert Team on Earth Observing System Design and Evolution (ET-EOSDE)

→ snow data exchange WMO regulation, BUFR template



Increase in available snow depth data from distinct SYNOP stations reporting in BUFR SYNOP on GTS from 2015 to 2020.

WIGOS Newsletter April 2020

Snow depth Optimal Interpolation (OI)

Based on Brasnett, j appl. Meteo. 1999

1. Observed first guess departure Δf_i are computed from the interpolated background at each observation location i.

2. Snow depth (S) analysis increments ΔS_k^a at each model grid point k are calculated from:

$$\Delta S_k^a = \sum_{i=1}^{N} w_i \times \Delta f_i$$

3. The optimum weights w_i are given for each grid point k by: $(\mathbf{P} + \mathbf{R})\, \mathbf{w} = \mathbf{p}$

p : **background error vector** between model grid point k and observation i (dimension of N observations) $p(i) = \sigma^2_b \,.\, \mu(i,k)$

P : correlation coefficient matrix of background field error between all pairs of observations ($N \times N$ observations); $P(i_1,i_2) = \sigma^2_b \times \mu(i_1,i_2)$ with the correlation coefficients $\mu(i_1,i_2)$.

R : **covariance matrix of the observation error** ($N \times N$ observations):

$\mathbf{R} = \sigma^2_o \times \mathbf{I}$

with and σ_b = 3cm the standard deviation of background errors, σ_o the standard deviation of observation errors (4cm in situ, 8cm IMS)

Snow depth Optimal Interpolation (OI)

Correlation coefficients $\mu(i_1,i_2)$ (structure function):

$$\mu(i_1,i_2) = \left(1+\frac{r_{i_1 i_2}}{Lx}\right)\exp\left(-\left[\frac{r_{i_1 i_2}}{Lx}\right]\right).\exp\left(-\left[\frac{z_{i_1 i_2}}{Lz}\right]^2\right)$$

Lx: horizontal length scale (55km); **Lz:** vertical length scale (500m)
$r_{i1,i2}$ and $Z_{i1,i2}$ the horizontal and vertical distances between points i_1 and i_2

Quality Control: reject observation if first guess departure > Tol $(\sigma_b^2 + \sigma_o^2)^{1/2}$ with Tol = 5
→Observation rejected if first guess departure larger than 25 cm for in situ (and 43 cm for IMS)

Redundancy rejection: use observation reports closest to analysis time
And use a maximum of 50 observations per grid point

Structure function

Horizontal component of the structure function →

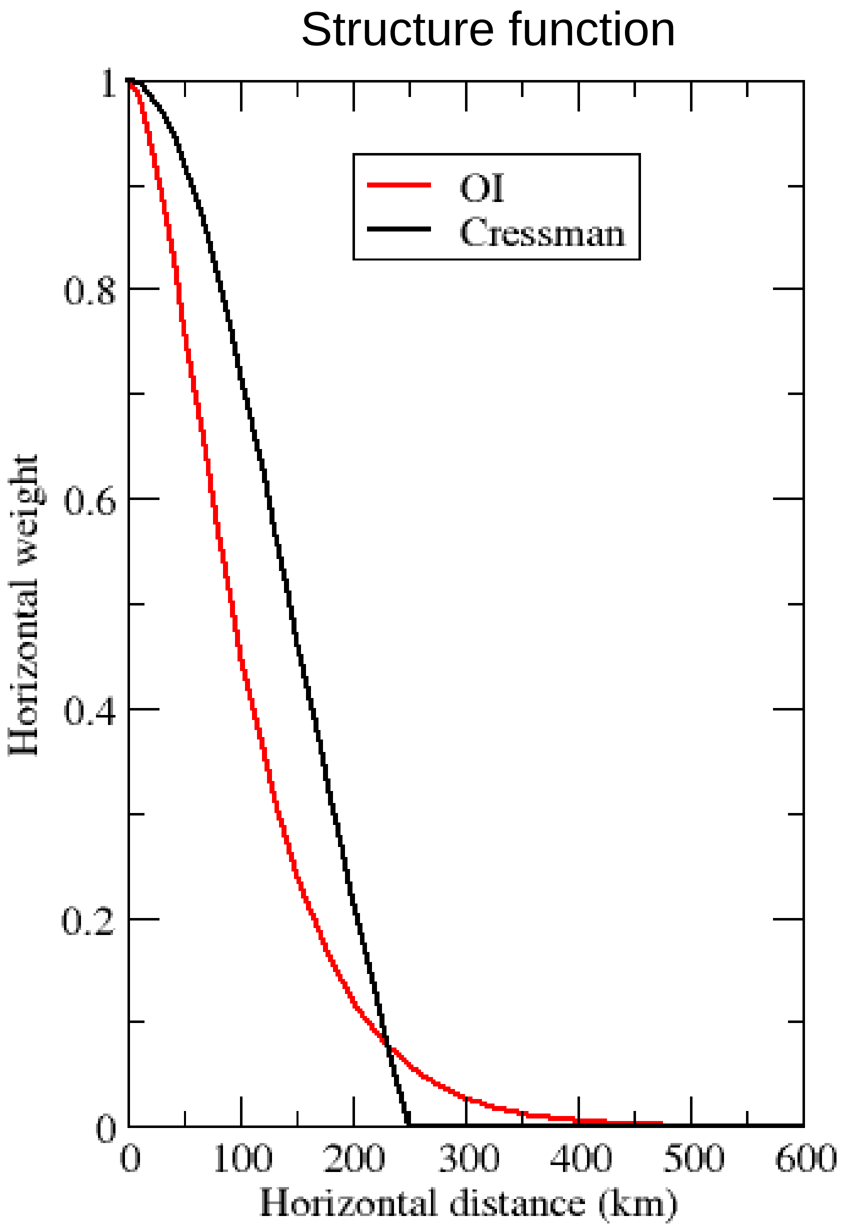
Cressman Interpolation: (Cressman, MWR 1959)

Used in NWP until 2010 and ERA-Interim

Optimal Interpolation:

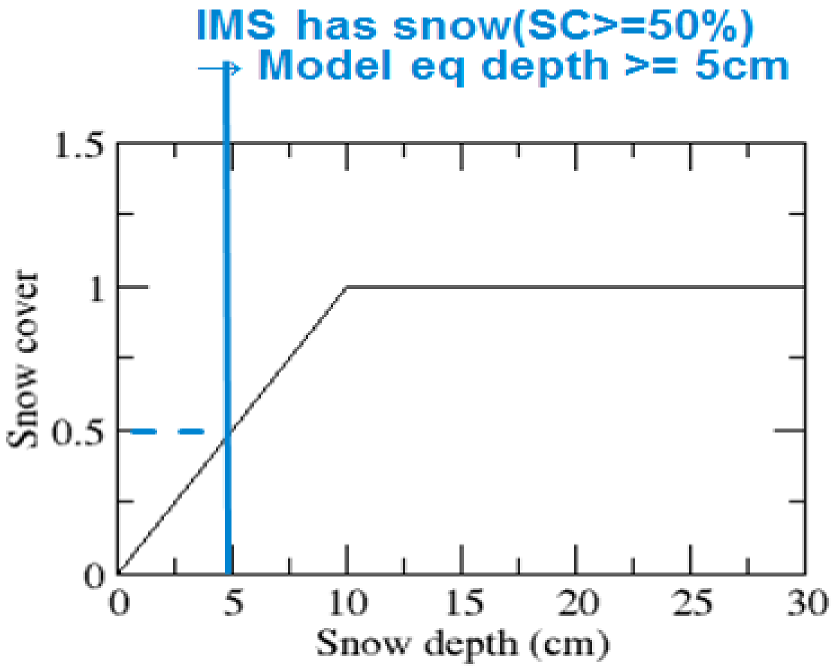
Used in NWP since 2010, ERA5 and ERA6

OI has longer tails than Cressman and considers more observations. Model/observation information optimally weighted using error statistics.



