Overview of ECMWF Surface activities

Presented at the 42nd **EWGLAM** & 27th **SRNWP** Meeting

Gianpaolo Balsamo

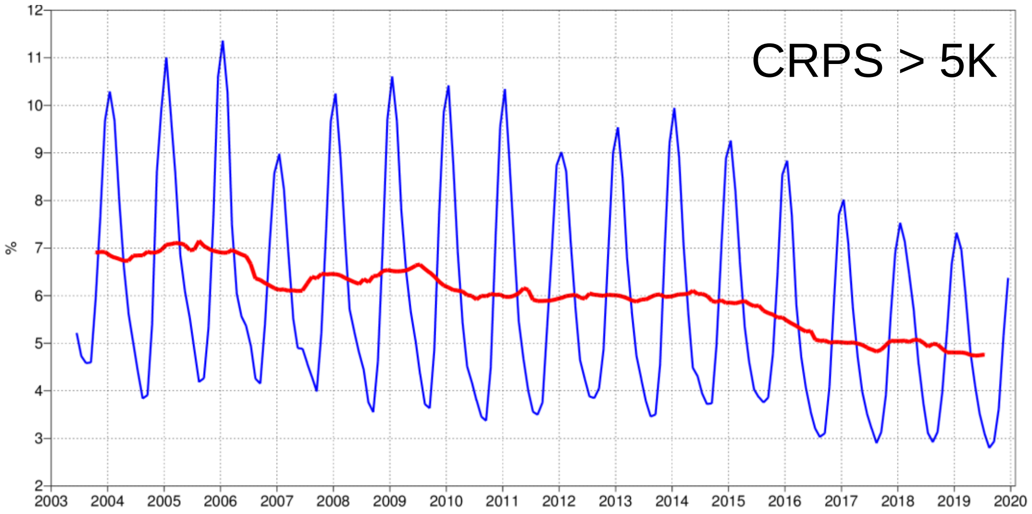
with input from

Irina Sandu, Thomas Haiden, Patricia de Rosnay, Anna Agusti-Panareda, Gabriele Arduini, Souhail Boussetta, Joe McNorton, Margarita Choulga Polly Schmederer, Jonny Day, David Fairbairn, Yoichi Hirahara, Pete Weston, Phil Browne, Dinand Schepers, Michail Diamantakis, Sam Hatfield, Steve English, Nils Wedi and many others

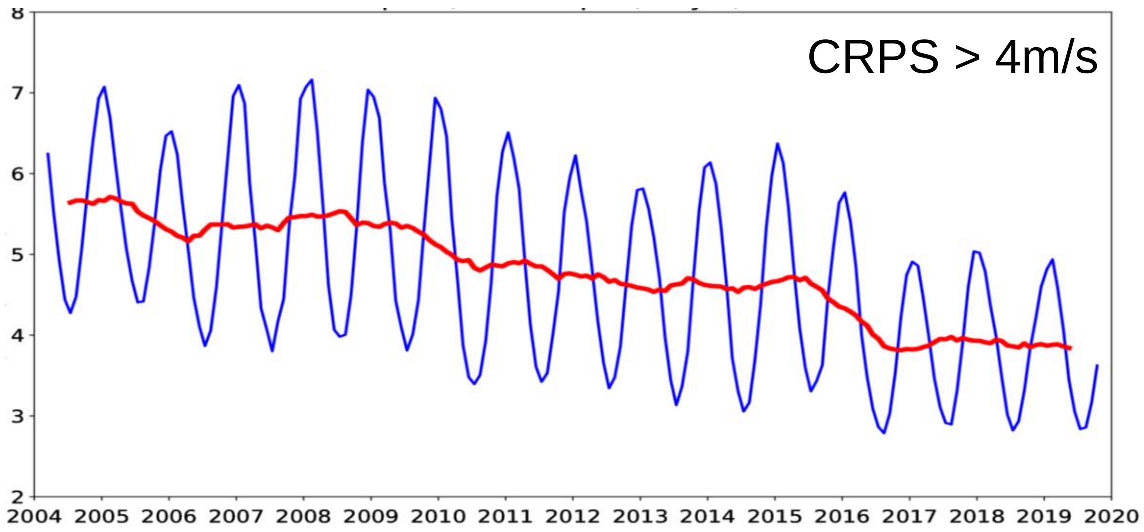
Systematic improvements of forecasts of near-surface weather parameters

Frequency of large errors (%)

2m temperature Day 5, Extratropics



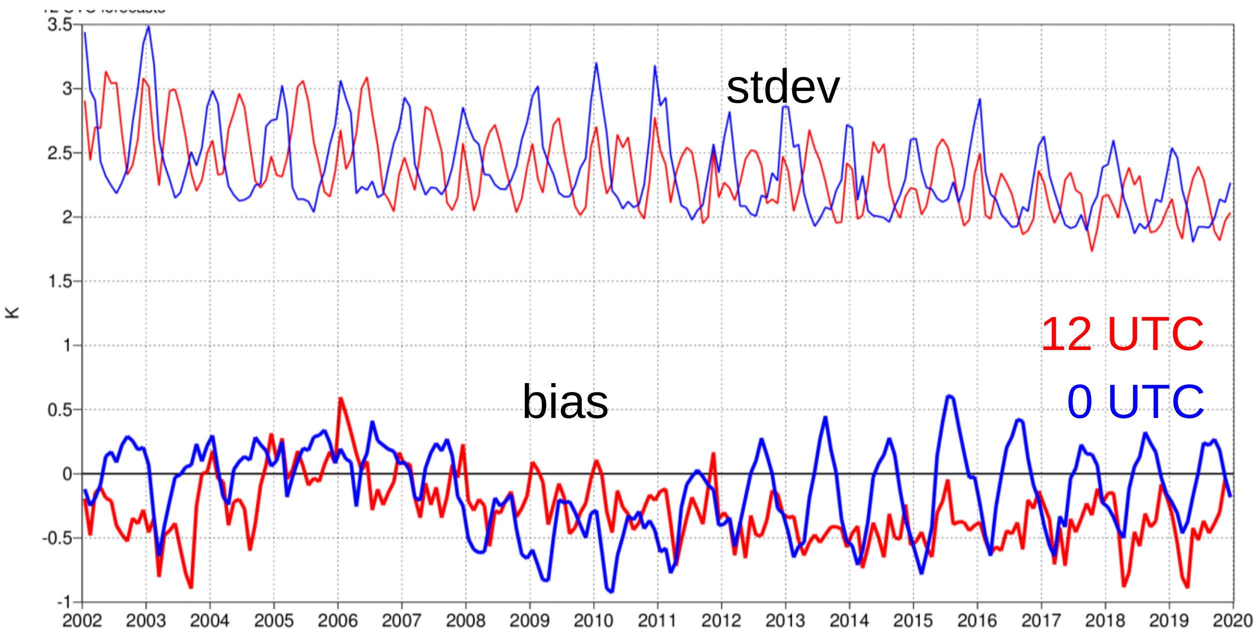
10 wind speed Day 5, Extratropics



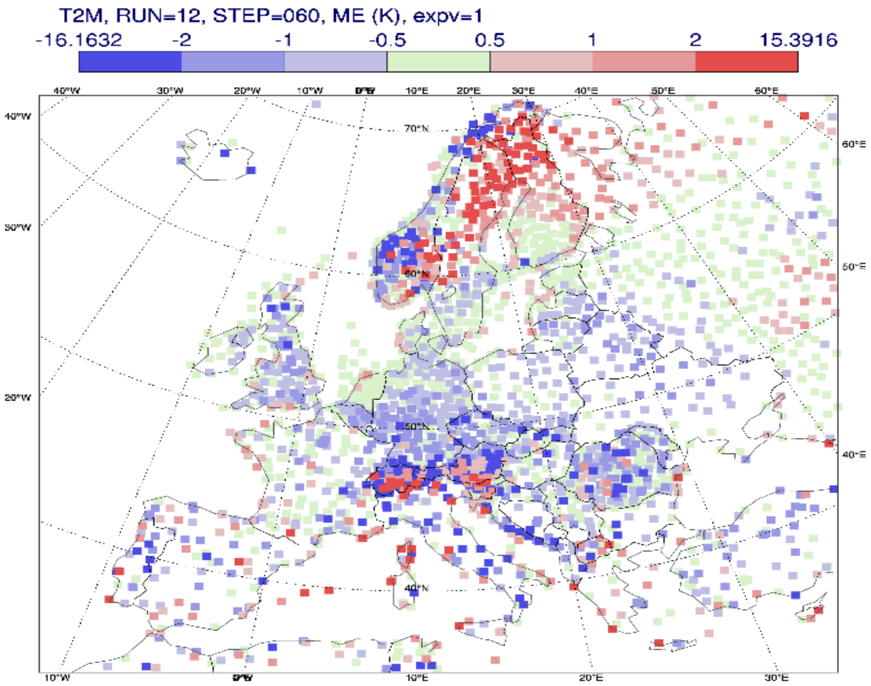
Forecasts of near-surface weather parameters (temperature, humidity, winds) are gradually improving, alongside upper-air forecasts due to improvements in NWP systems (see for e.g. Haiden et al. (2019))

But systematic forecast biases remain for all modelling systems (see recent WGNE survey, Reynolds et al. 2019)

2m temperature bias and stdev, day 3, Europe



2m temperature bias, day 3, winter, 0 UTC Europe



… with complicated temporal (diurnal, seasonal) and geographical patterns

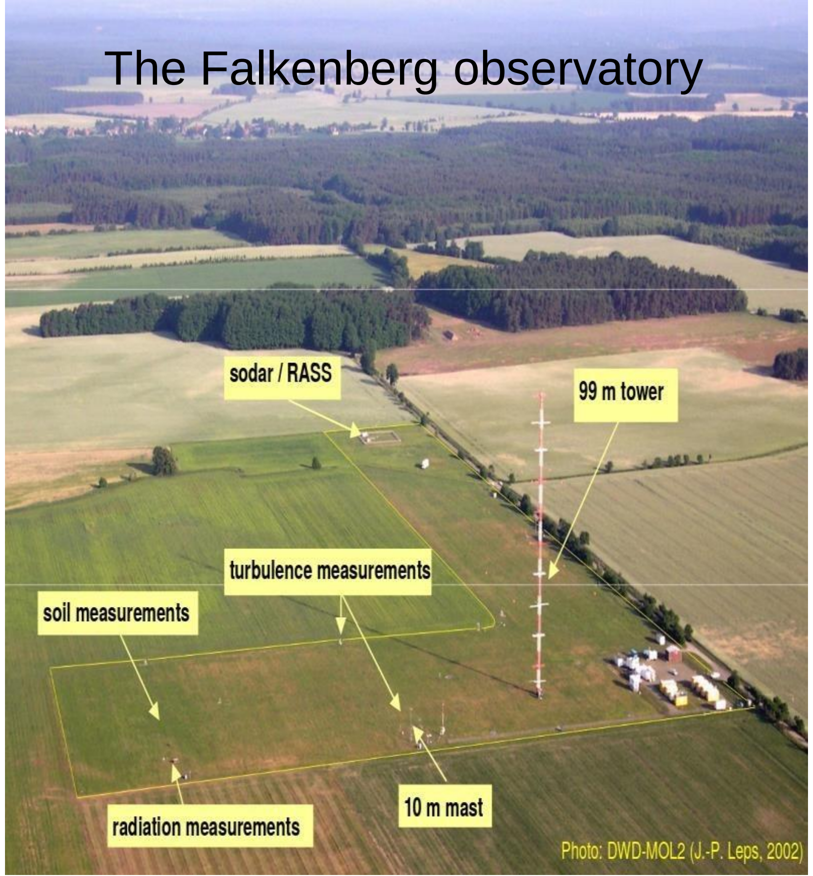
USURF – Understanding uncertainties in surface-atmosphere exchange

