ECMWF Data Assimilation Training course

Coupled land-atmosphere data assimilation

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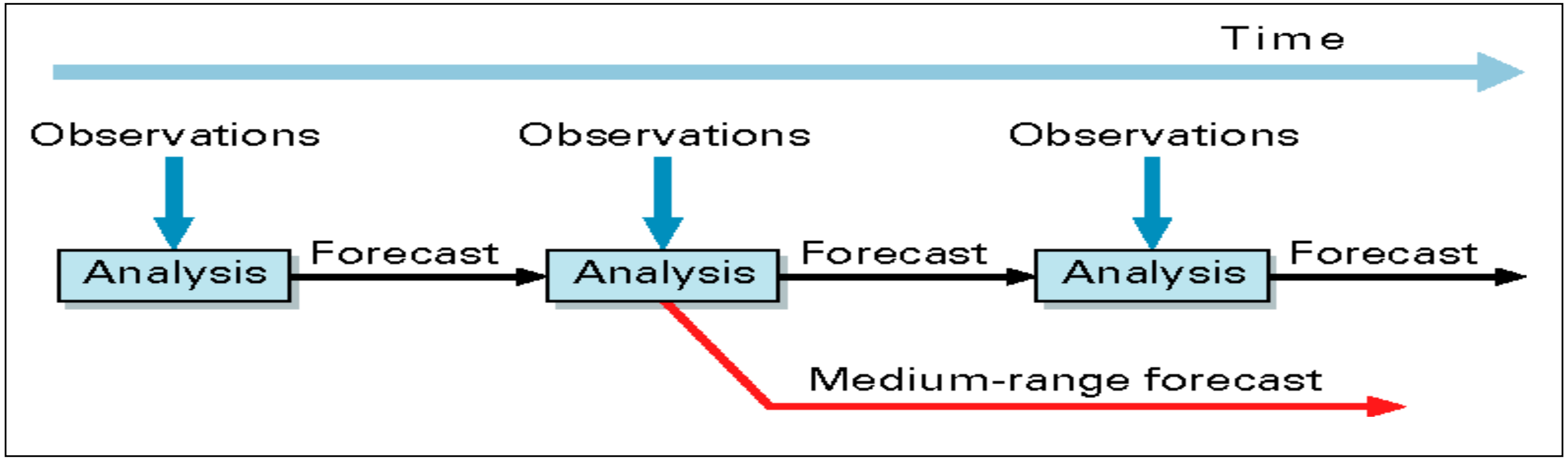
25 May 2023

Outline

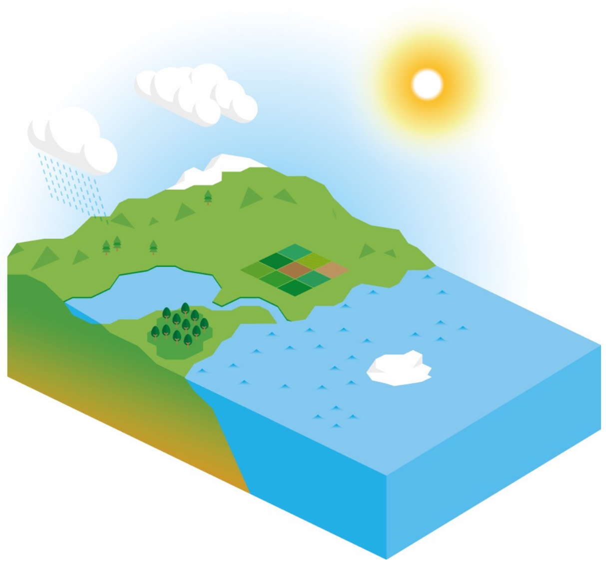
- **Introduction**
- Snow analysis
- Soil moisture analysis
- Summary

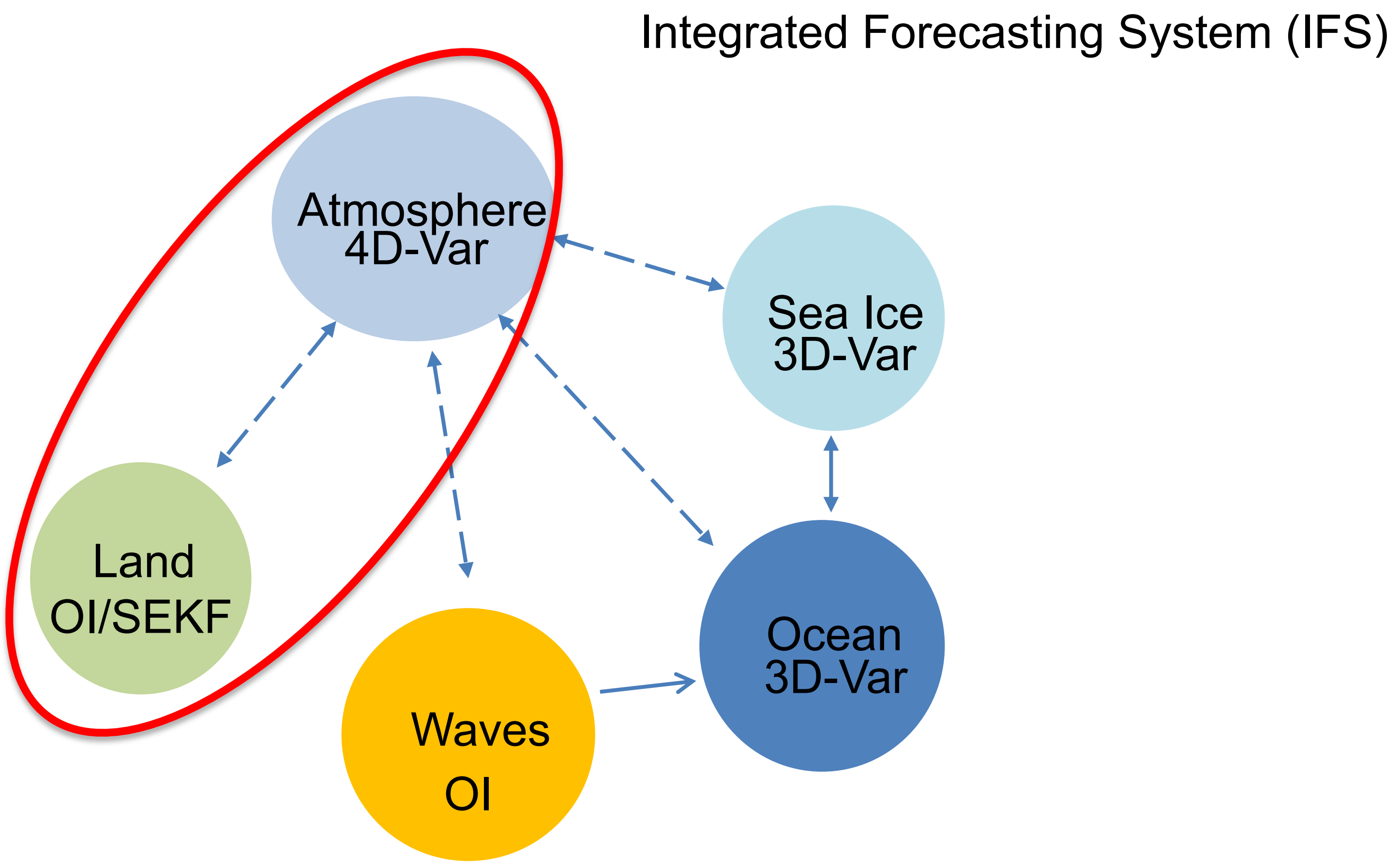
ECMWF Integrated Forecasting System (IFS)