Assimilation of IMS snow cover

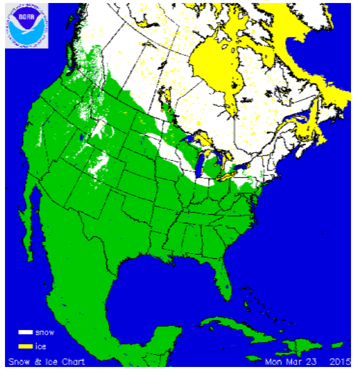
IMS NESDIS \ Fst Guess	Snow	No Snow
Snow	x	**DA** 5cm
No Snow	DA 0cm	DA 0cm



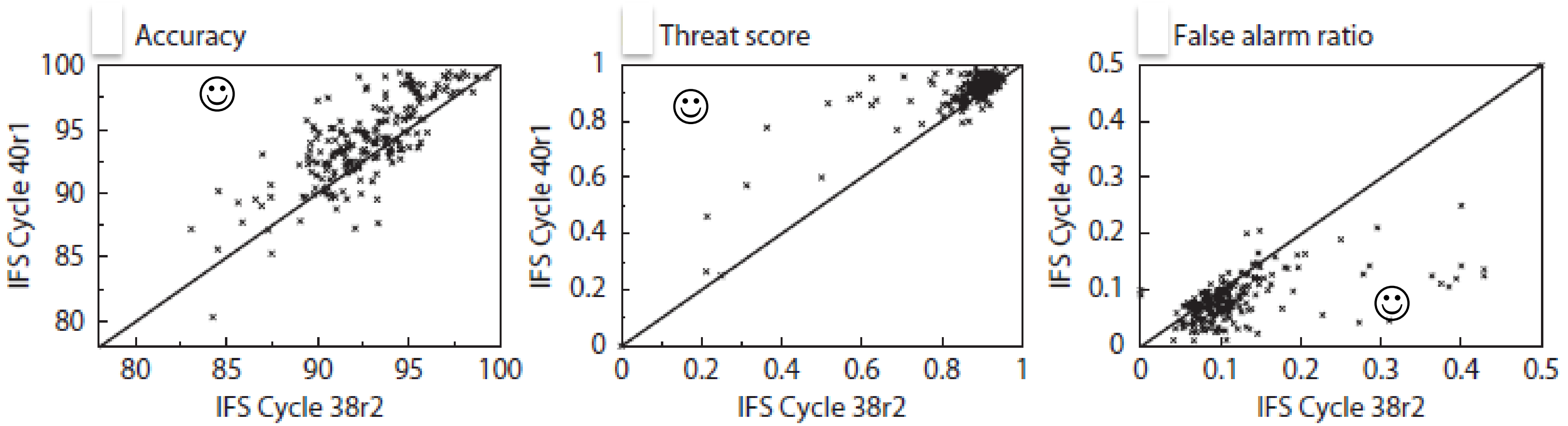
Model relation between SC and SD

Snow assimilation: Forecast impact

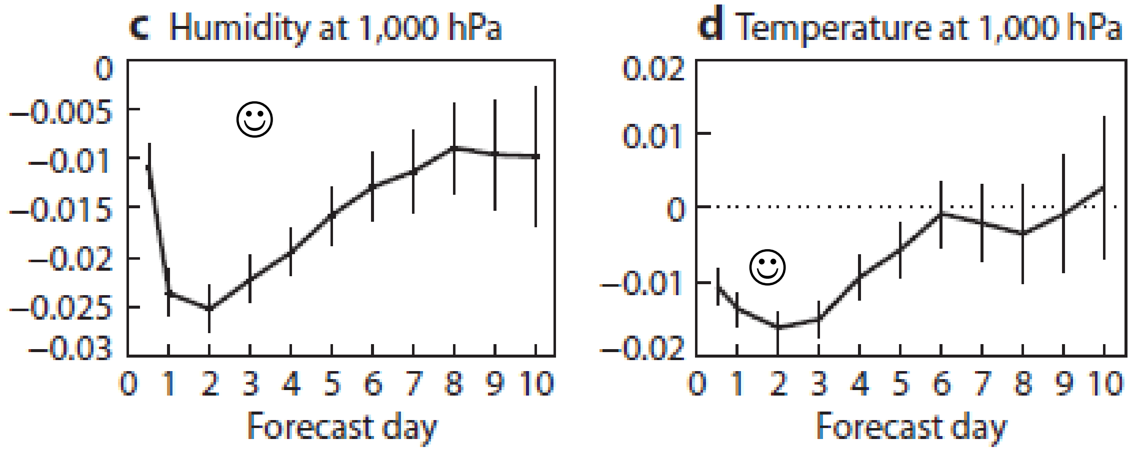
Revised IMS snow cover data assimilation (2013)



Impact on snow October 2012 to April 2013 (251 independent *in situ* observations)



Impact on atmospheric forecasts
October 2012 to April 2013 (RMSE new-old)

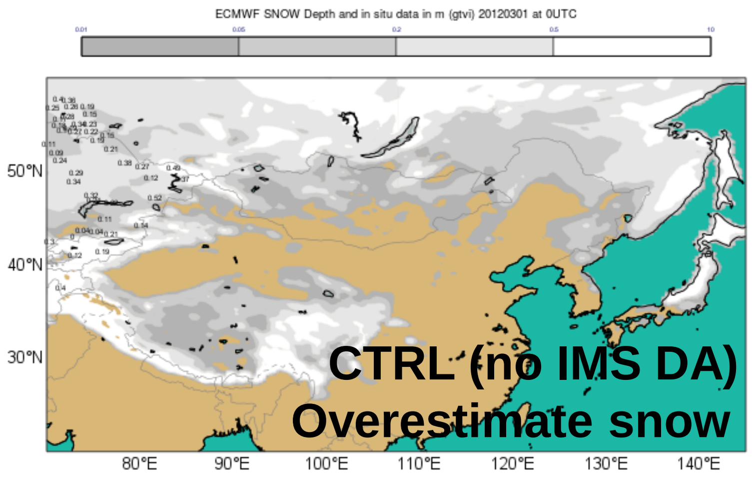


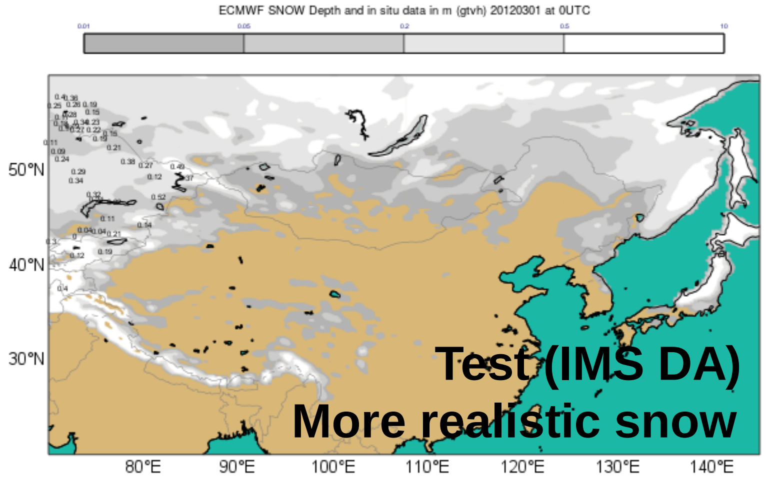
→ Consistent improvement of snow and atmospheric forecasts