Cross-departmental ECMWF project (2017-2019) aiming at:

- disentangling the contribution of individual processes to systematic forecast errors in near-surface weather parameters by using a range of diagnostics for stratifying and attributing errors
- identify the necessary model developments to reduce systematic forecast errors in near-surface weather parameters

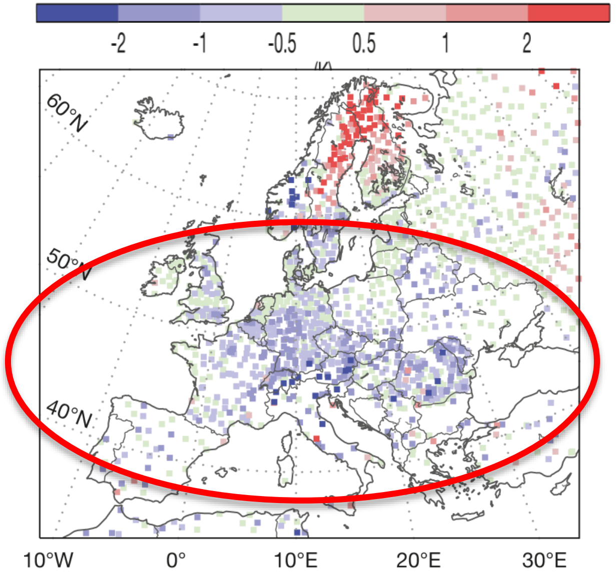
Guiding principles & methods

- start simple (focus on areas away from coasts, mountains)
- verify against routine (Synop) observations
- develop routine verification versus super-site observations
- use conditional verification (stratify errors in various ways: cloudy/clear, by land surface characteristics, etc)
- use model sensitivity experiments (to disentangle role of atmospheric and land surface processes)

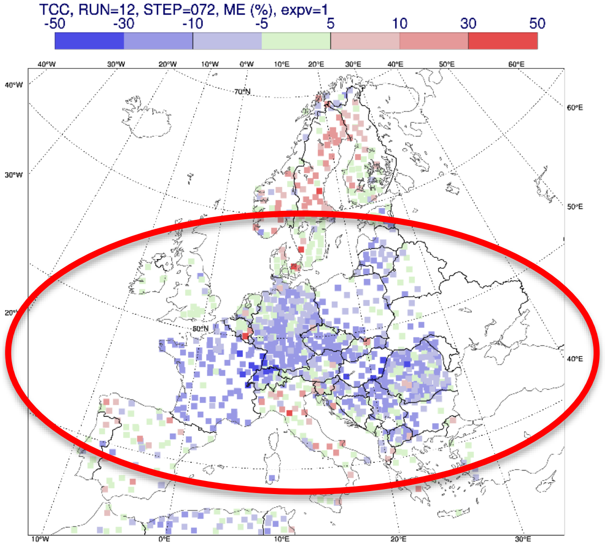


1. Causes of near-surface wintertime temperature biases

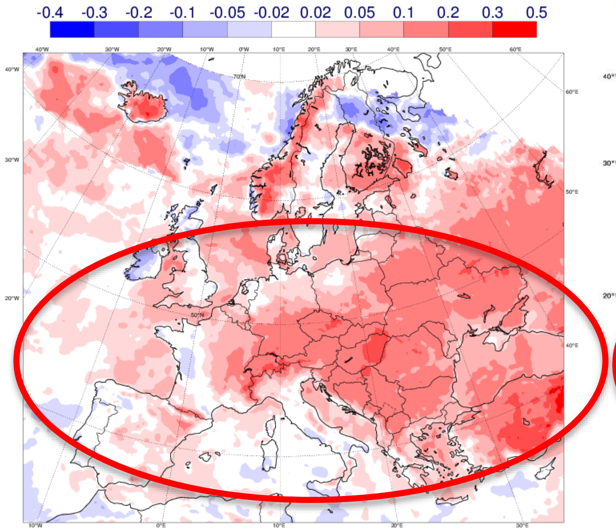
2m temperature bias (synops)



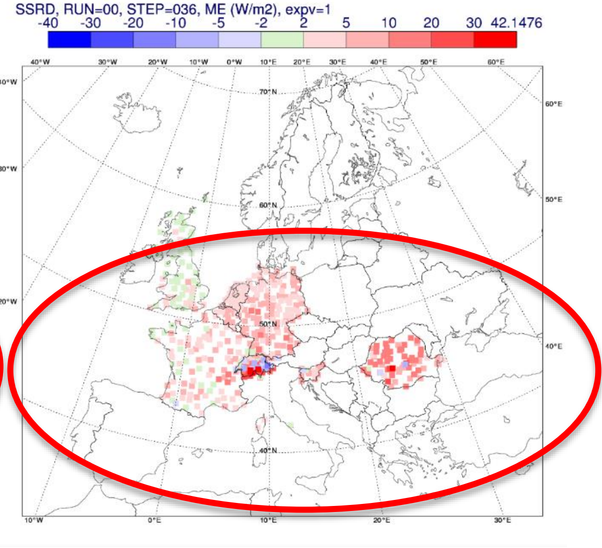
Cloud cover bias (synops)



Shortwave radiation downwelling (CM SAF)



Shortwave radiation downwelling (synops)



Cold bias over southern Europe partly related to cloud errors (approx. 5% underestimation of cloud cover)

Haiden et al, ECMWF newsletter, 157

1. Causes of near-surface wintertime temperature biases

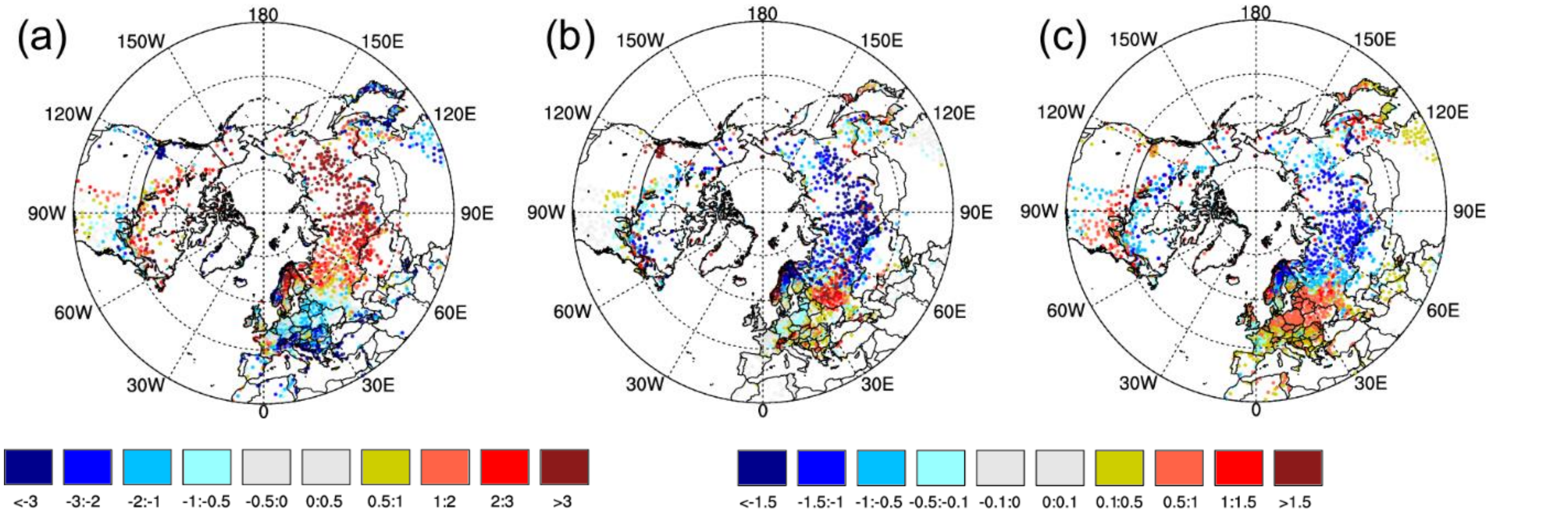
APPLICATE.eu
Advanced prediction in polar regions and beyond

Tmin bias

Change in absolute Tmin bias

Multi-layer vs single-layer snow

low vs high turbulent diffusion in stable conditions

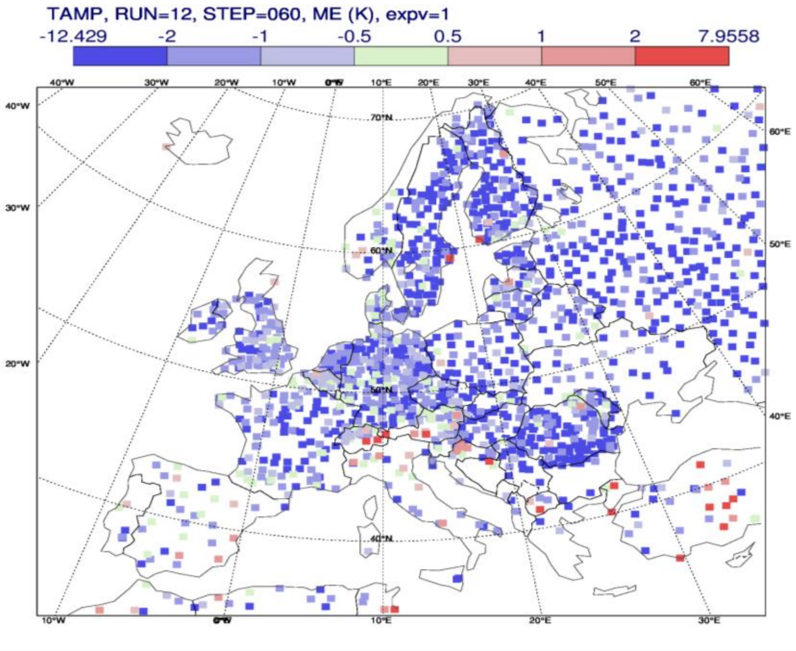


Warm bias at high latitudes warm bias partly related to snow and turbulent diffusion representation