- Coupled medium-range forecast model
- Data assimilation: atmosphere (4D-Var), land (SEKF,OI), waves (OI), ocean/sea ice (3D-Var)

Earth system approach

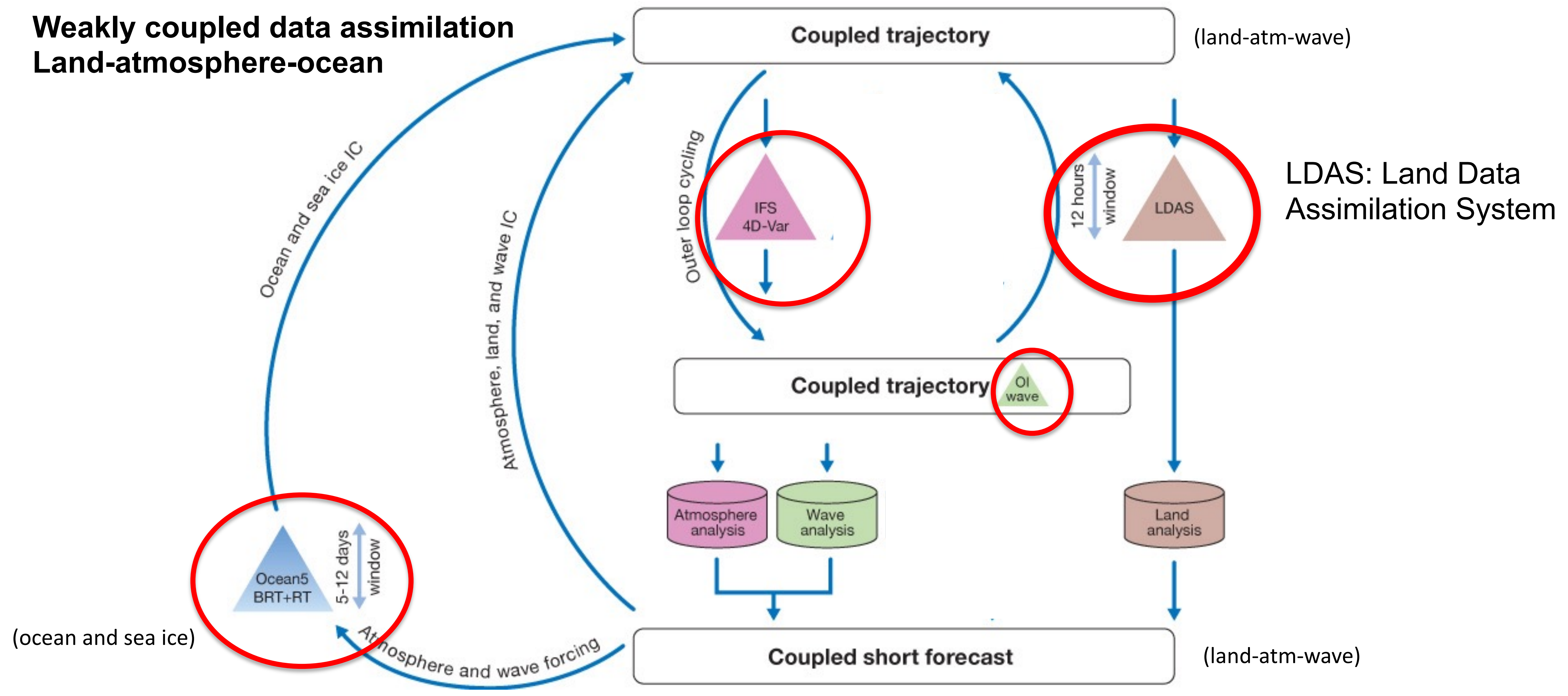




- Consistency of the infrastructure and coupling approaches across the different components
- Modularity to account for the different components in coupled assimilation
- Relevance of interface observations

Coupled Assimilation for operational NWP at ECMWF

Weakly coupled data assimilation
Land-atmosphere-ocean



Relevant lectures:
Ocean and sea ice DA → H Zuo
Coupled DA → P. Browne

Land Surface Data Assimilation (LDAS) for NWP

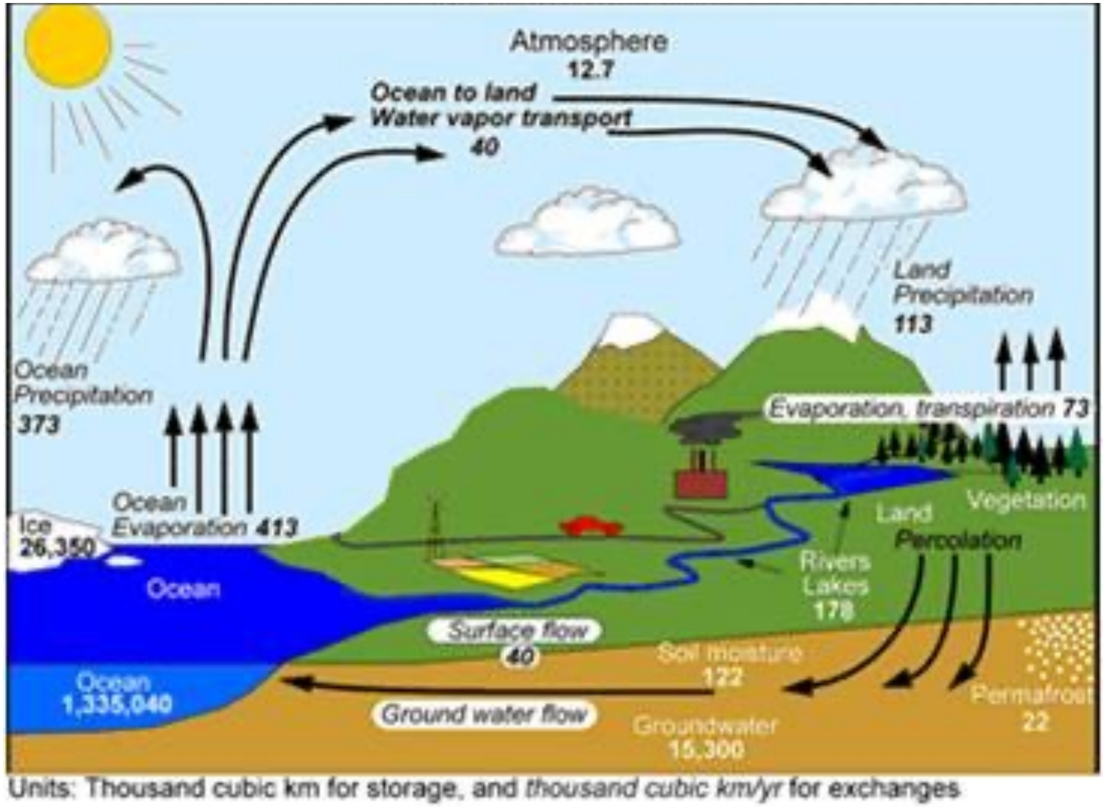


Image: Trenberth et al J. Hydrometeorol. 2007

- 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 (OI) (ECMWF operational and ERA5, Env. Canada Clim. Ch., JMA)
- Conventional Observations: *in situ* snow depth
- Satellite data: NOAA/NESDIS IMS Snow Cover Extent (ECMWF), H-SAF snow cover (UKMO in dvpt)

Soil Moisture

- Methods:
  - -1D Optimal Interpolation (Météo-France, Env. Canada CC, ALADIN and HIRLAM)
  - 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), SMOS (ECMWF)

Soil Temperature and Snow temperature

- 1D OI for the first layer of soil and snow temperature (ECMWF, Météo-France)