de Rosnay et al., ECMWF Newsletter 143, Spring 2015

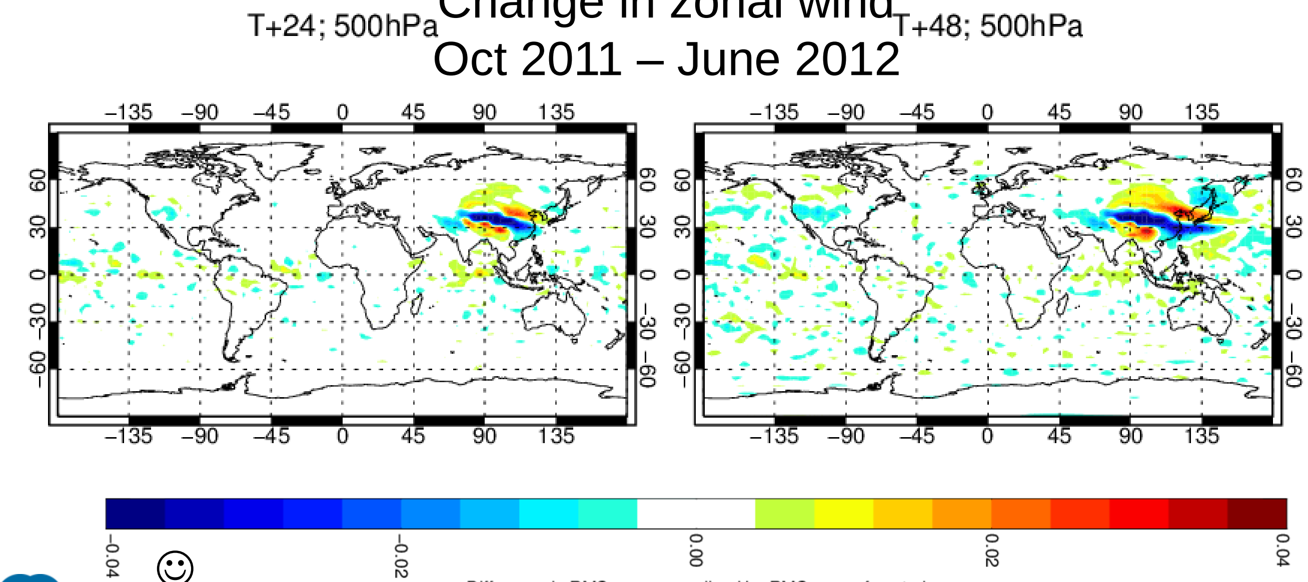
Snow cover coupled data assimilation impact over the Tibetan Plateau

Impact on albedo and momentum
→ Modifies the jet circulation



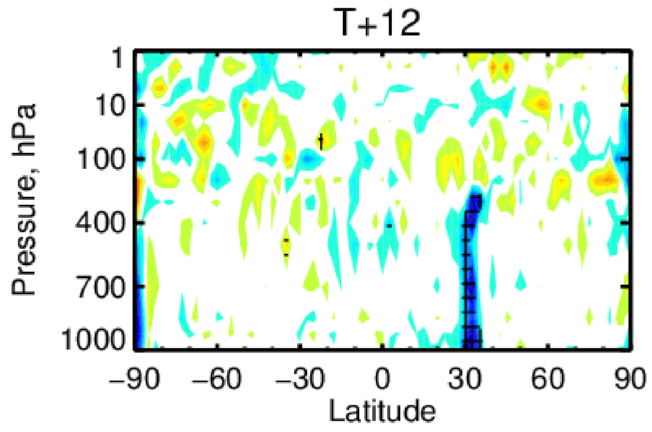


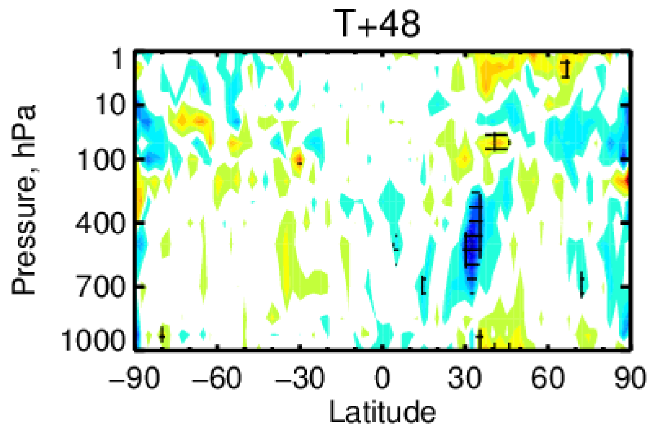
Change in zonal wind
Oct 2011 – June 2012



Difference in RMS error normalised by RMS error of control

Change in humidity FC error
Oct 2011 – June 2012





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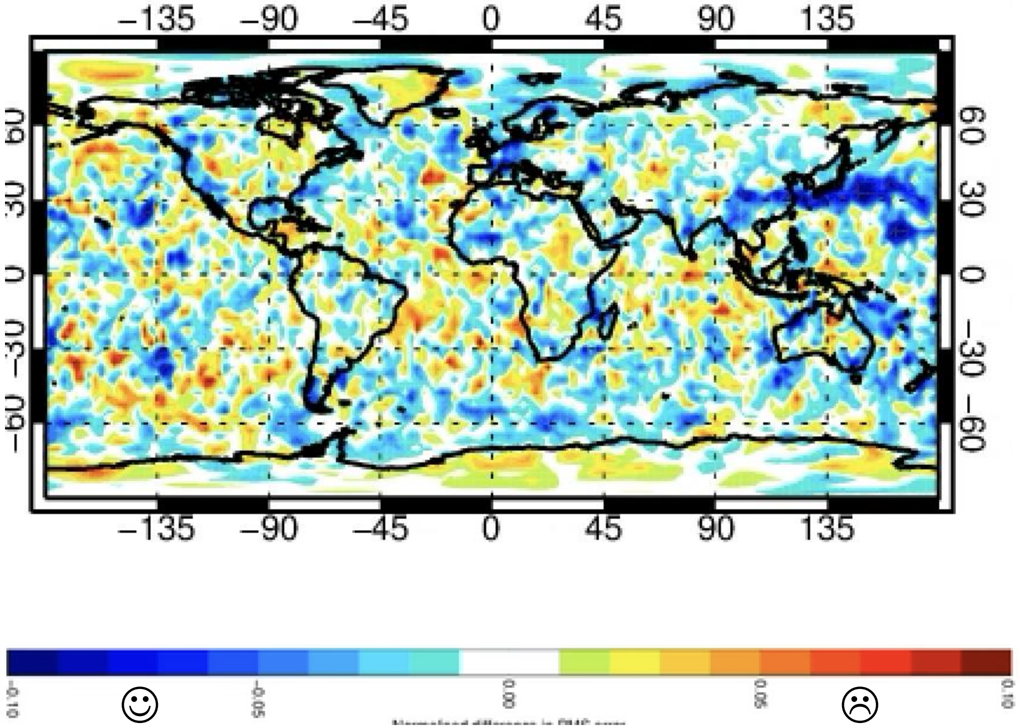
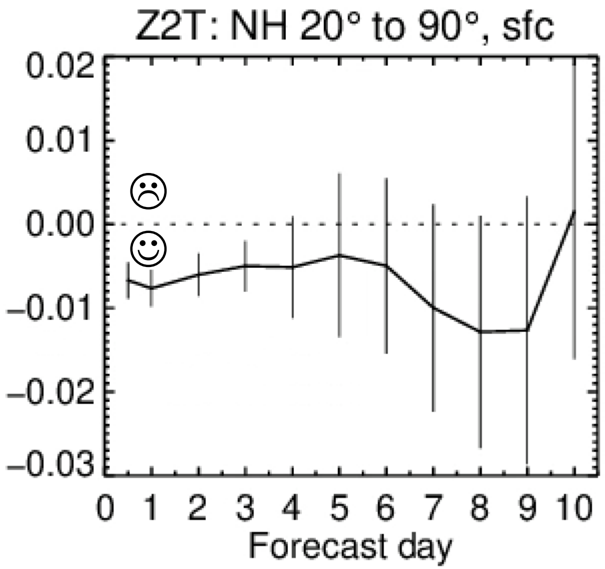
Recent snow data assimilation implementation for NWP (49r1) & ERA6 (49r2)