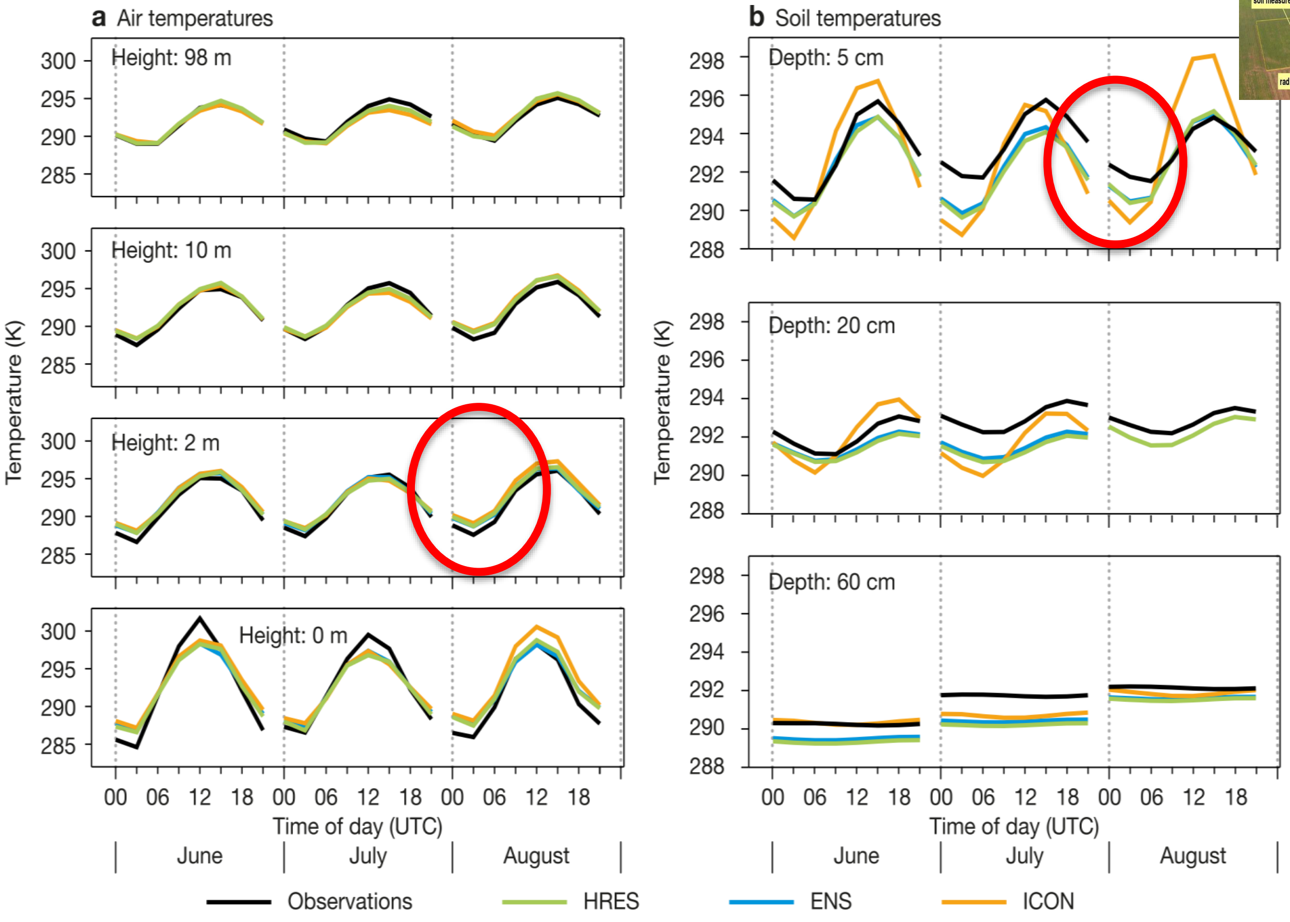
Arduini et al., JAMES, 2019, Day et al., JAMES, 2020

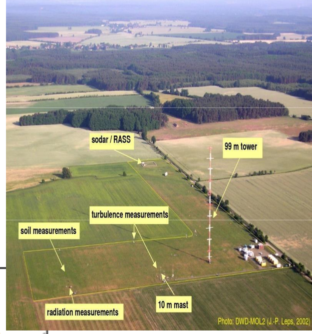
2. Causes of underestimation of diurnal cycle amplitude in summer

underestimation of diurnal cycle amplitude for 2m temperature



Falkenberg evaluation for temperature





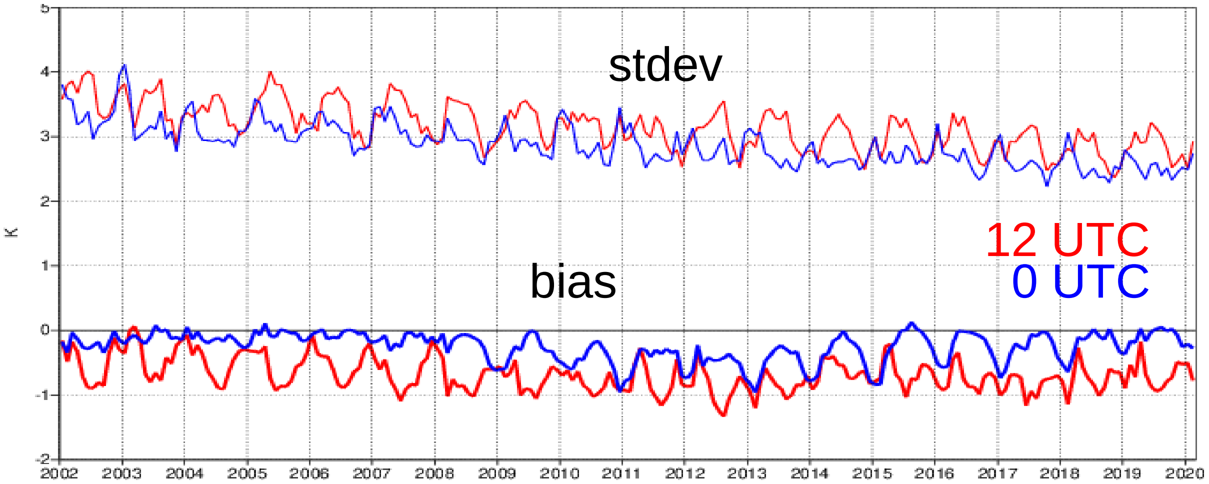
OBS
HRES
ENS
ICON

Partially due to too strong land-atmosphere coupling, but representation of vegetation, surface characteristics, etc, can also play a role