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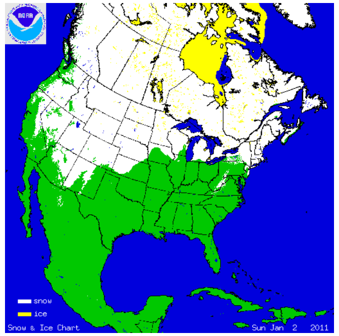
Snow in the ECMWF IFS for NWP

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,
- Multi-layer snowpack from June 2023 (Arduini et al., James 2019)

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

Prognostic variables

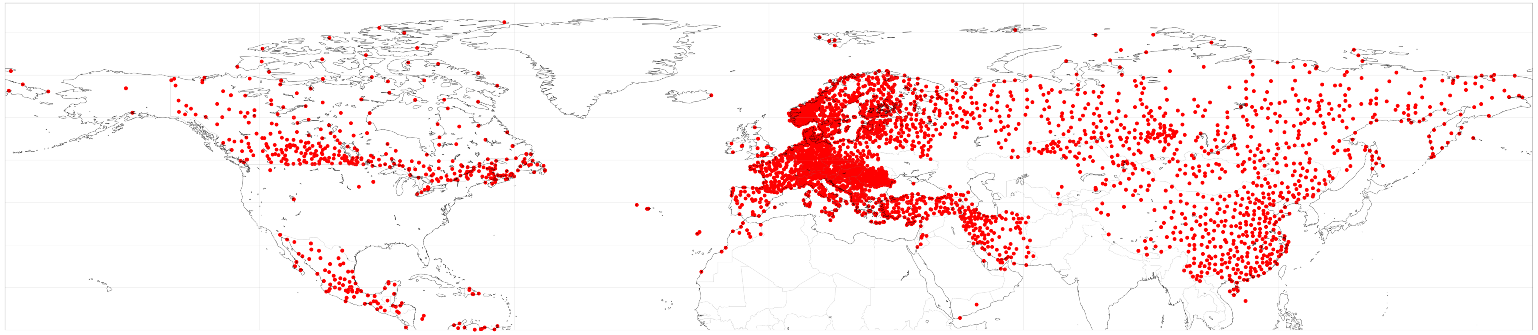
Observations: **de Rosnay et al ECMWF Newsletter 2015**
- Conventional snow depth data: SYNOP and National networks
- Snow cover extent: NOAA NESDIS/IMS daily product (4km)



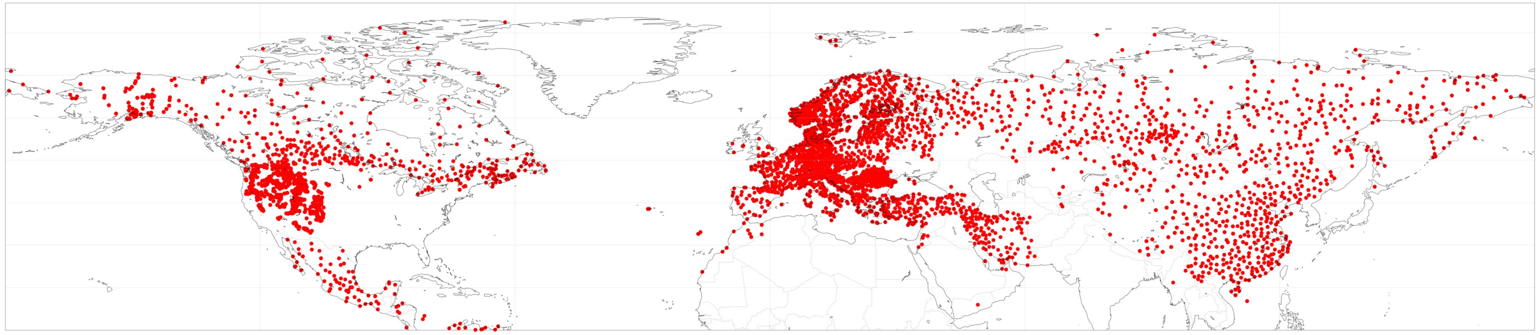
Data Assimilation: **de Rosnay et al SG 2014**
- Optimal Interpolation (OI) is used to optimally combine the model first guess, in situ snow depth and IMS snow cover
- Analysis of SWE and snow density
  → used to initialize NWP.

Land observing system: the example of in situ snow depth

Near-Real-Time access to observations



Prior 29 March 2023



From 29 March 2023

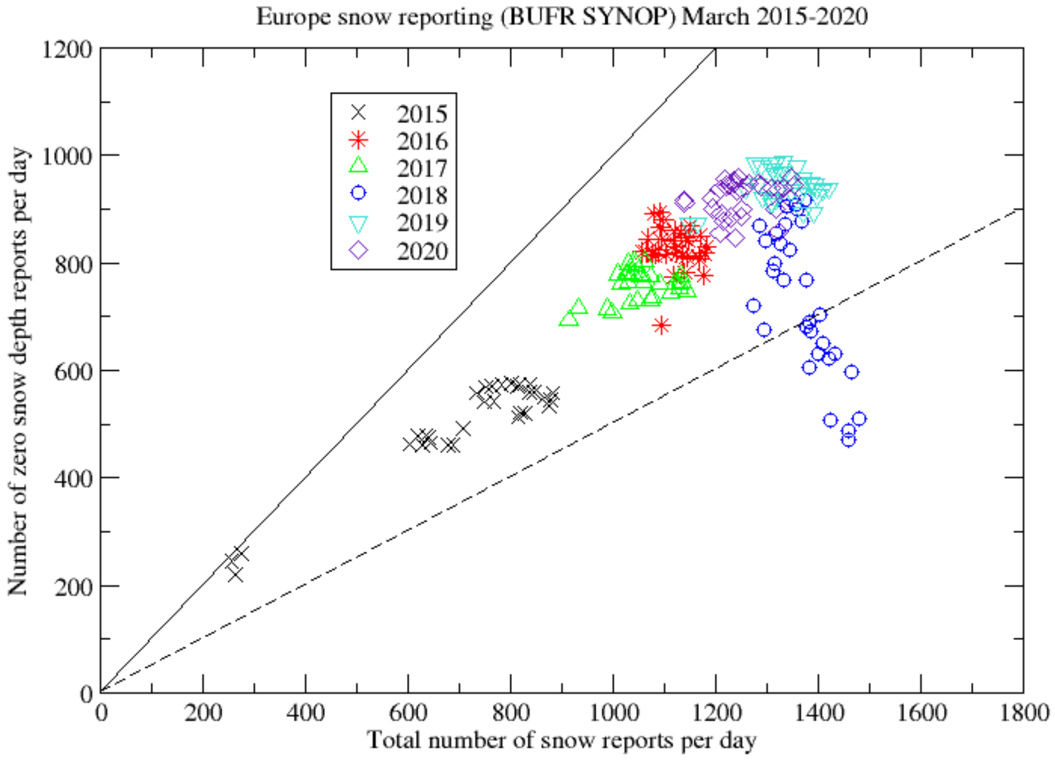
Snow depth availability on the Global Telecommunication System (GTS)

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)
  - Joint Expert Team on Earth Observing System Design and Evolution (JET-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: (**P** + **R**) **w** = **p**

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

P : correlation coefficient matrix of background field error between all pairs of observations (N × 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 × 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):

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

Lz; vertical length scale: 800m, **Lx:** horizontal length scale: 55km
$r_{i1,i2}$ 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 →