Positive impact of IMS snow cover assimilation in mountainous areas

T+72; 500hPa

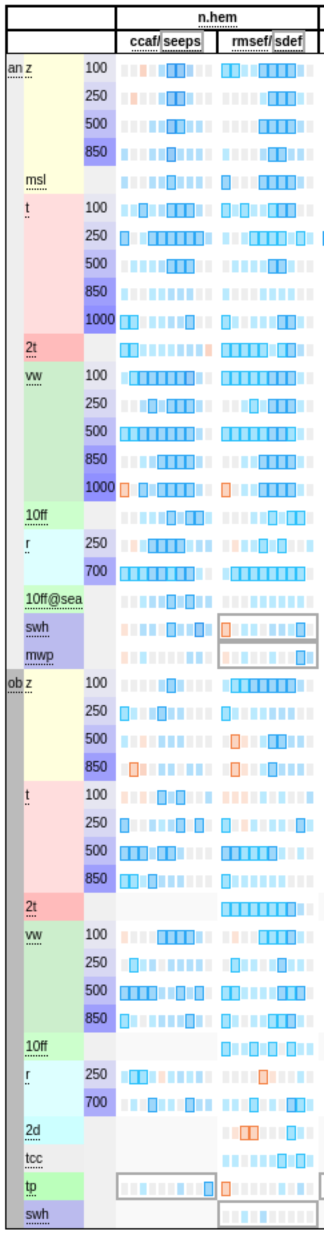
Vector wind error reduction





Surface air temperature improvement

Scorecard →
(blue= improved
red=degraded)



Kenta Ochi et al.

Summary on snow analysis

1. Snow initialisation has a large impact on Numerical Weather Forecast

2. Not all NWP systems have a snow analysis. Snow data assimilation in NWP systems relies on relatively simple approaches, with in situ snow depth and satellite snow cover assimilated → importance of access to snow depth reports on the GTS

4. Current and future developments: aim at using level 1 satellite data to analyse snow water equivalent (mass) → Require appropriate satellite mission and adequate observation operators

Outline

- Introduction
- Snow analysis
- **Soil moisture analysis**
- Land-atmosphere coupling

A history of soil moisture analysis at ECMWF

- **Nudging scheme (1995-1999): soil moisture increments Δx (m^3m^{-3}):**

$$\Delta x = \Delta t \, D \, C_v \left(q^a - q^b\right)$$

D: nudging coefficient (constant=1.5g/Kg), Δt = 6h, q specific humidity
Uses upper air analysis of specific humidity
Prevents soil moisture drift in summer

- **Optimal interpolation 1D OI (1999-2010)**

$$\Delta x = \alpha \left(T^a - T^b\right) + \beta \left(Rh^a - Rh^b\right)$$

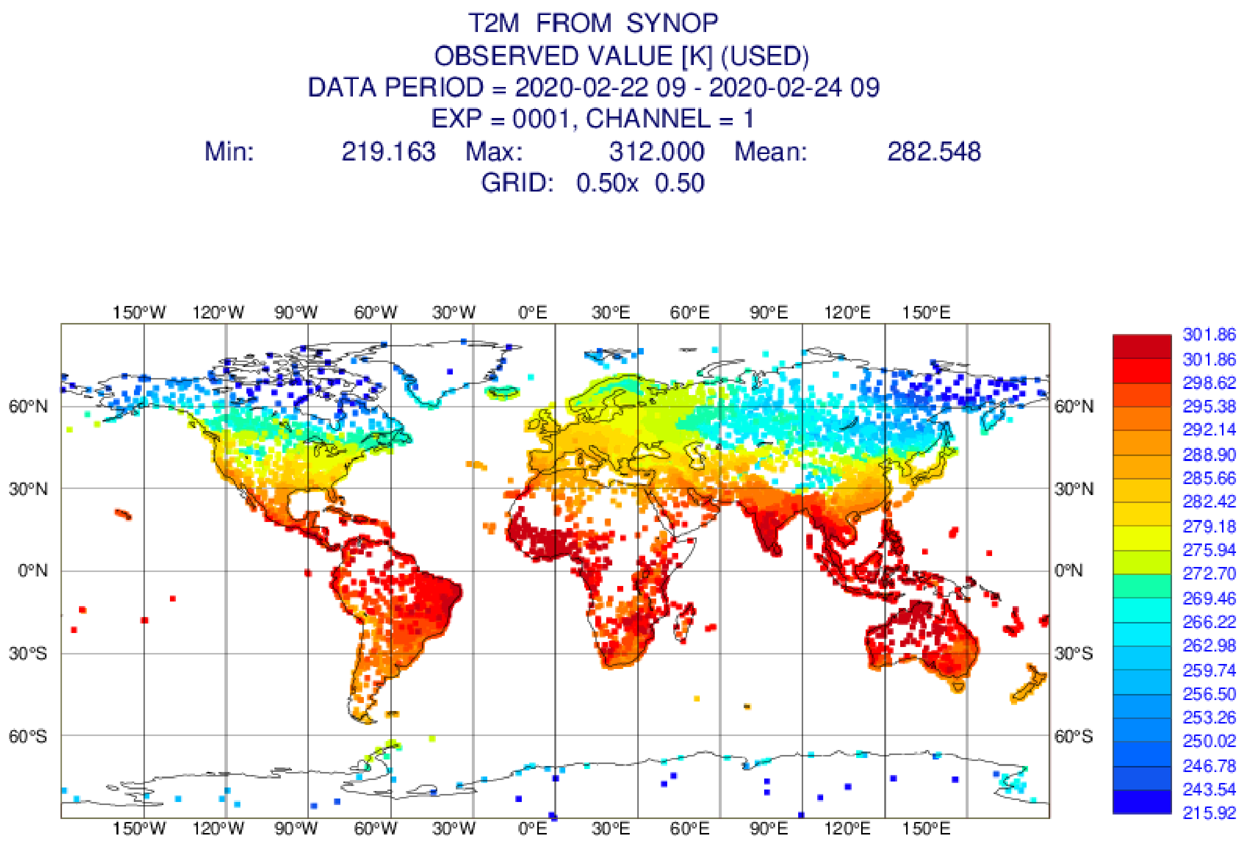
α and β: optimal coefficients
OI soil moisture analysis based on a dedicated screen level parameters (T2m Rh2m) analysis

Mahfouf, ECMWF News letter 2000,
Douville et al., Mon Wea. Rev. 2000

- **Simplified Extended Kalman Filter (SEKF), Since 2010**
  - Motivated by better using T2m, RH2m
  - Opening the possibility to assimilate satellite data related to surface soil moisture
  - EDA-SEKF (since 2019) uses the Ensemble Data Assimilation to compute the SEKF Jacobians