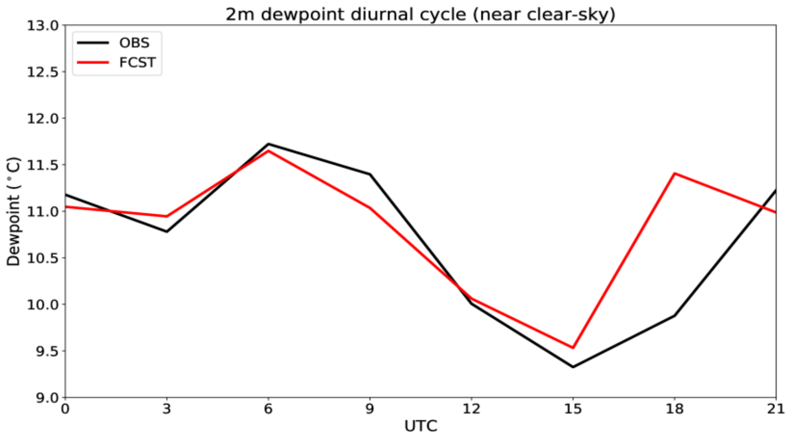
Schmederer et al, ECMWF newsletter, 161

3. Causes of dry summer daytime bias

2m dew point bias and stdev, day 3, Europe

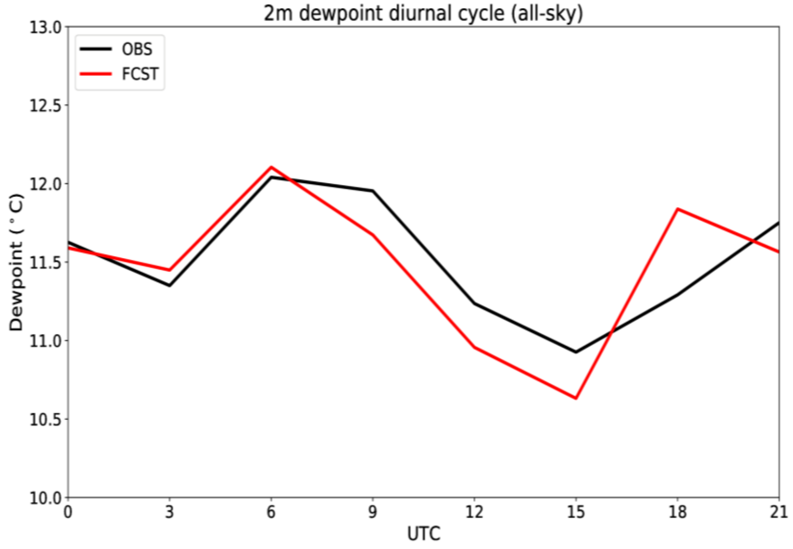


2m dew point bias, day 3, Europe, clear sky



OBS
HRES

2m dew point bias, day 3, Europe, all sky



Partially related to mixing in cloudy (convective) boundary layers

4. Important to take into account observation representativeness

summer day 4

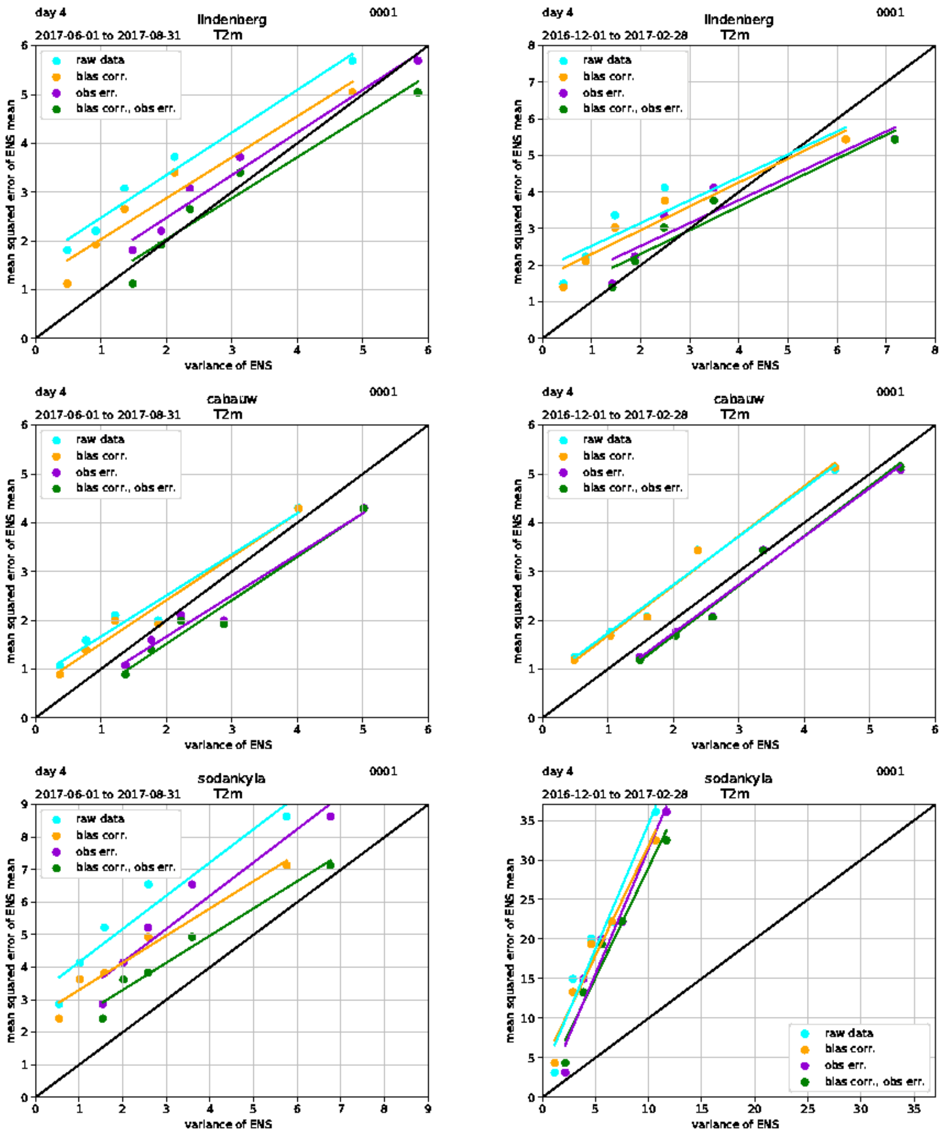
winter day 4

Falkenberg

Cabauw

Sodankyla

Mean squared error of ENS mean



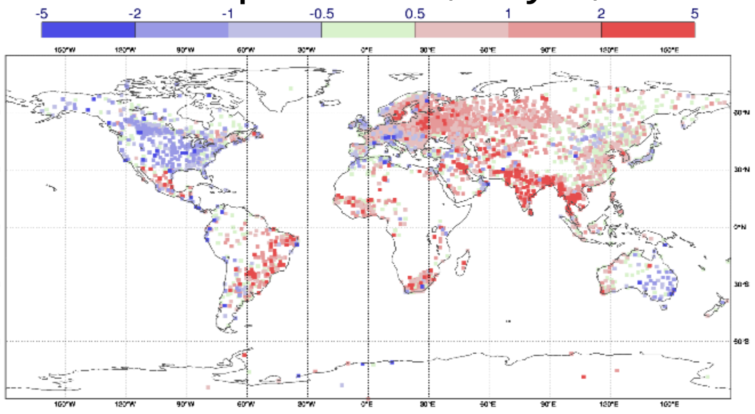
Variance of ENS

Raw data
Bias corr.
Obs. Err
Bias corr + obs err

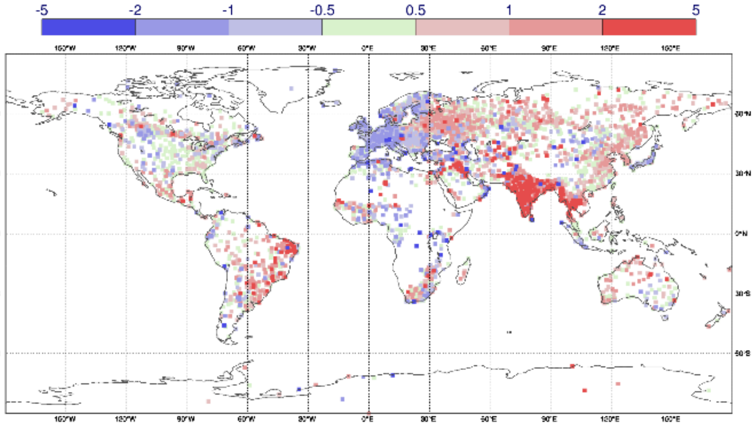
Schmederer et al, ECMWF newsletter, 161
Boullegue et al, 2020

5. Wind errors (summertime)

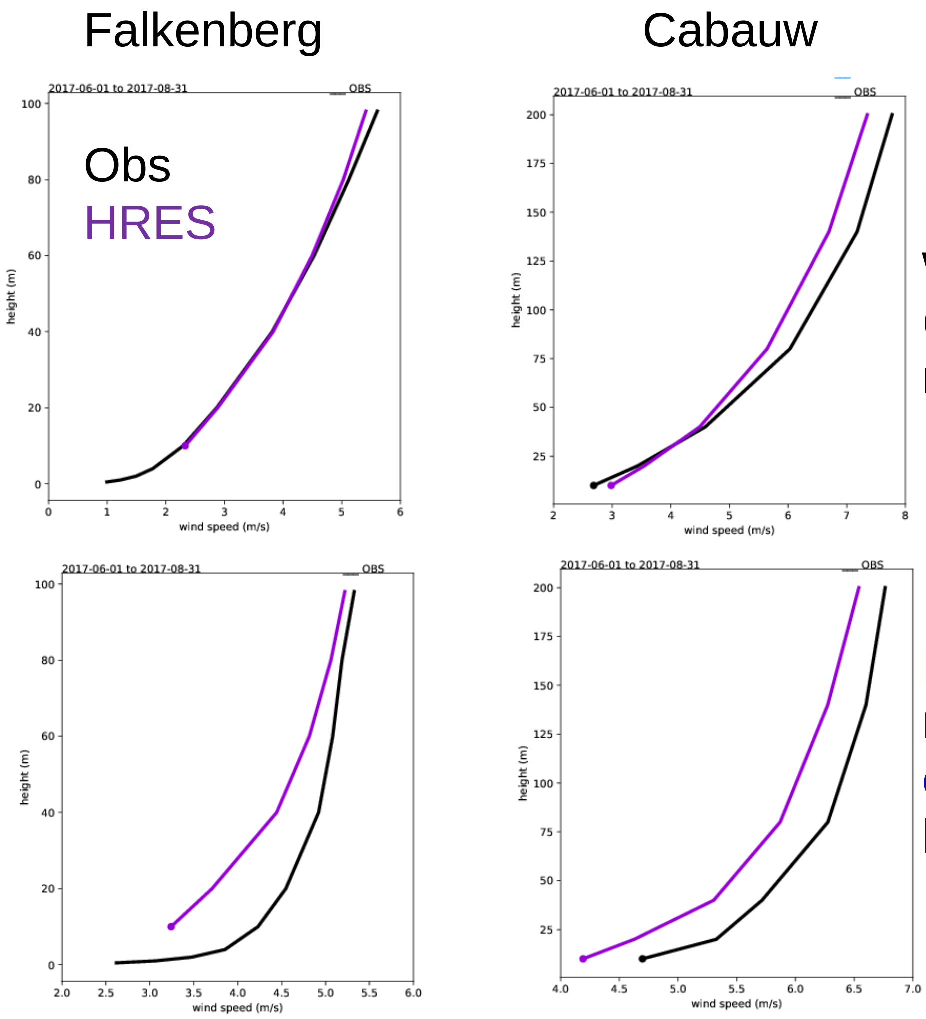
10m wind speed bias, day 3, 00 UTC



10 m wind speed bias, day 3, 12 UTC



10 m wind speed depends on the quality of the underlying vegetation maps



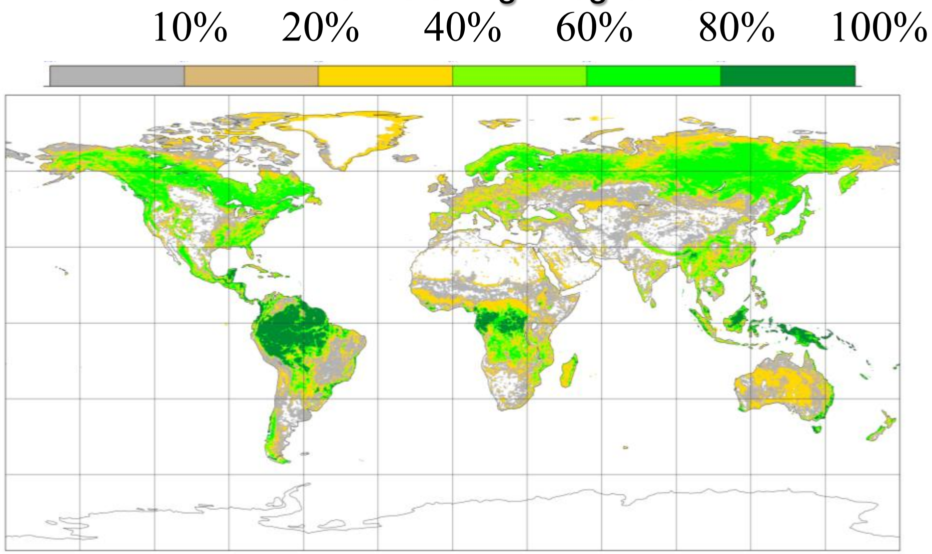
Nighttime low-level winds have improved (Sandu et al, ECMWF newsletter, 138)

Daytime biases partially related to mixing in cloudy (convective) boundary layers

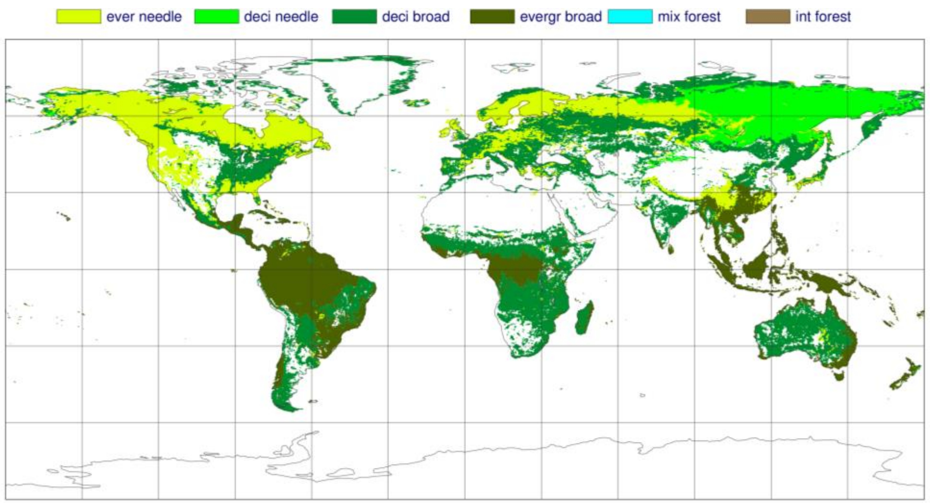
Perspectives of a new land-use for calibrating weather parameters