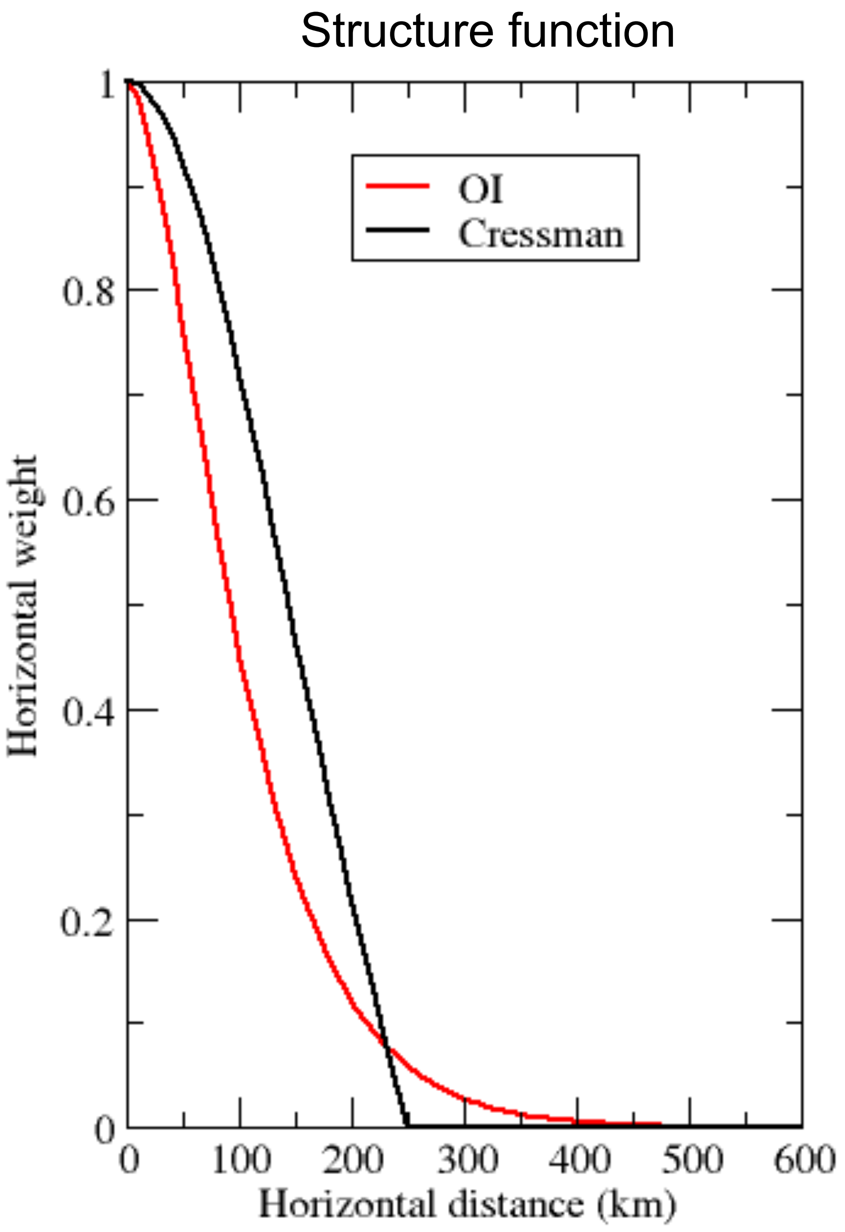
Cressman Interpolation: (Cressman, MWR 1959)

Used in ERA-Interim and NWP until 2010

Optimal Interpolation:

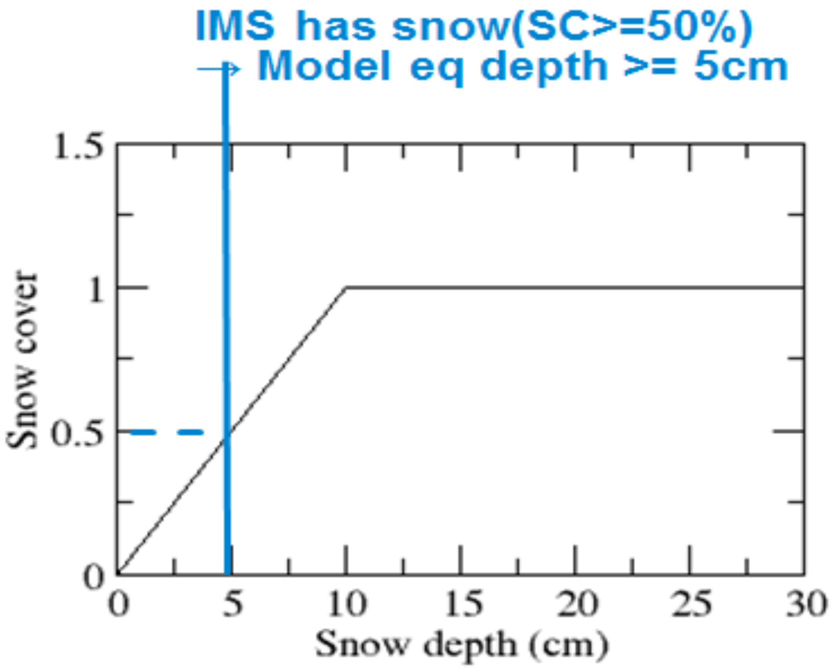
Used in ERA5 and NWP since 2010.

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



Assimilation of IMS snow cover

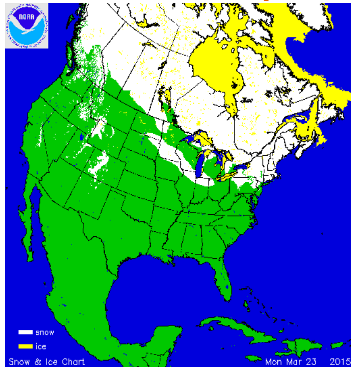
IMS NESDIS \ Fst Guess	Snow	No Snow
Snow	x	**DA** 5cm
No Snow	DA 0cm	DA 0cm