Drusch et al., GRL, 2009
de Rosnay et al., QJRMS 2013

SYNOP T2m, RH2m in situ data assimilated in a 2D-OI

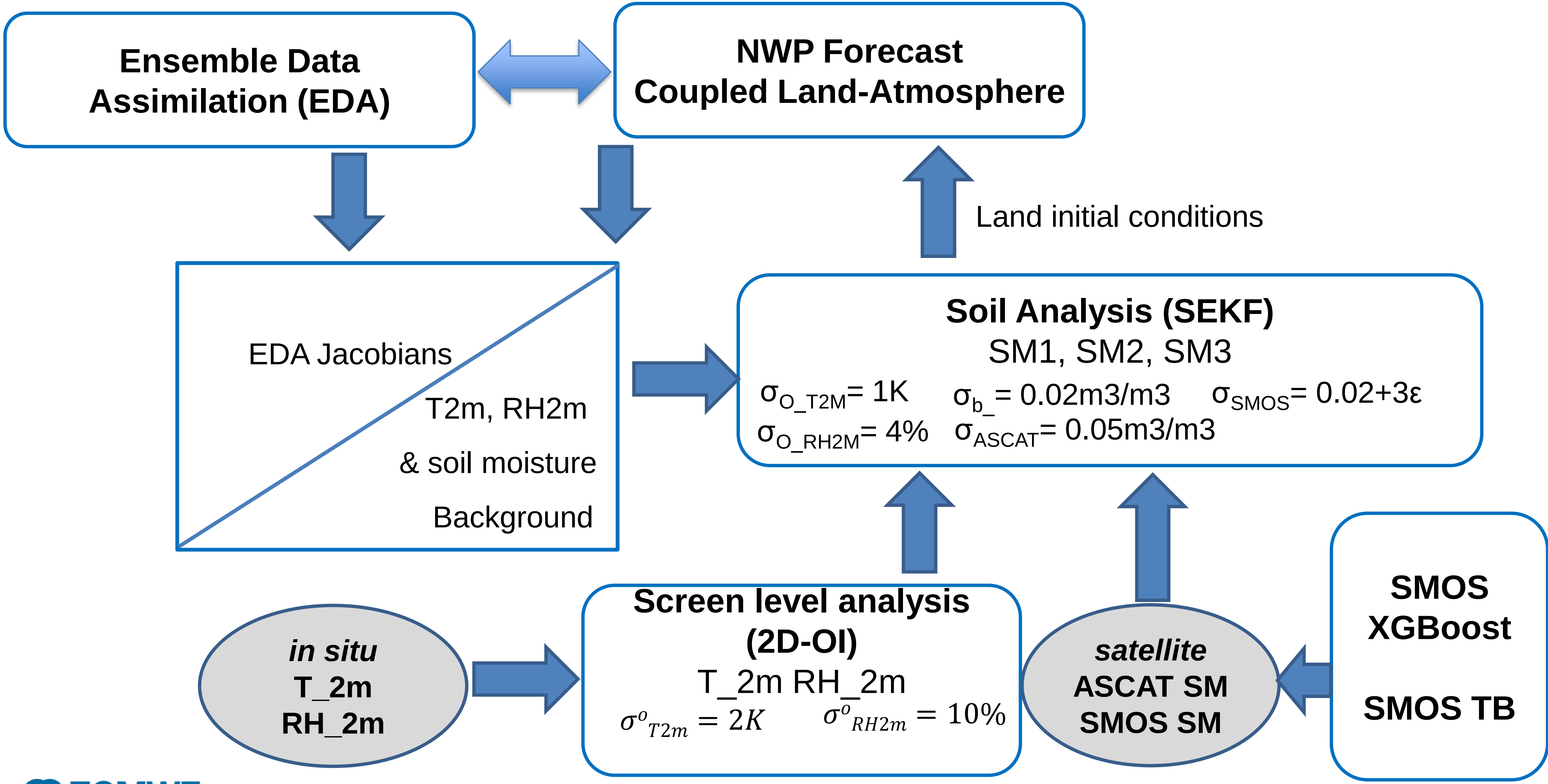


Screen level observations are:
- T2m, two meter temperature
- RH2m, relative humidity (RH2m)

Diversity of Report types:
Automatic and manual SYNOP stations, METAR (METeorological Airport Reports), etc…

The output of the 2D-OI fields, the analysed T2m and RH2m, are used as input of the soil analysis

ECMWF Soil Analysis for NWP



Soil moisture satellite observations assimilated operationally

Active microwave data:

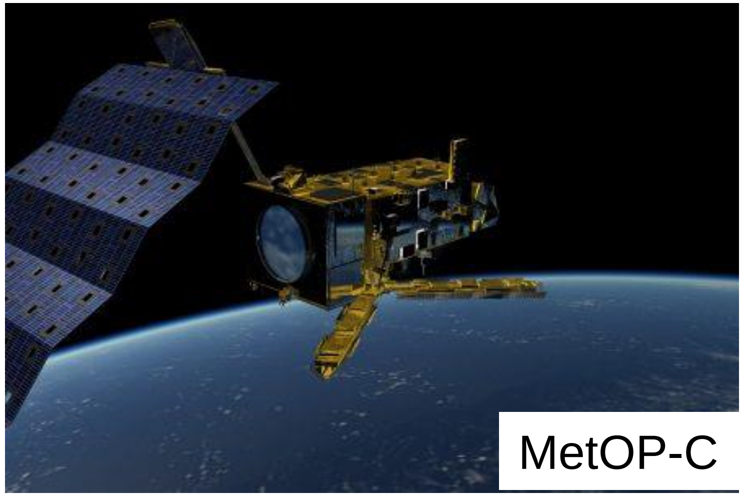
ASCAT: Advanced Scatterometer

On MetOP-A (2006-2021),

MetOP-B (2012-), MetOP-C (2018-)

C-band (5.6GHz) backscattering coefficient

EUMETSAT Operational mission



MetOP-C

Scatterometer soil moisture also used in ERA5 (ERS-SCAT, Metop/ASCAT)

Passive microwave data:

SMOS: Soil Moisture & Ocean Salinity (2009-)

L-band (1.4 GHz) Brightness Temperature

ESA Earth Explorer, dedicated soil moisture mission

(Munoz-Sabater et al., 2020, Rodriguez-Fernandez et al., 2019, Salonen et al in prep 2025)