Land Use: Vegetation cover & Vegetation types & Statistics

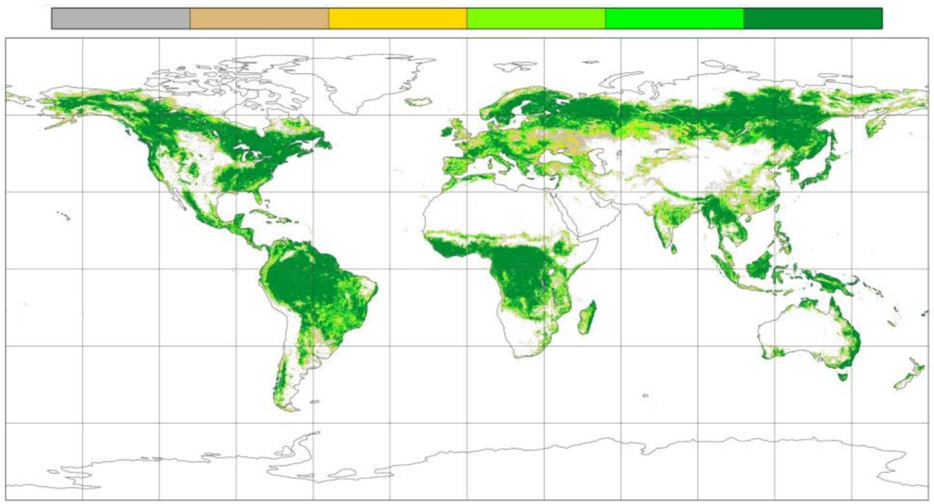
NEW ESA-CCI high veg cover



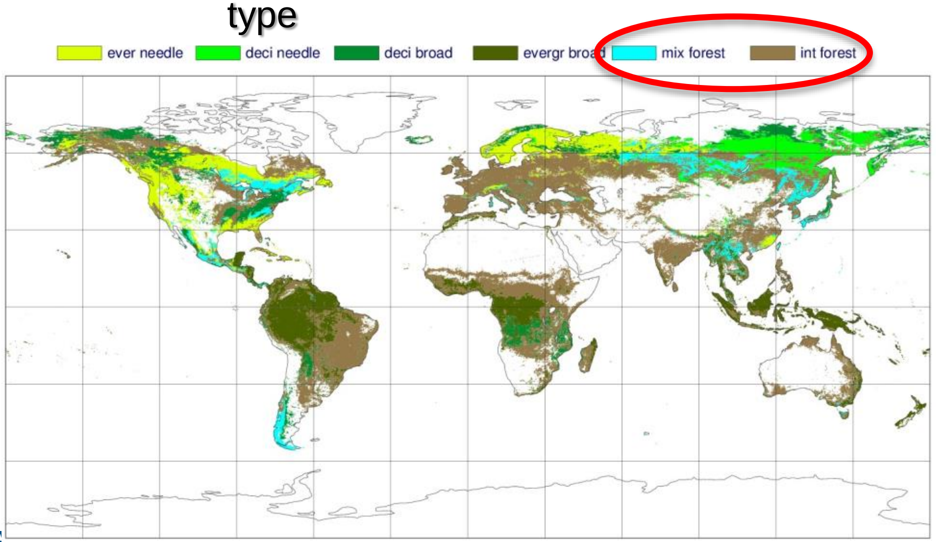
NEW ESA-CCI high veg type



IFS CURRENT GLCC1.2 high veg cover



IFS CURRENT GLCC1.2 high veg type



	Vegetation type	Percentage of land points	
Index		**ESA-CCI**	**GLCC1.2**
	Low vegetation		
1	crops	23.50%	18.00%
2	sh grass	38.70%	9.00%
7	ta grass	0.00%	12.80%
9	tundra	0.70%	6.00%
10	irr crops	1.90%	3.90%
11	semidesert	0.00%	11.60%
13	bog/marsh	0.00%	1.50%
16	ever shrub	5.10%	1.20%
17	deci shrub	4.70%	3.90%
	Remaining points	25.00%	31.40%
	High Vegetation		
3	ever needle	11.70%	5.40%
4	deci needle	4.70%	2.50%
5	deci broad	29.50%	5.60%
6	ever broad	18.20%	12.90%
18	mix forest	0.00%	3.00%
19	int forest	0.00%	24.70%
	Remaining points	35.60%	45.50%

Sandu et al. (2012) large reduction in wind speed error with land-use calibrated z_0 but Interrupted forest type was a clear limitation for calibration

Increased realism in water cycle reservoirs representation at 1km (snow case)

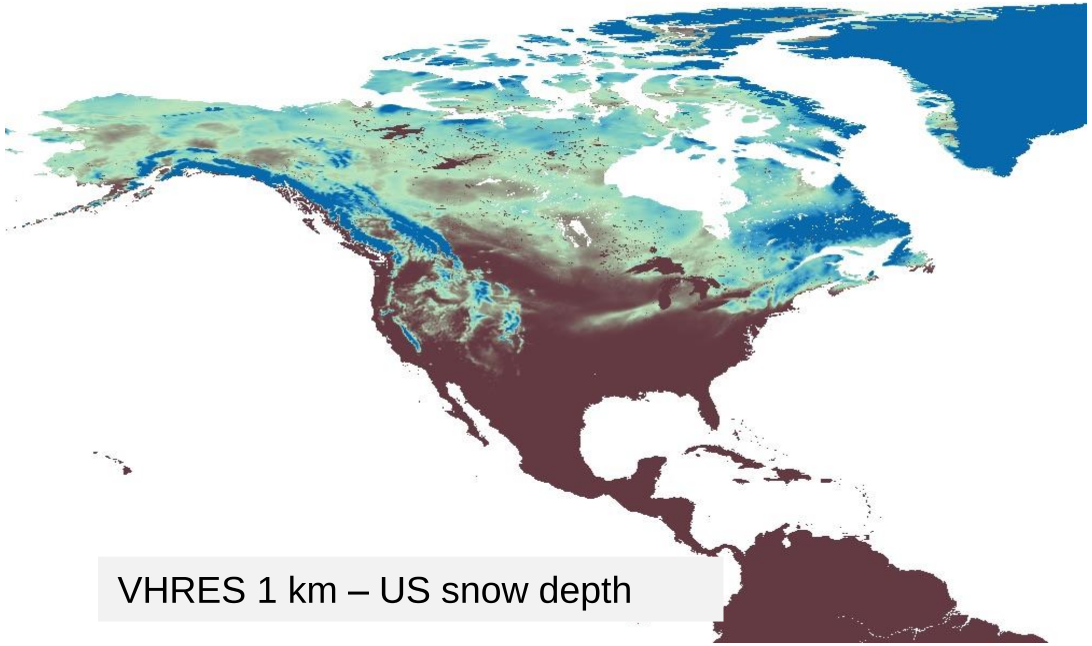
Ioan Hadade, Gabriele Arduini, Souhail Boussetta, Margarita Choulga et al.

The Offline Surface Modelling (OSM) **increased performance** allows to run the surface at **1km at ECMWF**

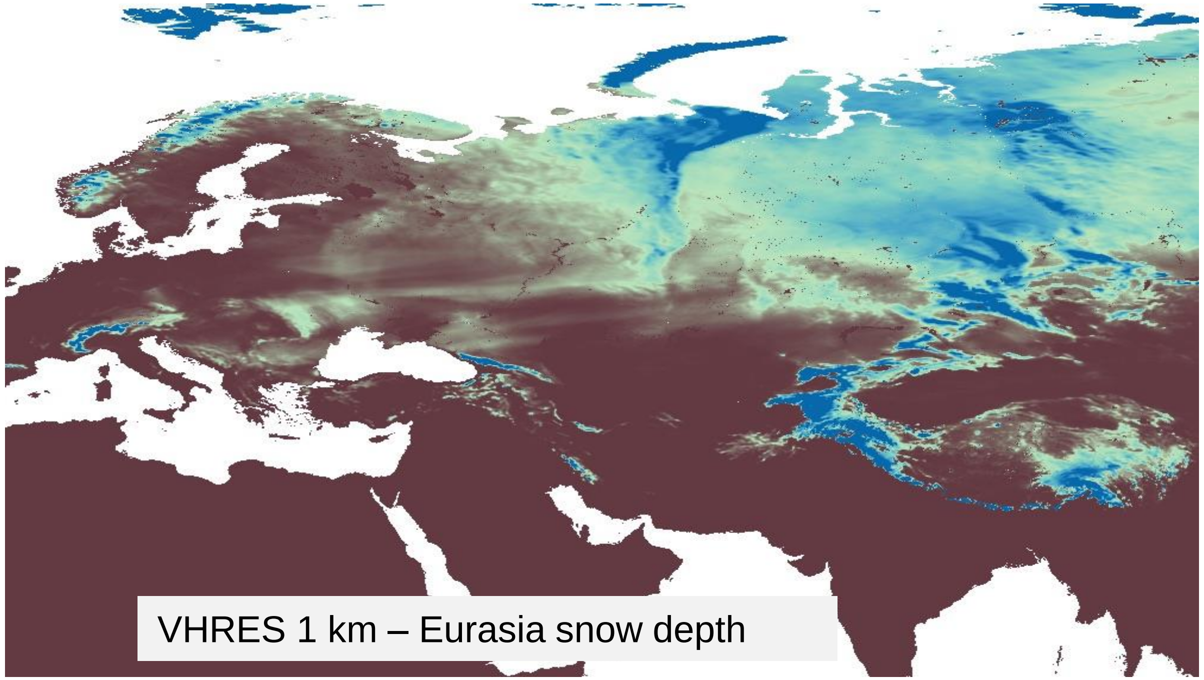
Towards 1km increase realism will bring benefits

- Land use and land cover (use of ESA-CCI)
- Coastal areas and lakes (use of GSWE)
- Snow over orography & catchment hydrology
- Improved skin temperature for data assimilation

Resolution	Configuration	Performance (simulated years per day)
9km (**HRES** & ERA5Land)	TCo1279	with MPI (**8 year/day**) *Currently ERAL (14 days/day)*
1km (VHRES) & prepare ERA 1k	TCo7999	with MPI (**0.8 year/day**)