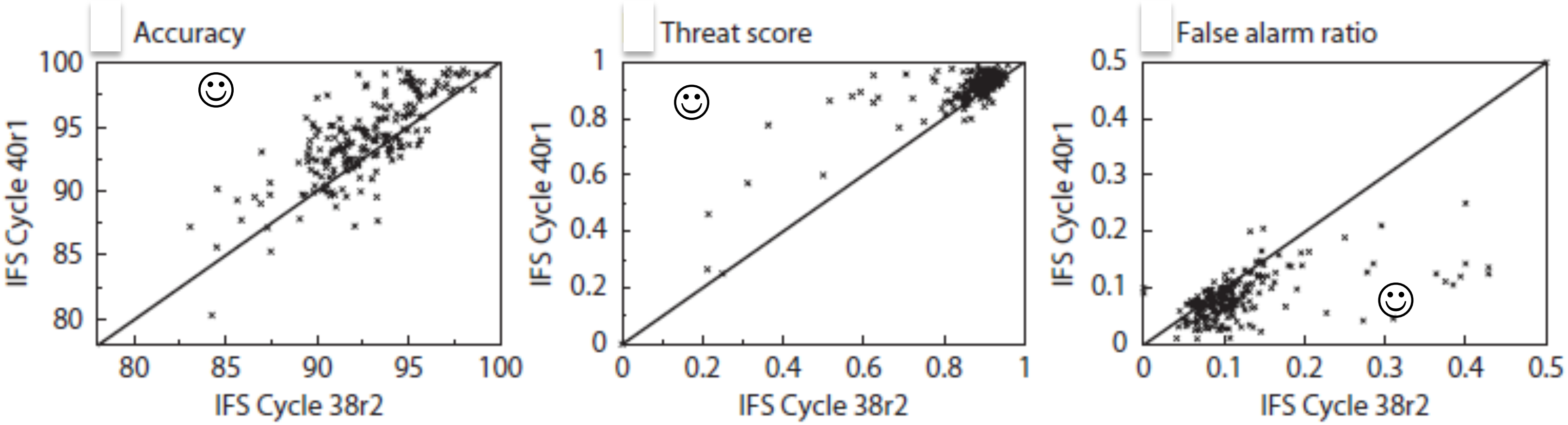
Model relation between SC and SD

Snow assimilation: Forecast impact

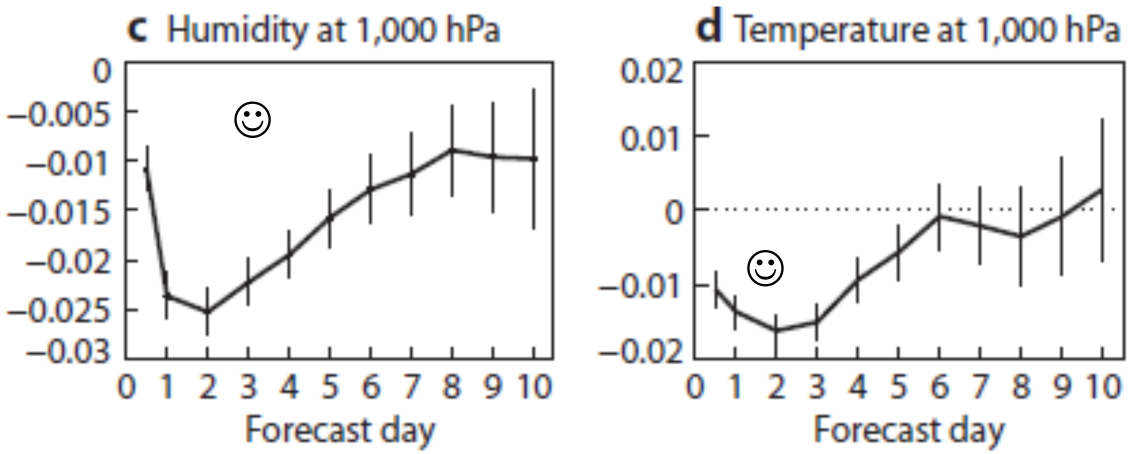
Revised IMS snow cover data assimilation (2013)



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)

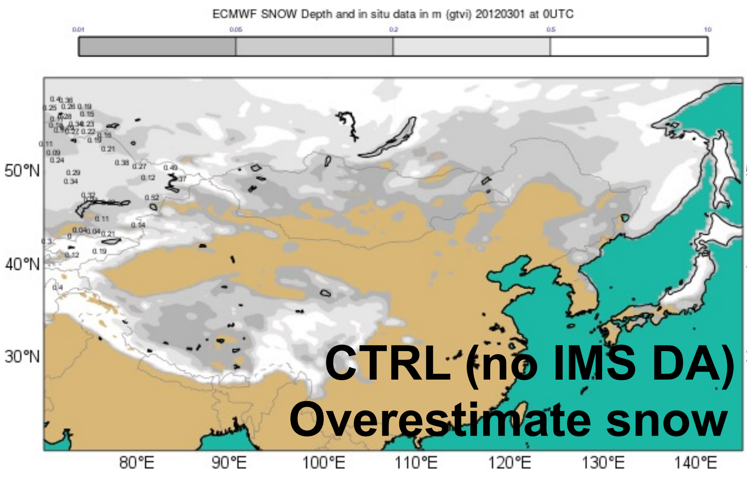


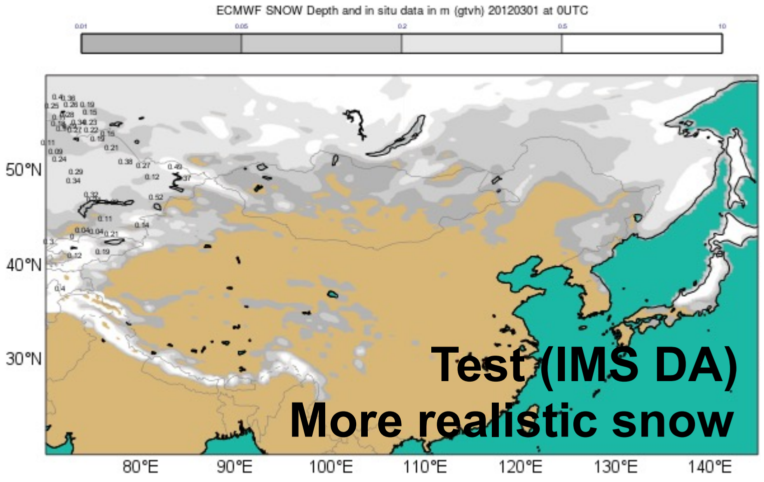
→ Consistent improvement of snow and atmospheric forecasts