SMOS

Simplifed EKF soil moisture analysis

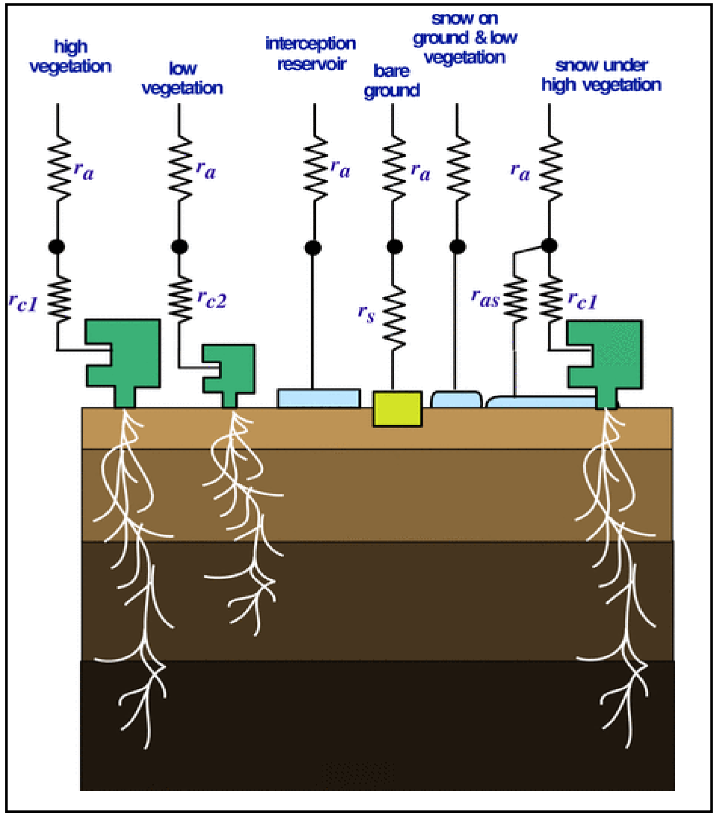
For each grid point, analysed soil moisture state vector $\boldsymbol{x}_a$:

$$\boldsymbol{x}_a = \boldsymbol{x}_b + \boldsymbol{K}(\boldsymbol{y} - \mathcal{H}[\boldsymbol{x}_b])$$

$\boldsymbol{x}$ background soil moisture state vector,
$\mathcal{H}$ non linear observation operator
$\boldsymbol{y}$ observation vector
$\boldsymbol{K}$ Kalman gain matrix, fn of
H (linearsation of $\mathcal{H}$), **P** and **R** (covariance matrices of background and observation errors).

Used at ECMWF (NWP, ERA5, ERA6), DWD, UKMO

The simplified EKF is used to corrects the soil moisture trajectory of the Land Surface Model



Drusch et al., GRL, 2009
de Rosnay et al., QJRMS, 2013
Fairbairn et al., JHM 2019
Munoz-Sabater et al QJRMS, 2019
Rodriguez-Fernandez et al, RS 2019

Simplifed EKF soil moisture analysis

$\boldsymbol{x}_a = \boldsymbol{x}_b + \boldsymbol{K}\,(\boldsymbol{y} - \mathcal{H}[\boldsymbol{x}_b])$

Elements of the SEKF for each individual grid point in the case of:

- Assimilation of 4 observations: T2m, RH2m, ASCAT_{sm}, SMOS_{sm}
- State vector **x**: volumetric soil moisture (SM) of the model layers, l1, l2, l3 (in m3/m3)

Control vector

$$\mathbf{x}\mathrm{b}_{(t)} = \begin{bmatrix} SM_{l1(t)} \\ SM_{l2(t)} \\ SM_{l3(t)} \end{bmatrix}$$

Observations vector

$$\mathbf{y}\ (\mathrm{tobs}) = \begin{bmatrix} \mathrm{T}_{2\mathrm{m}} \\ RH_{2m} \\ ASCATsm \\ SMOS_{SM} \end{bmatrix} \quad \begin{matrix} [\mathrm{K}] \\ [\%] \\ [\mathrm{m}^3/\mathrm{m}^3] \\ [\mathrm{m}^3/\mathrm{m}^3] \end{matrix}$$

Observations operator

$$\mathcal{H}\,[\mathrm{x}_b^{\,t}]) = \begin{bmatrix} \mathrm{T}_{2\mathrm{m}} \\ RH_{2m} \\ SM_{top} \\ SM_{top} \end{bmatrix}$$

Observation error

$$\mathbf{R} = \begin{bmatrix} 1^2 & 0 & 0 & 0 \\ 0 & 4^2 & 0 & 0 \\ 0 & 0 & 0.05^2 & 0 \\ 0 & 0 & 0 & Esmos \end{bmatrix}$$

Background error

$$\mathbf{P} = \begin{bmatrix} 0.02^2 & 0 & 0 \\ 0 & 0.02^2 & 0 \\ 0 & 0 & 0.02^2 \end{bmatrix}$$

Simplifed EKF soil moisture analysis

<u>Jacobians computation in Finite differences</u>: in ERA5 and NWP until June 2019

Estimated by finite differences by perturbing individually each component x_j of the control vector **x** by a small amount δx_j . One perturbed model trajectory is computed for each control variable

In the ECMWF soil analysis, the perturbation size is set to $0.01 m^3 m^{-3}$

$$H = \begin{bmatrix} \frac{T_{2m}pert1 - T_{2m}}{\delta SM_{l1}} & \frac{T_{2m}pert2 - T_{2m}}{\delta SM_{l2}} & \frac{T_{2m}pert3 - T_{2m}}{\delta SM_{l3}} \\ \frac{RH_{2m}pert1 - RH_{2m}}{\delta SM_{l1}} & \frac{RH_{2m}pert2 - RH_{2m}}{\delta SM_{l2}} & \frac{RH_{2m}pert3 - RH_{2m}}{\delta SM_{l3}} \\ \frac{SM_{l1}pert1 - SM_{l1}}{\delta SM_{l1}} & \frac{SM_{l1}pert2 - SM_{l1}}{\delta SM_{l2}} & \frac{SM_{l1}pert3 - SM_{l1}}{\delta SM_{l3}} \\ \frac{SM_{l1}pert1 - SM_{l1}}{\delta SM_{l1}} & \frac{SM_{l1}pert2 - SM_{l1}}{\delta SM_{l2}} & \frac{SM_{l1}pert3 - SM_{l1}}{\delta SM_{l3}} \end{bmatrix}$$

Simplifed EKF soil moisture analysis

<u>Jacobians computation based on the EDA</u>: in NWP since June 2019 (see IFS cycle 49r1 Doc)

Use the EDA (Ensemble Data Assimilation) spread to compute covariances and the SEKF Jacobians

In the case of assimilation of four observations T2m, RH2m, ASCAT, SMOS:

09:00 21:00

Single trajectory

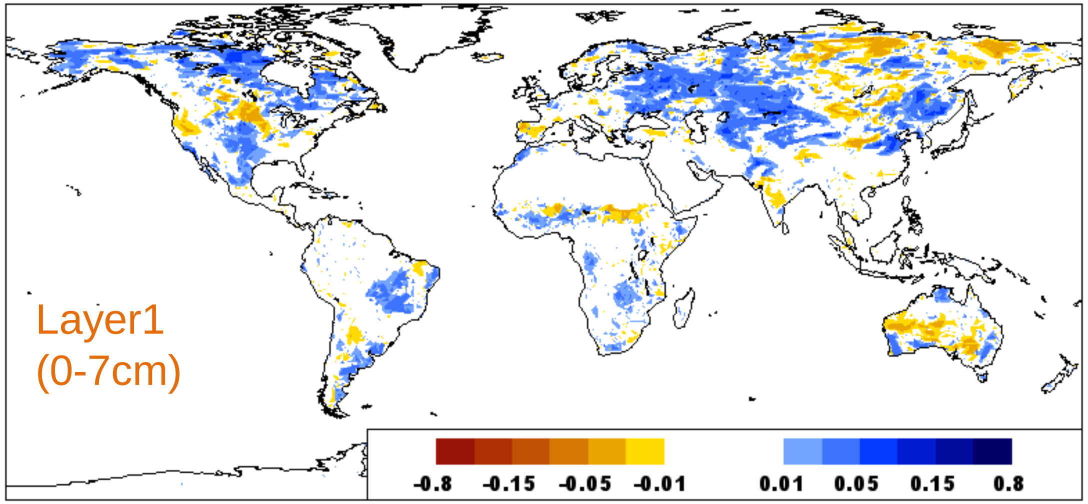
$$H = \begin{bmatrix} \frac{Covar(T_{2m},SM_1)}{Var(SM_1)} & \frac{Covar(T_{2m},SM_2)}{Var(SM_2)} & \frac{Covar(T_{2m},SM_3)}{Var(SM_3)} \\ \frac{Covar(RH_{2m},SM_1)}{var(SM_1)} & \frac{Covar(RH_{2m},SM_2)}{Var(SM_2)} & \frac{Covar(RH_{2m},SM_3)}{Var(SM_3)} \\ \frac{Covar(SM_1,SM_1)}{var(SM_1)} & \frac{Covar(SM_1,SM_2)}{Var(SM_2)} & \frac{Covar(SM_1,SM_3)}{Var(SM_3)} \\ \frac{Covar(SM_1,SM_1)}{var(SM_1)} & \frac{Covar(SM_1,SM_2)}{Var(SM_2)} & \frac{Covar(SM_1,SM_3)}{Var(SM_3)} \end{bmatrix} \circ \begin{bmatrix} \rho_1 & \rho_2 & \rho_3 \\ \rho_1 & \rho_2 & \rho_3 \\ \rho_1 & \rho_2 & \rho_3 \\ \rho_1 & \rho_2 & \rho_3 \end{bmatrix}$$