VHRES 1 km – US snow depth



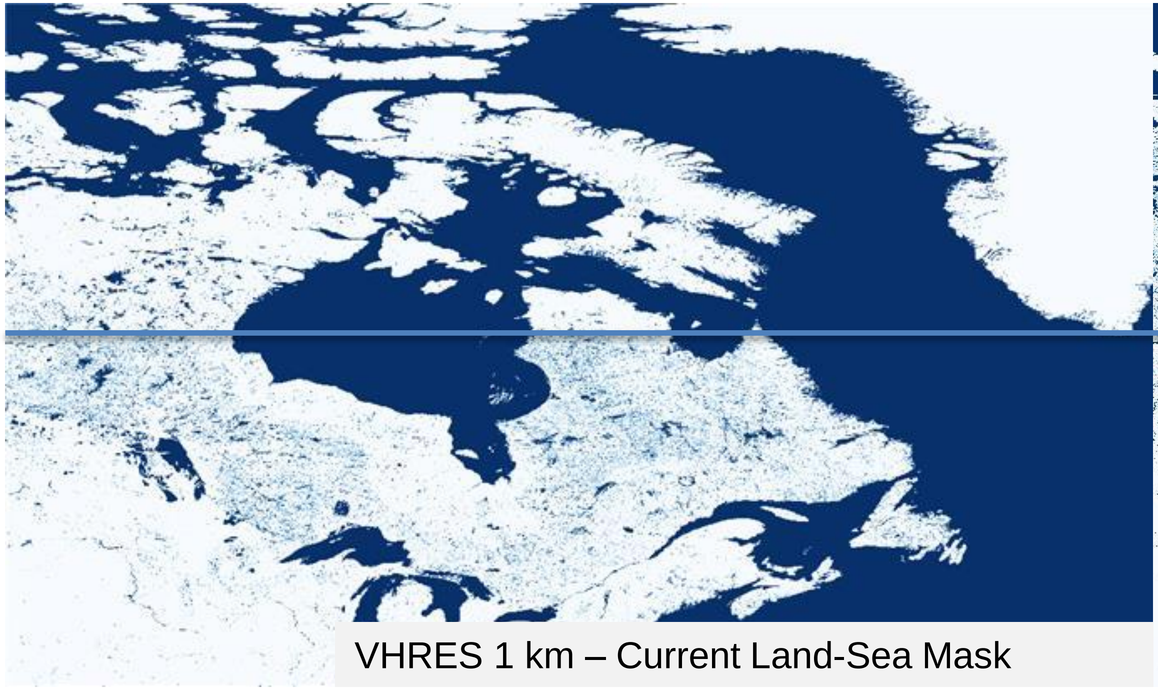
VHRES 1 km – Eurasia snow depth

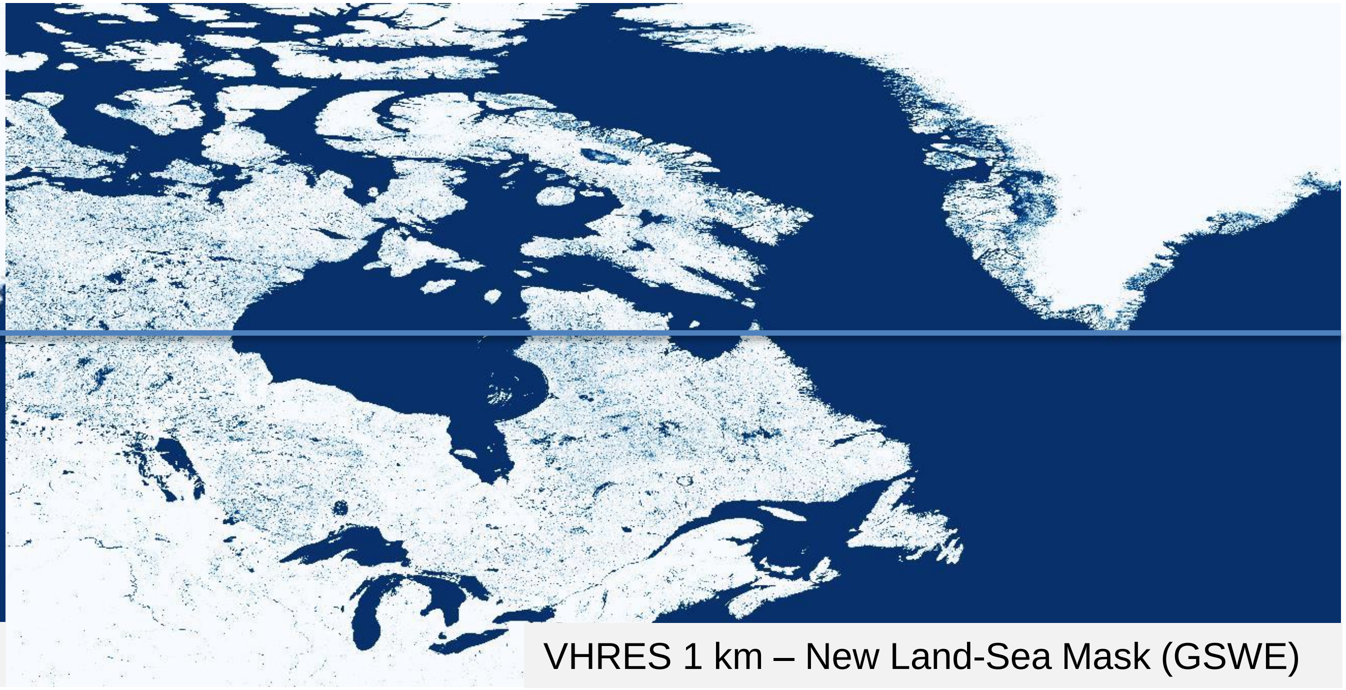
The role of km-scale resolution for inland water surfaces (the lake case)

Margarita Choulga, Souhail Boussetta et al.

Moving towards native 1km enable resolving more of the inland water surfaces affecting the surface temperature

Mapping water surfaces correctly is essential to have an inter-consistent treatment of land surface





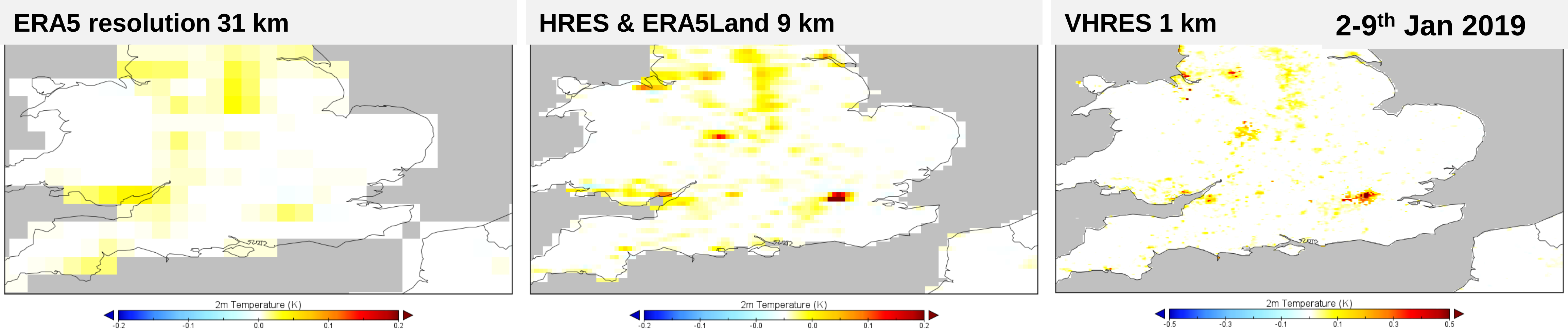
Choulga et al. 2021 (in prep). Example of land sea mask obtained by the global 30m resolution GSWE aggregated to 1km on Google Earth Engine

The role of km-scale resolution for anthropogenic surfaces (the urban case)

Joey McNorton, Margarita Choulga, Gabriele Arduini, Souhail Boussetta et al.

Moving toward 1km helps to resolve anthropogenic surfaces, which affect surface temperatures

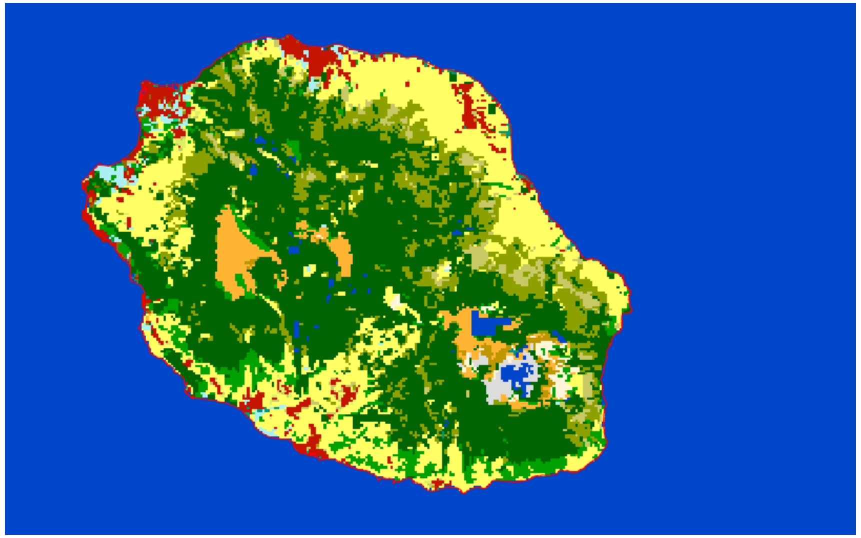
Several research initiatives are focusing towards **improving the mapping** (EO based) and parameterisation to represent the main urban anthropogenic effects (**Urban Heat Island, Hydrology & CO2 emissions**).

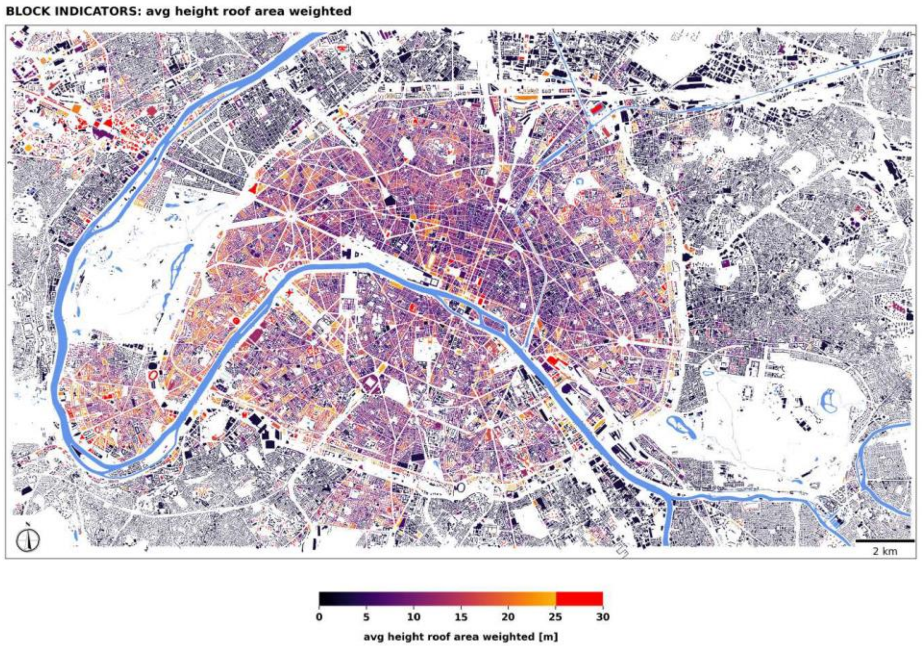


McNorton et al. 2020 (in prep). Example of 2m temperature sensitivity to urban tile (using ECOCLIMAP-SG), Collaboration with Reading Uni and MF on urban

Surface Land Information Mapping – A Copernicus initiative

- C3S issued an Invitation to Tender to produce global 1km urban maps integrated with land-use, water-bodies for use in Global and Regional models.
- Météo-France, CNRS, LabSticc responded to ITT with the SLIM proposal
- Patrick LeMoigne is the SLIM coordinator
- Data from CGLS, C3S, GSWE, GLDB3, ECOCLIMAP-SG, OpenStreetMap, …