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

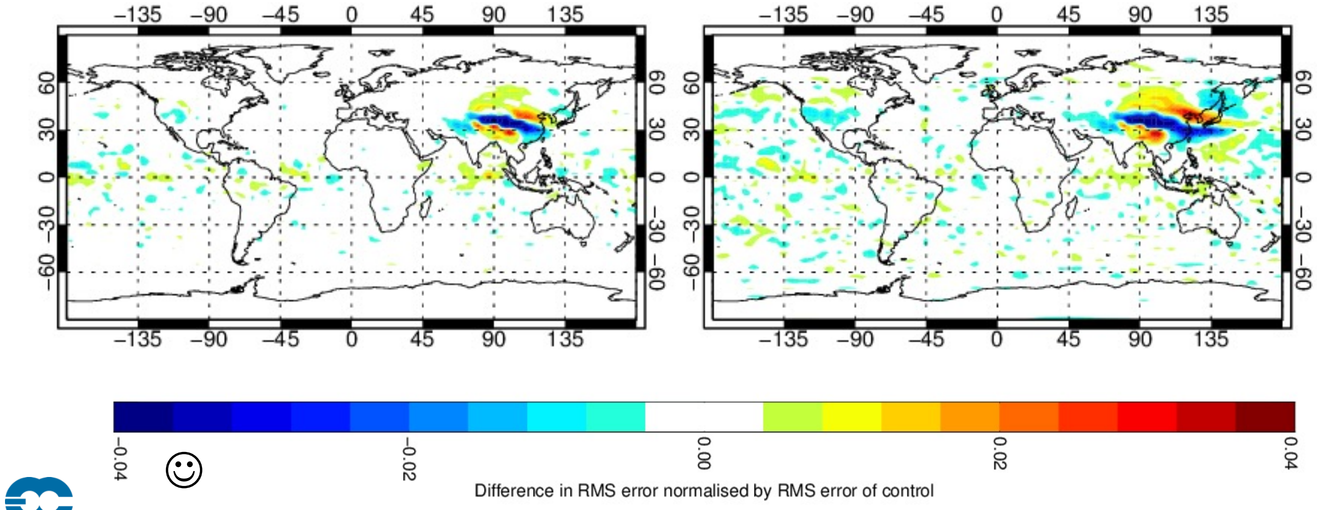




Change in zonal wind
Oct 2011 – June 2012

T+24; 500hPa

T+48; 500hPa



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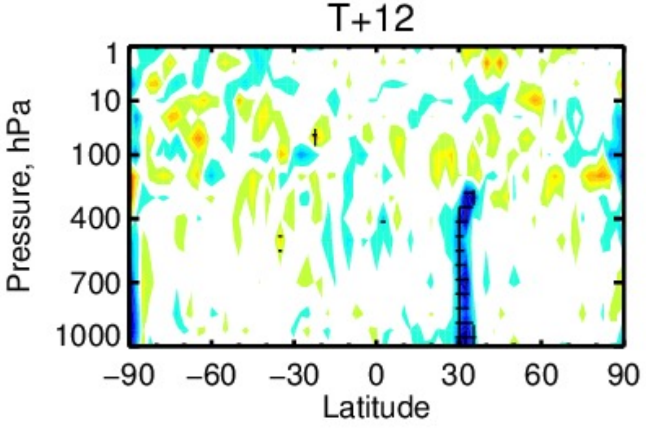
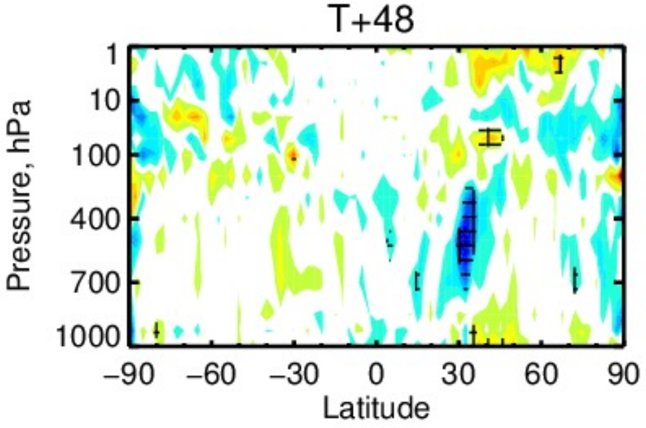
Change in humidity FC error
Oct 2011 – June 2012





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

3. DA of *in situ* snow depth and snow cover (IMS used at ECMWF)
   - In situ snow depth reporting: issues on availability and reporting practices
   - National Met services encouraged to improve snow depth reports availability on the Global Telecommunication System (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 operator

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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)**

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

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

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

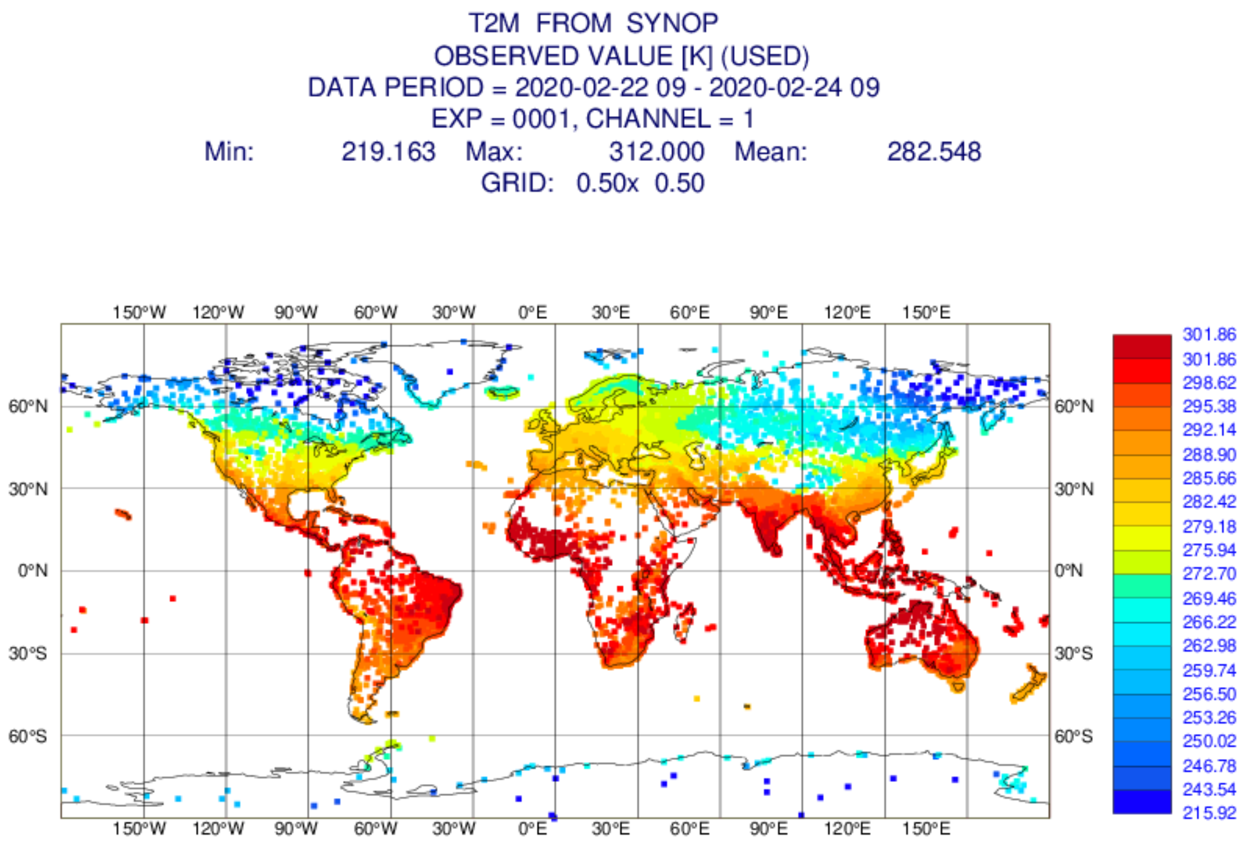
- **Simplified Extended Kalman Filter (SEKF), Nov 2010-2019**

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

  - Motivated by better using T2m, RH2m
  - Opening the possibility to assimilate satellite data related to surface soil moisture

- **EDA-SEKF (since 2019)**
  - Use the Ensemble Data Assimilation to compute the SEKF Jacobians