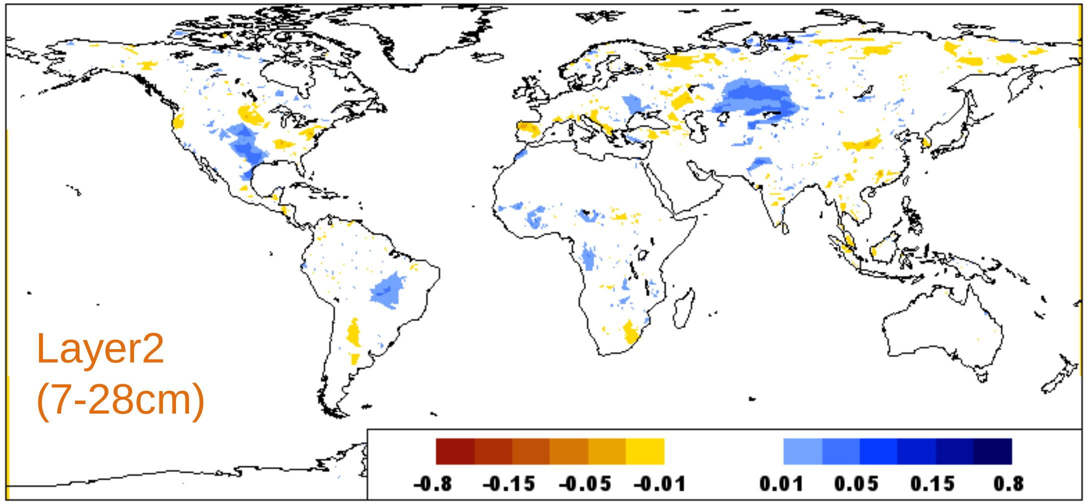
with i soil layer index, $\rho_i = 1/[1+ (i-1)\,\alpha_{sekf}]$ and $\alpha_{sekf} = 0.6$ tapering coefficient

ECMWF

Soil moisture increments: Case study with ASCAT, T2m, RH2m

Volumetric Soil Moisture increments (m^3/m^3) (accumulated) 25-30 June 2013





Vertically integrated Soil Moisture increments (stDev in mm)

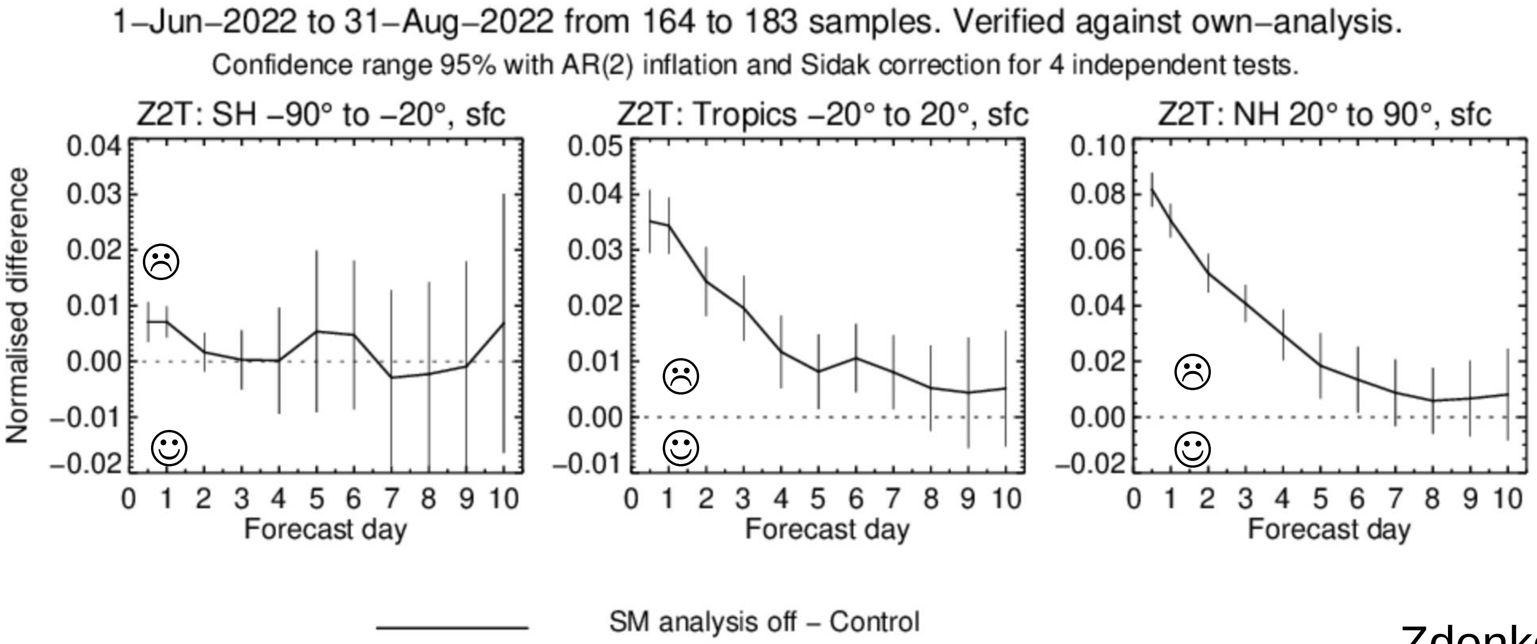
	SYNOP	ASCAT
Layer 1	0.68	**1.43**
Layer 2	**1.48**	0.68
Layer 3	**4.28**	0.46

ASCAT more increments than SYNOP at surface
SYNOP give more increments at depth
→ For 12h DA window, link obs to root zone stronger for T2m,RH2m than for surface soil moisture observations

Soil analysis: impact on the atmospheric forecast

Temperature RMSE

JJA 2022
IFS cycle 49r1



Zdenko Heyvaert

Significant positive impact of soil moisture DA on low level atmospheric temperature forecasts