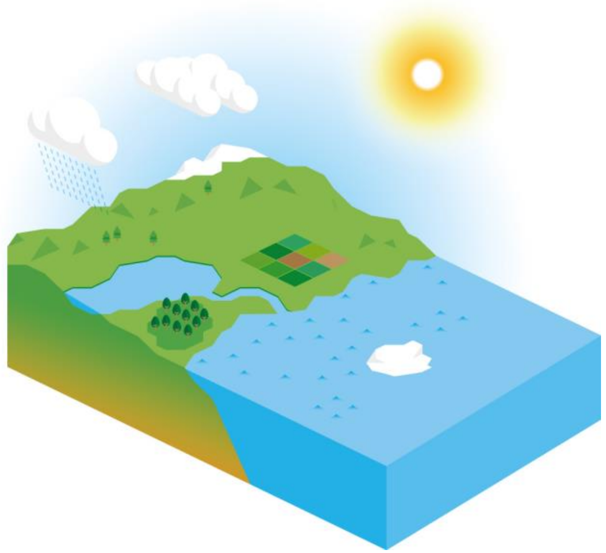




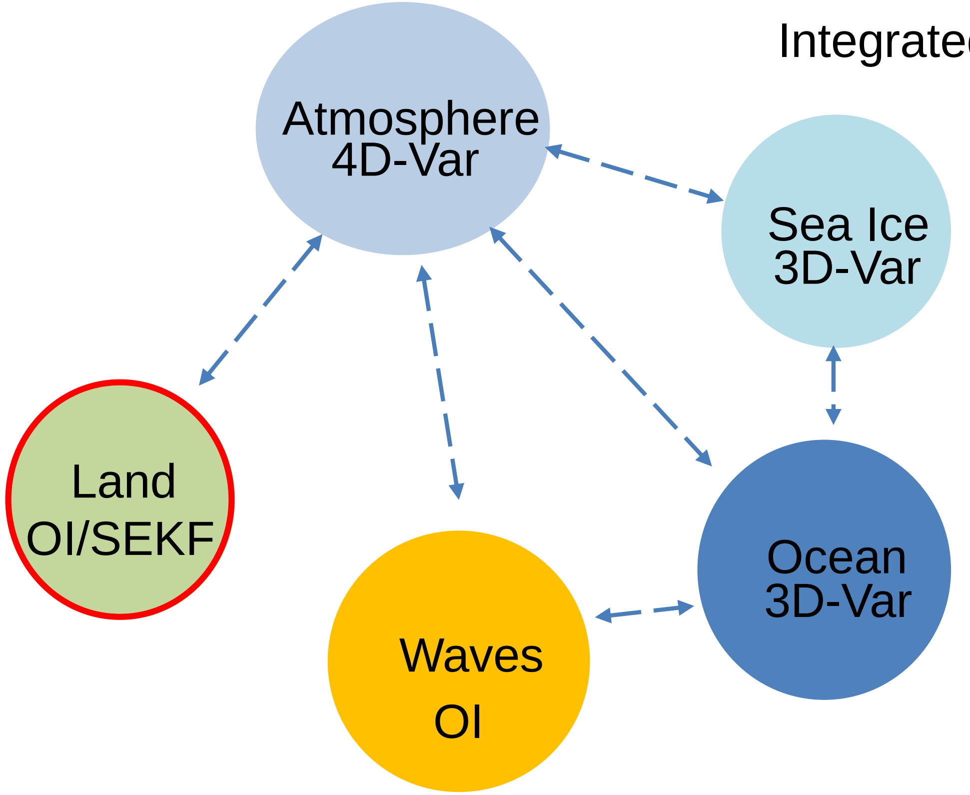
Summary and outlook for Land Modelling

- multi-layer snow scheme (developed in APPLICATE project, planned for implementation in Bologna) – will reduce wintertime temperature and snow biases (Arduini et al, 2019, Day et al, 2020)
- Vegetation maps (with Meteo-France & IPMA) and vegetation seasonality – can help reduce summertime and transition seasons biases in near-surface temperature, dew point and winds – optimisation of uncertain parameters will be needed
- Integrating a Urban tile modelling and lakes with river discharges are foreseen developments to improve the realism of the energy and water cycle at the surface.
- The benefit of global km-scale modelling for land surface can be explored as computationally affordable in stand-alone configurations.
- The SLIM project will aim at providing interconsistent global surface mapping at 1km resolution for use in Global and Regional Modelling (available via Copernicus data portal in 2021/2022)

Earth System Data Assimilation Approach



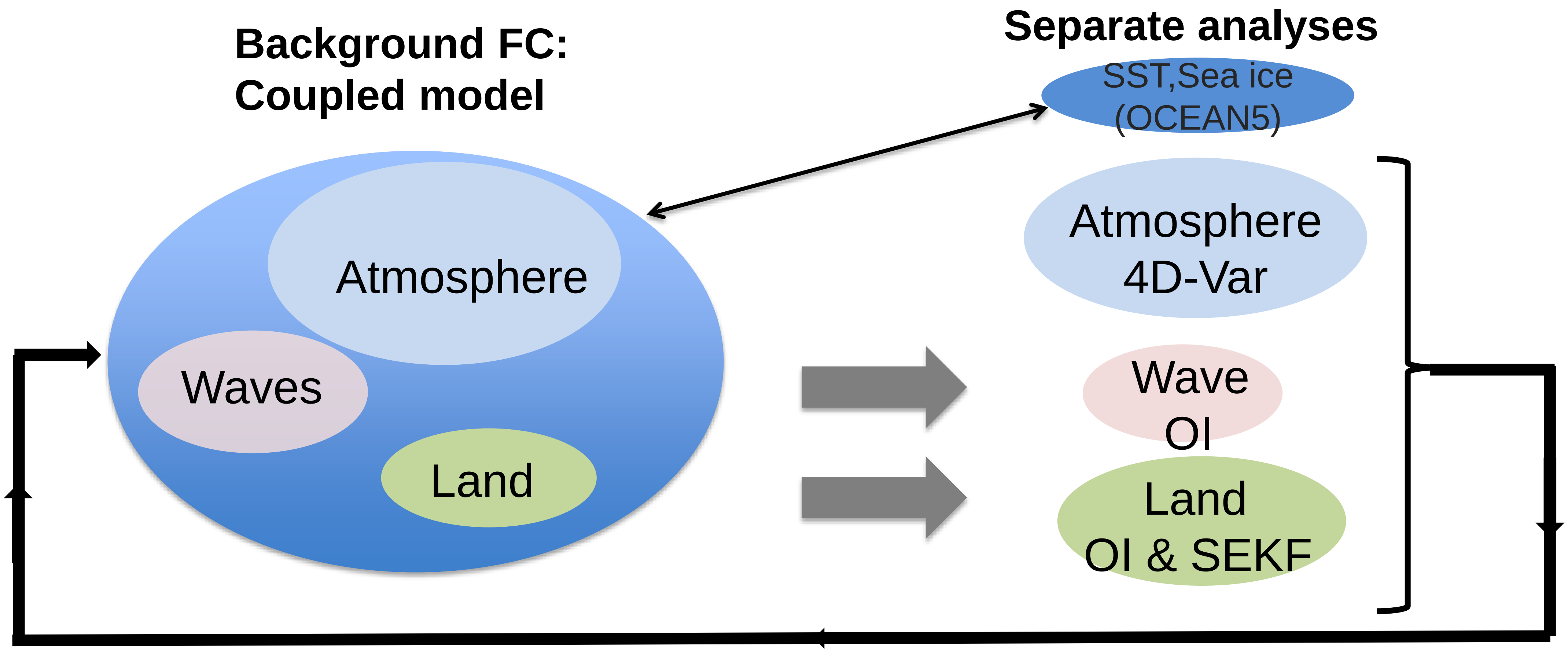
Integrated Forecasting System (IFS)



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

Current operational NWP system at ECMWF

Weakly coupled land-atmosphere-wave and sea ice assimilation

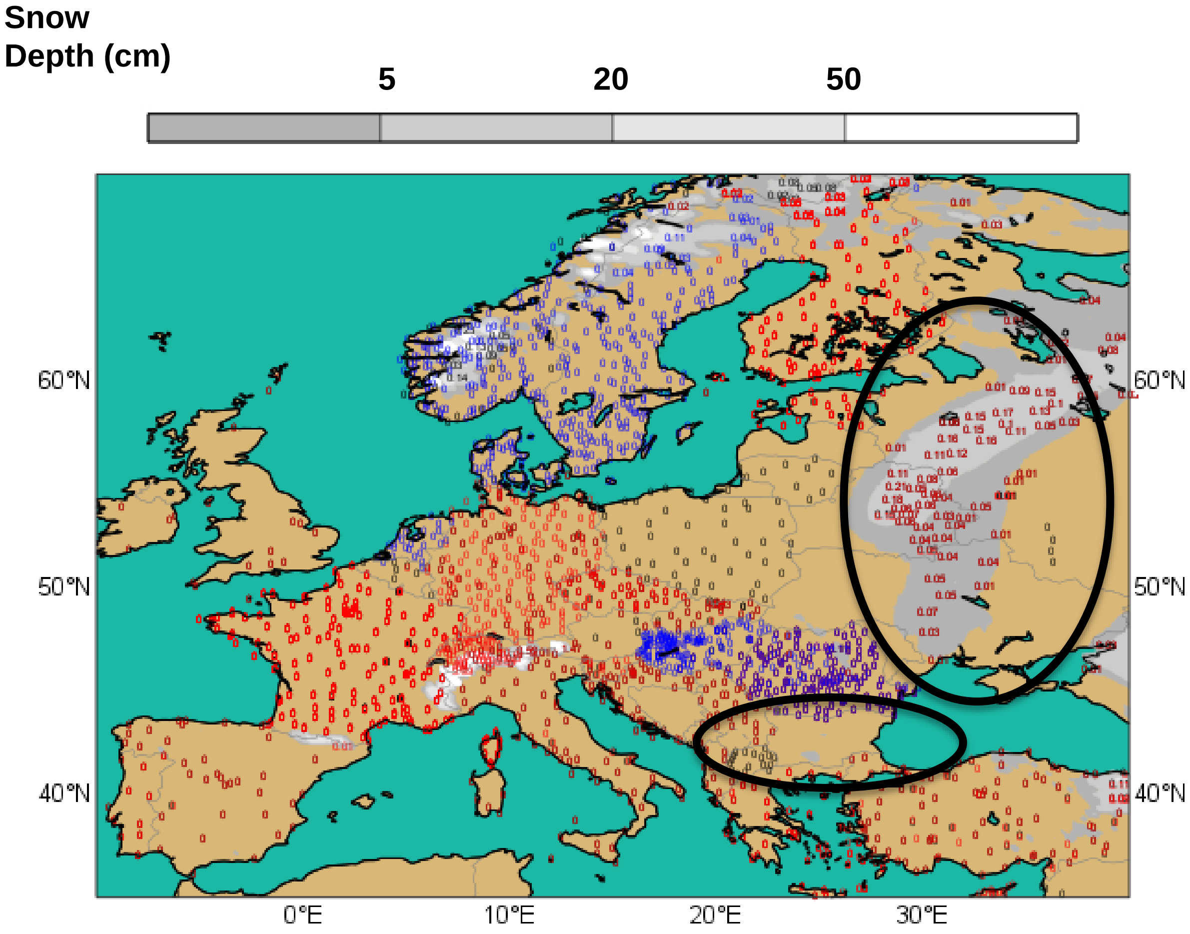


→ Importance of the interface observations for consistent initialisation of coupled land-atmosphere forecasts