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

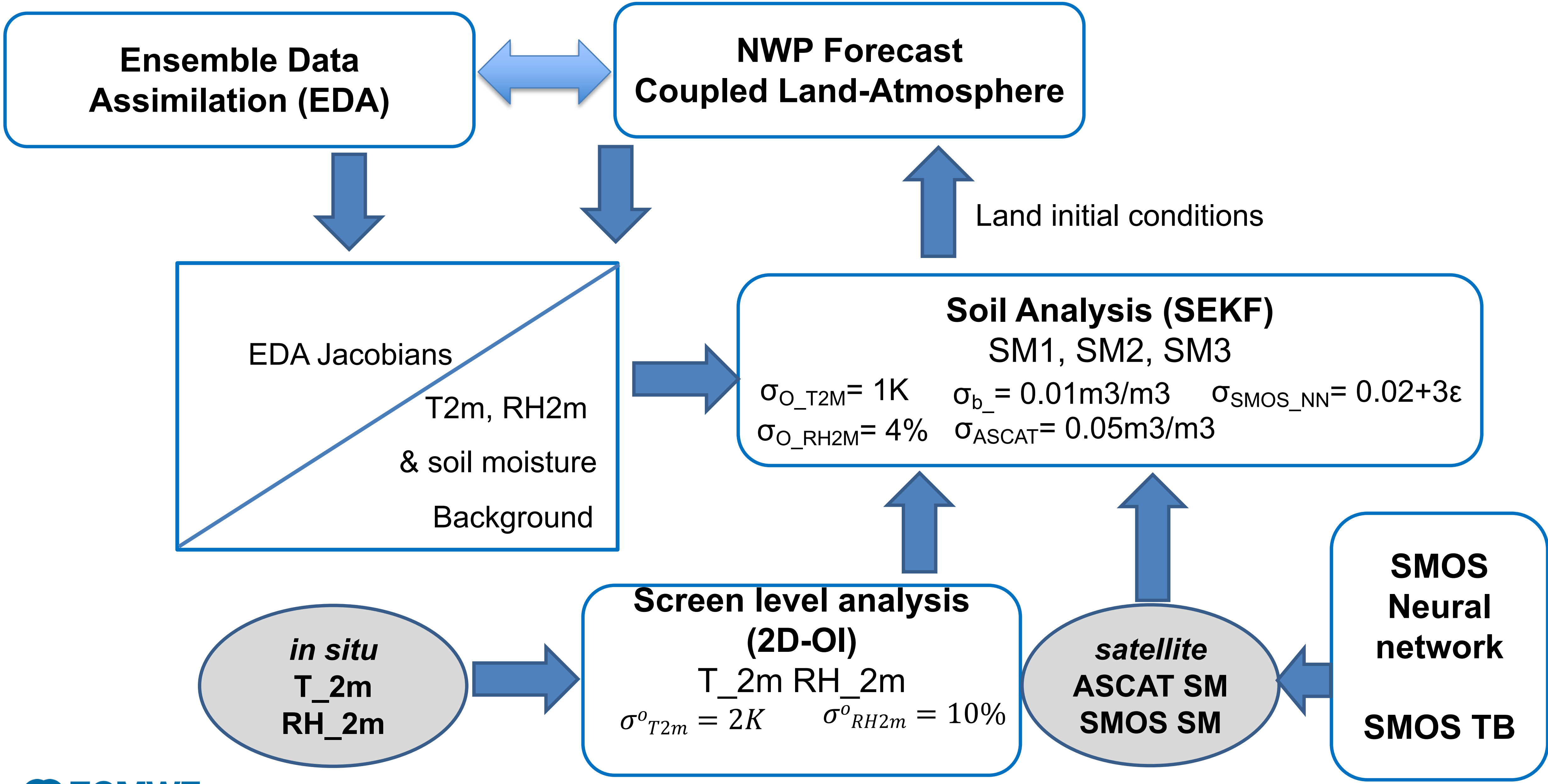


Screen level observations are:
- T2m, two meter temperature
- RH2m, relative humidity (RH2m)

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 used operationally

Active microwave data:

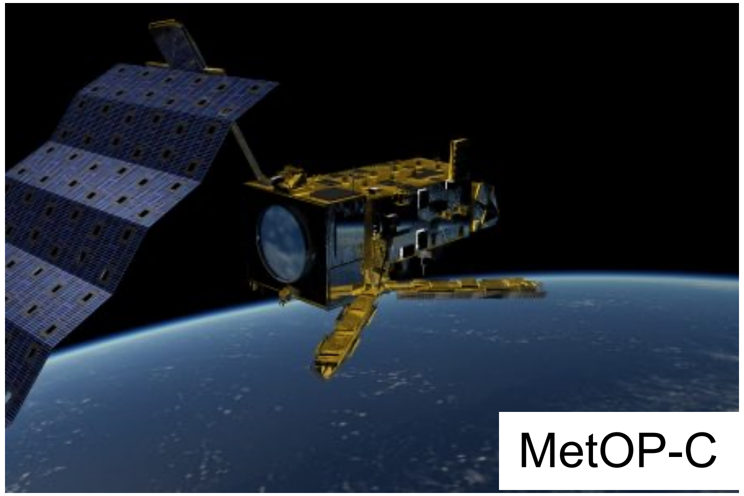
ASCAT: Advanced Scatterometer

On MetOP-A (2006-2021),

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

C-band (5.6GHz) backscattering coefficient

EUMETSAT Operational mission



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)

Simplifed EKF soil moisture analysis

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

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

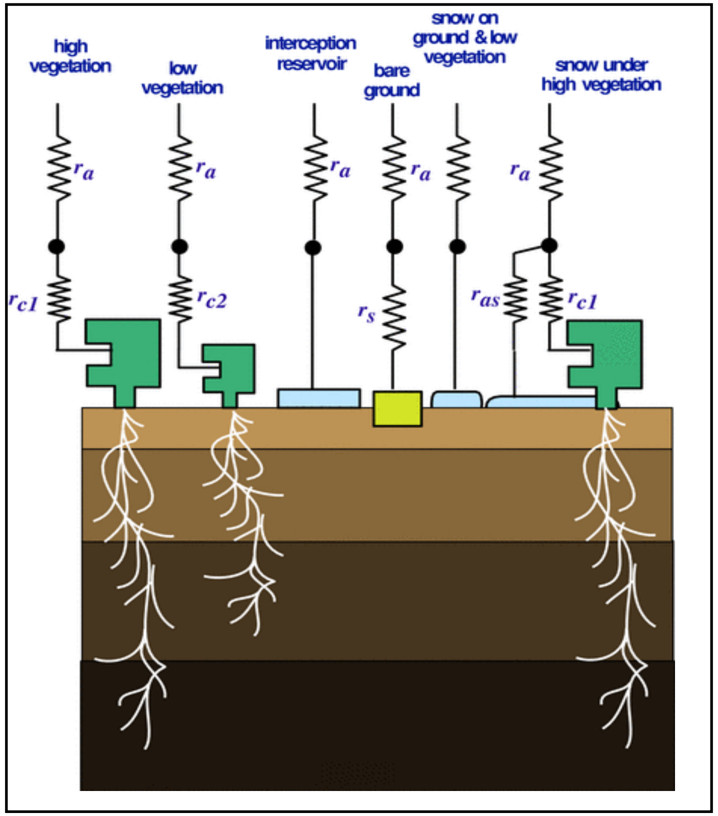
→ See KF lecture from M. Bonavita

$\boldsymbol{x}$ 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 (operations and ERA5), DWD, UKMO

Observations used at ECMWF:
For operational NWP:
- •Conventional SYNOP pseudo observations (analysed T2m, RH2m)
- •Satellite: MetOp-B/C ASCAT and SMOS soil moisture

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., ECMWF News Letter 127, 2011
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

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

Observations vector

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

Observations operator

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

Observation error

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

Background error

$$\mathbf{P} = \begin{bmatrix} 0.01^2 & 0 & 0 \\ 0 & 0.01^2 & 0 \\ 0 & 0 & 0.01^2 \end{bmatrix}$$

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 $\mathbf{x}$ by a small amount δx_j . One perturbed model trajectory is computed for each control valriable

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 (IFS cycle 46r1 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