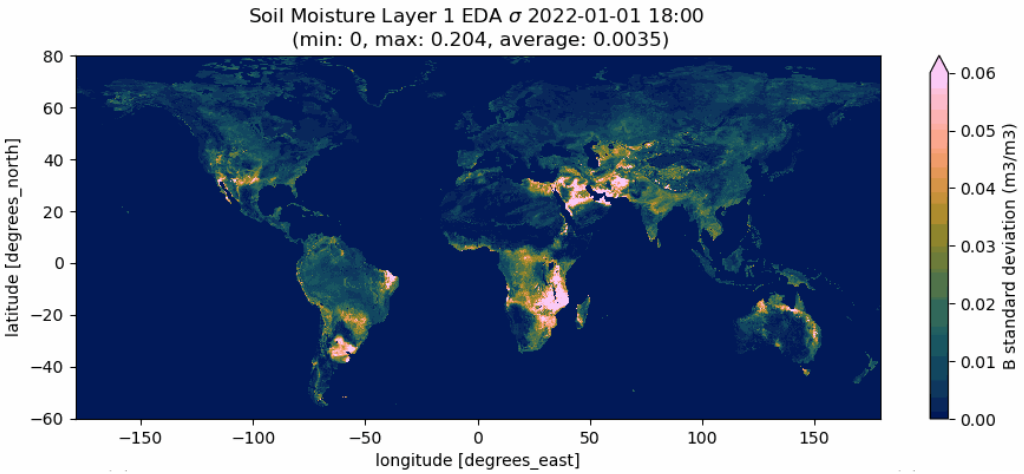
Upcoming changes: Ensembles for the Land Surface

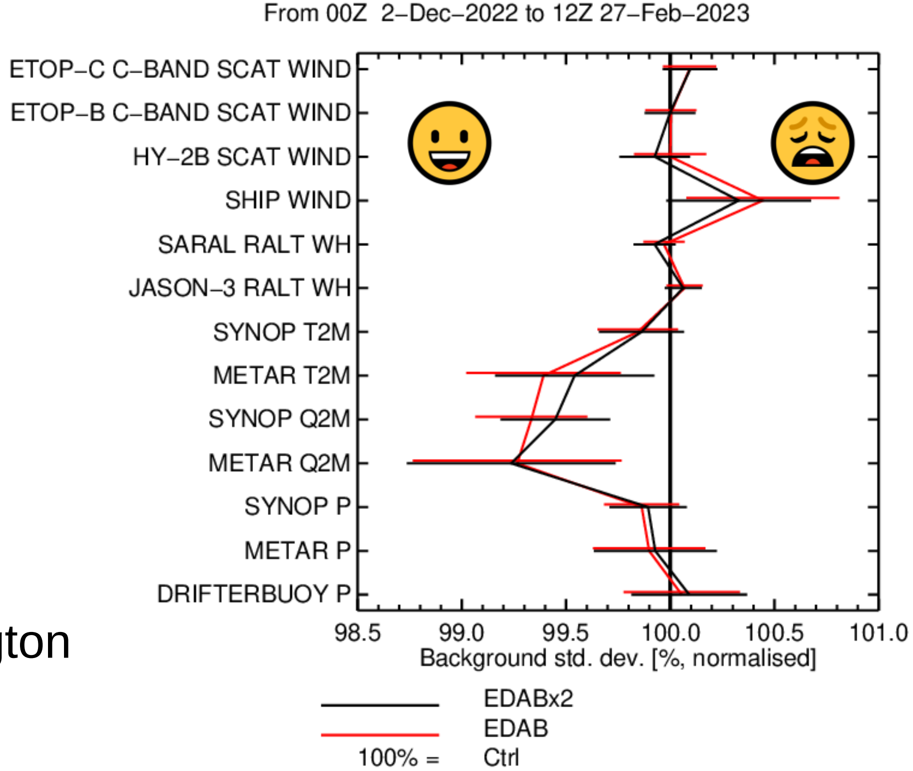
- Background errors currently static

- Spread in Ensemble of Data Assimilations (EDA) soil moisture up to 10x larger than current specified static Background error (0.02 m^3 m^{-3})

- Find improvement in surface temperature and humidity scores against observations when using flow-dependent **B**

→ Flow-dependent **B** matrix in CY50R1 (2025)





Ewan Pinnington

Summary on soil moisture analysis

- Significant **impact** of soil moisture analysis on low level atmospheric forecasts
- **Approaches**: **1D-OI** (Météo-France, ECMWF ERA-I); **SEKF** (DWD, ECMWF/ERA5, UKMO); **SEKF-EDA**(ECMWF/NWP)
- **Data**: Most Centres rely on screen level data (**T2M and RH2m**) through a dedicated 2D-OI analysis, **ASCAT** (UKMO, ECMWF NWP & EUMETSAT H-SAF), **SMOS** soil moisture (ECMWF)

Outline

- Introduction
- Snow analysis
- Soil moisture analysis
- **Summary**

Summary

- Coupled land-atmosphere data assimilation
  - → Current operational systems are weakly coupled
  - → Strongly coupled data assimilation based on outer loop coupling in development
- Soil and snow variables are analysed in NWP systems
  - → Significant impact on NWP
- Variety of DA methods for snow and soil moisture at ECMWF and other NWP centres
  - → Ensemble approaches to compute the Jacobians and in developments for flow dependent B

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Snow reanalysis from ERA5 to ERA6

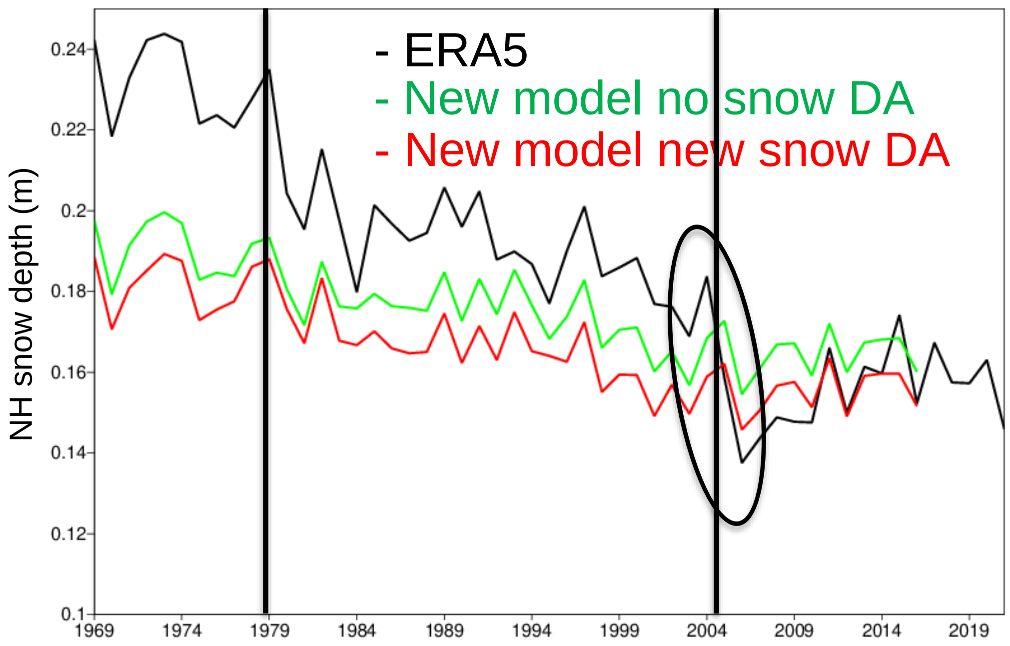
- Step change in the ERA5 snow mass from 2004 (IMS snow cover started to be assimilated)
- Snow DA reduced the positive snow cover bias, but it amplified the snow mass negative trend

Funded by the European Union

ERA6-Land 1st prototype (1939-2022)

ERA6:

- Snow model and a set of snow data assimilation improvements
- ESA CCI Cryoclim (1987-2010) + NOAA/NESDIS IMS (2010-NRT)



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