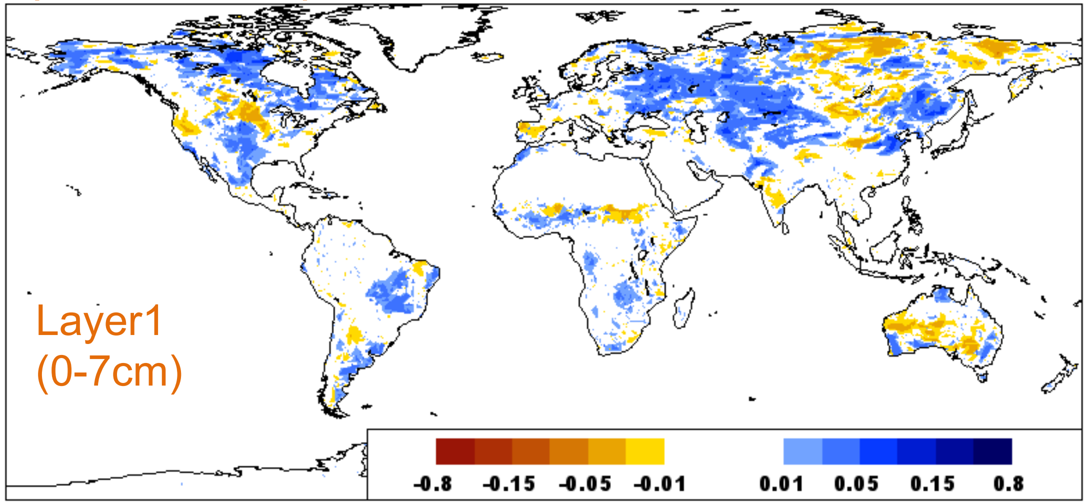
Single trajectory

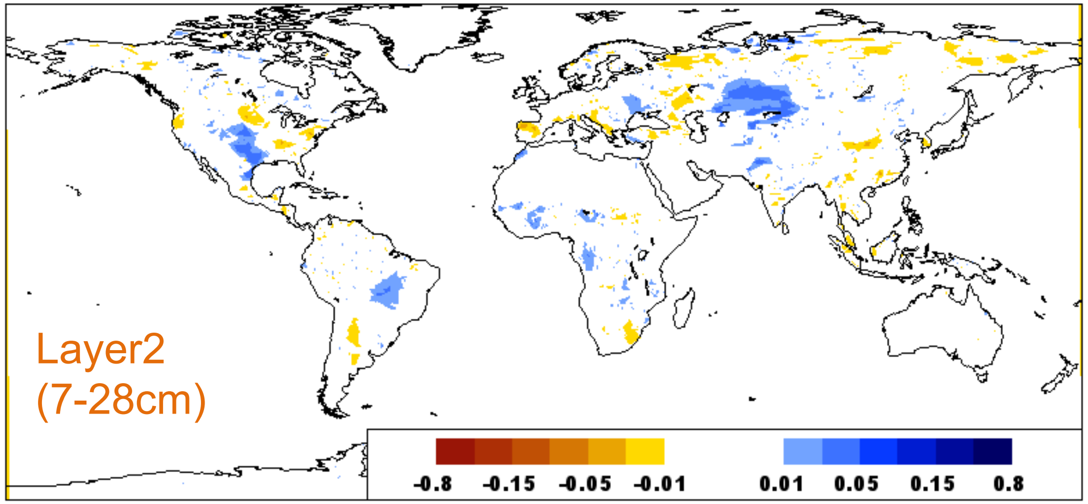
$$H = \begin{bmatrix} \frac{Covar(T_{2m},SM_1)}{Var(SM_1)} & \frac{Covar(T_{2m},SM_2)}{Var(SM_2)} & \frac{Covar(T_{2m},SM_3)}{Var(SM_3)} \\ \frac{Covar(RH_{2m},SM_1)}{var(SM_1)} & \frac{Covar(RH_{2m},SM_2)}{Var(SM_2)} & \frac{Covar(RH_{2m},SM_3)}{Var(SM_3)} \\ \frac{Covar(SM_1,SM_1)}{var(SM_1)} & \frac{Covar(SM_1,SM_2)}{Var(SM_2)}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

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

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)

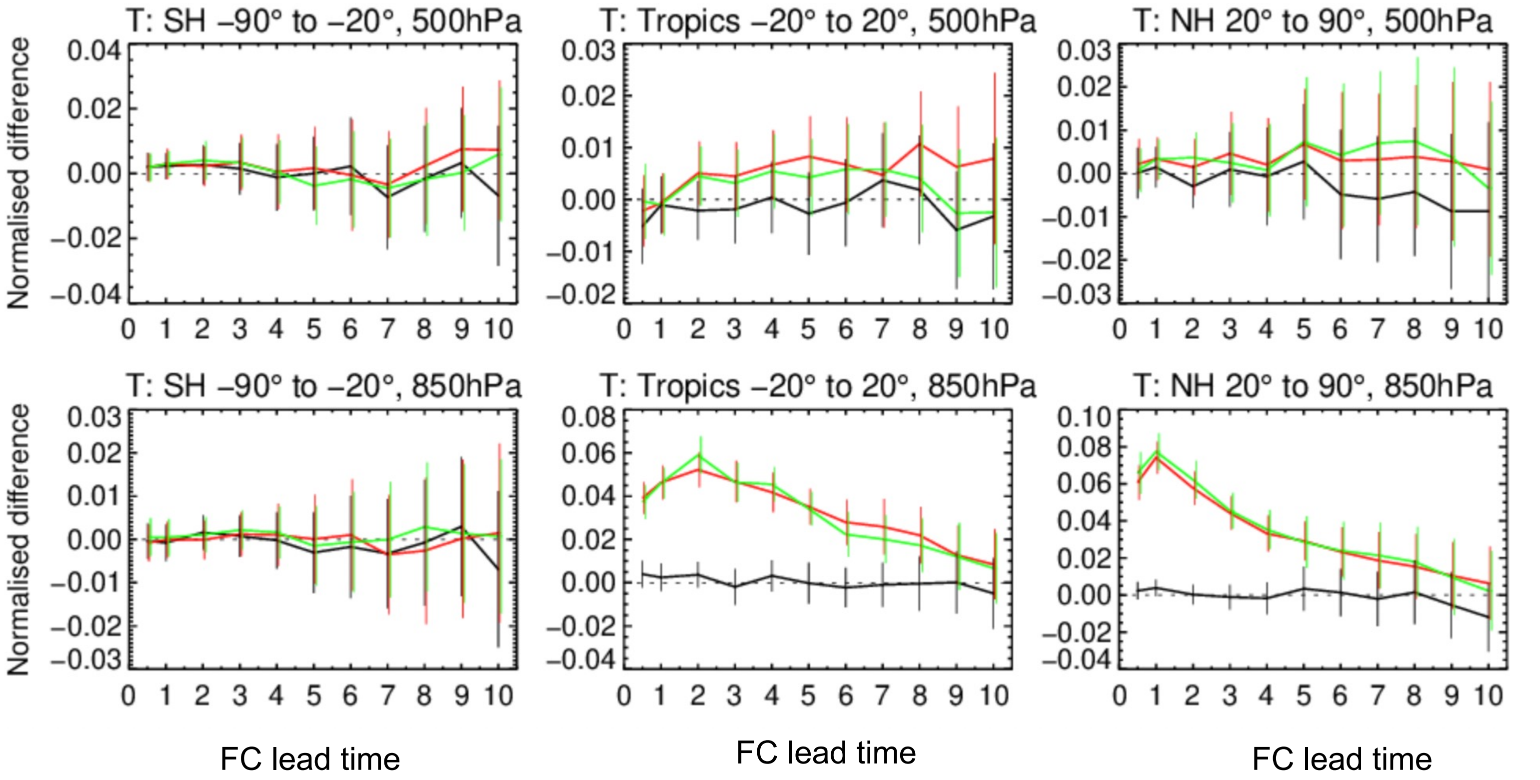
	SYNOP	ASCAT
Layer 1	0.68	**1.43**
Layer 2	**1.48**	0.68
Layer 3	**4.28**	0.46

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 for NWP: impact on the atmospheric forecast

Temperature RMSE

JJA 2020
IFS cycle 48r1



Soil. Moisture DA:
Without without

With

Sébastien Garrigues

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)

Summary

- Soil moisture and snow water equivalent are analysed in NWP systems
- Variety of DA methods for snow and soil moisture at ECMWF and other NWP centres
- Land Data Assimilation Systems: run separately from the atmospheric data assimilation, but first guess forecast is coupled → weakly coupled assimilation,
- Ensemble-based approach at ECMWF to compute the Jacobians enhances coupling
- Stronger coupling plans with outer-loop land-atmosphere developments

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