→ Soil moisture and snow observations highly relevant for coupled assimilation

Snow Observations

SYNOP and National Network data in Europe



2018 11 15 at 06UTC

In general, good coverage in Europe, but …

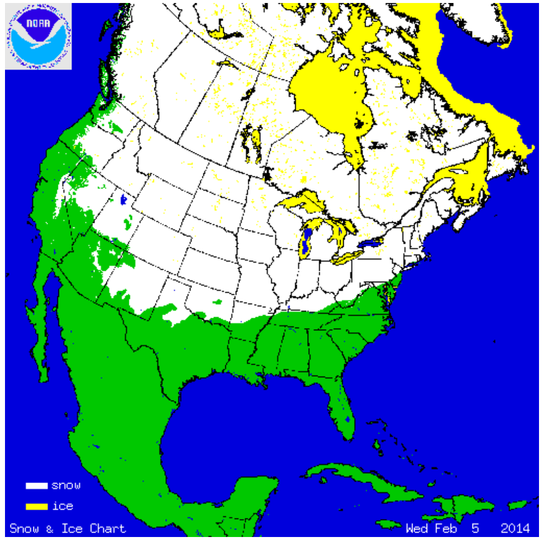
- Zero snow depth reporting is an issue with some countries providing observations only when snow depth > zero (e.g. Ukraine)
- Still areas with relatively few snow depth reports

Dedicated network to exchange meteorological data: Global Telecommunication System (GTS)

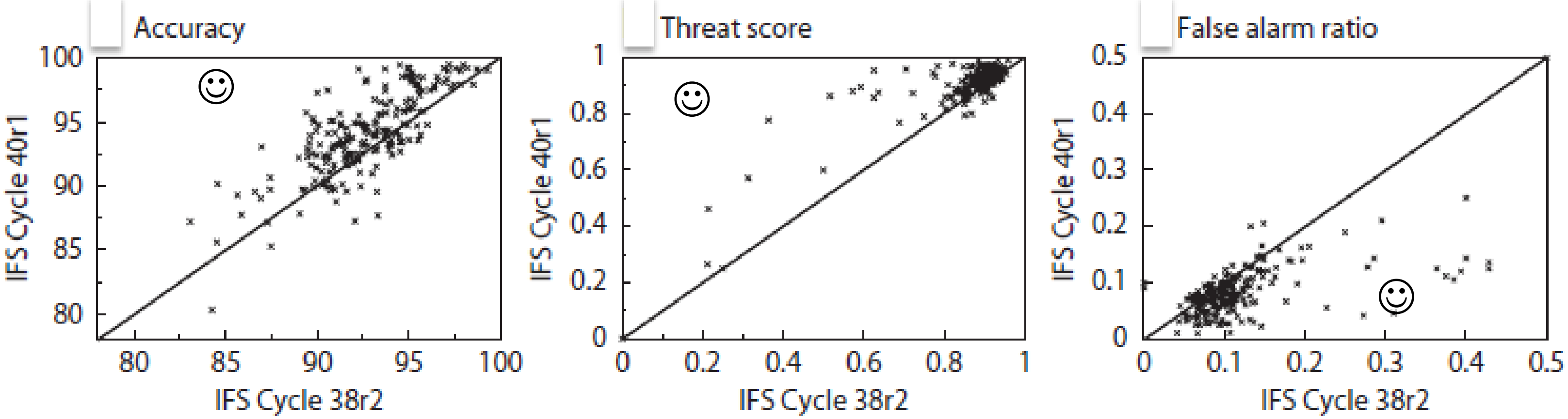
Snow analysis: Forecast impact

Revised snow cover assimilation (2013)

NOAA/NESDIS IMS data

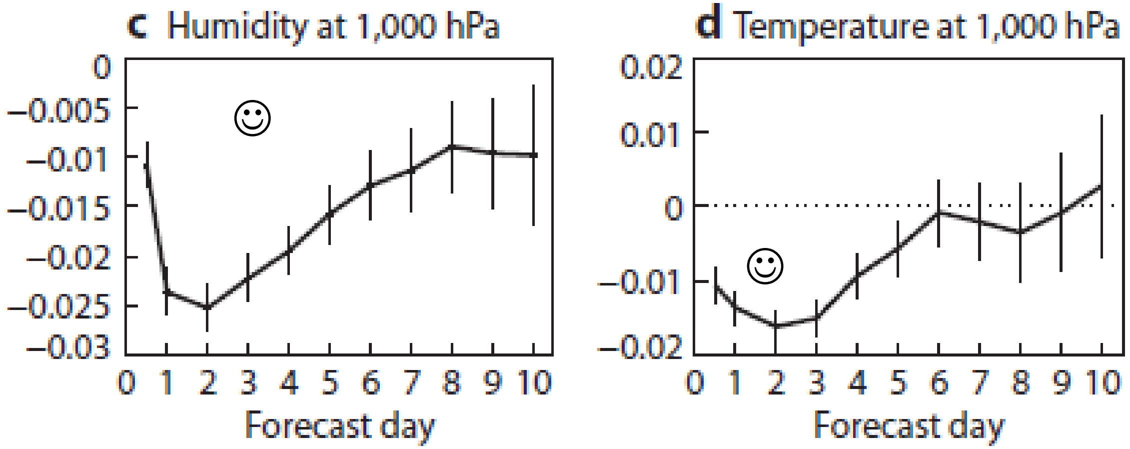


Impact on snow October 2012 to April 2013 (251 independent *in situ* observations)



Impact on atmospheric forecasts

October 2012 to April 2013 (RMSE new-old)

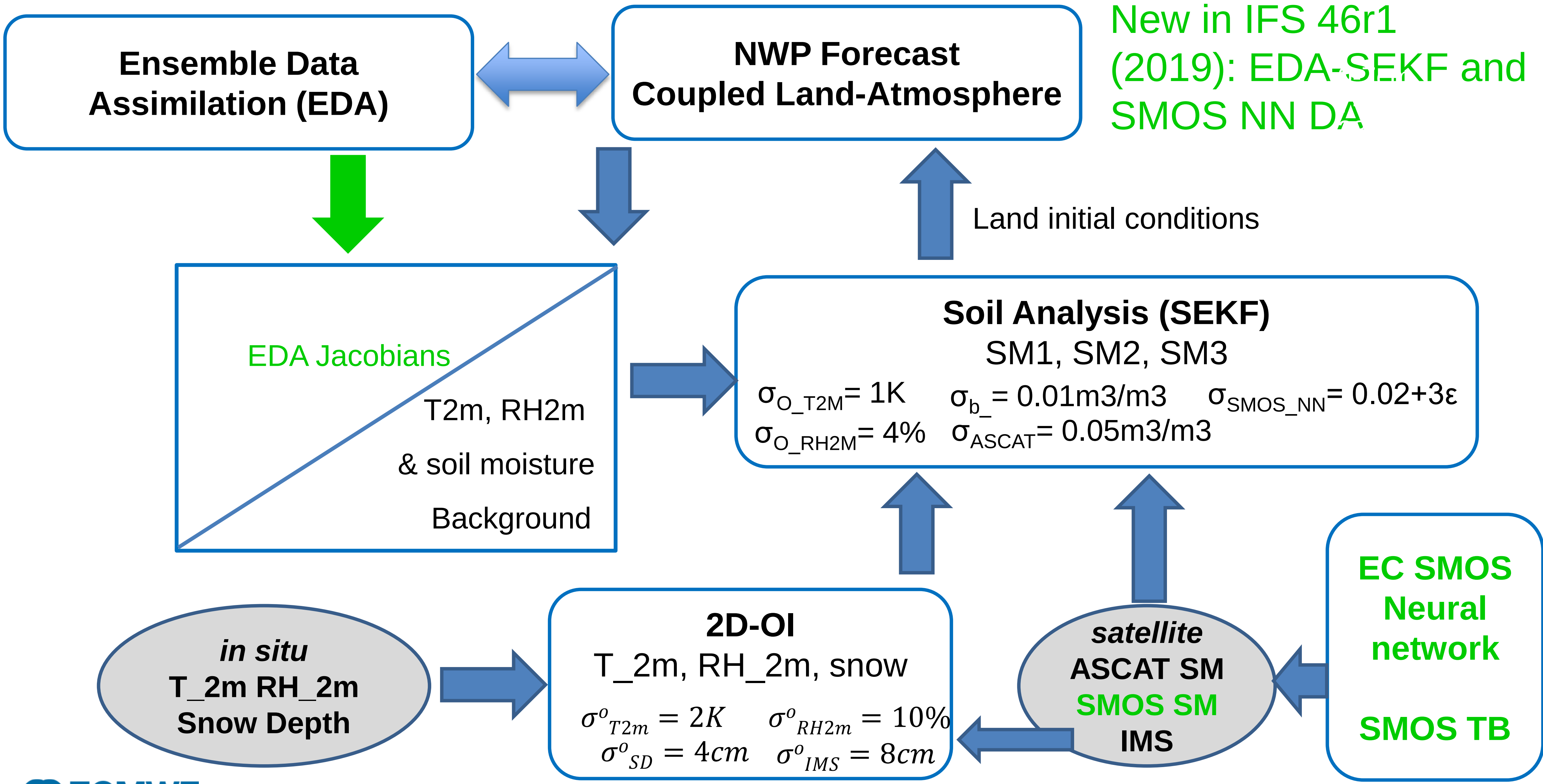


→ Consistent improvement of snow and atmospheric forecasts

→ Importance of snow cover observations

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

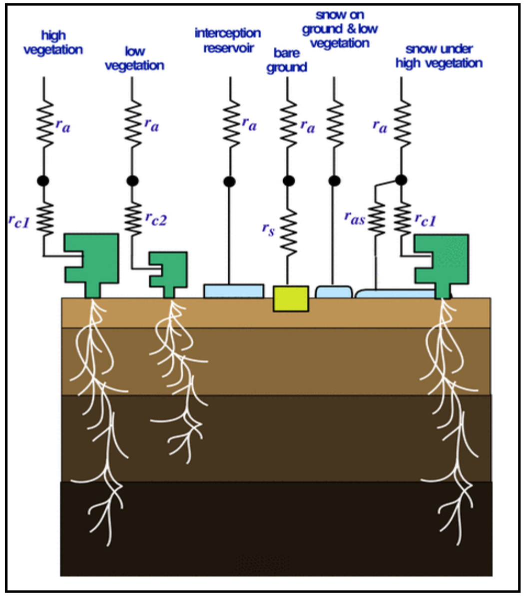
Overview of ECMWF Land DA for NWP



Simplifed EKF soil moisture analysis

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

de Rosnay et al., QJRMS, 2013



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

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

Observations vector

$$y_{(tobs)} = \begin{bmatrix} T_{2m} \\ RH_{2m} \\ ASCAT_{sm} \\ SMOS_{sm} \end{bmatrix} \quad \begin{matrix} [K] \\ [\%] \\ [m^3/m^3] \\ [m^3/m^3] \end{matrix}$$

Observations operator

$$\mathcal{H}[x_b^t]) = \begin{bmatrix} T_{2m} \\ RH_{2m} \\ SMtop \\ SM_{top} \end{bmatrix}$$

Observation error

$$R = \begin{pmatrix} 1^2 & 0 & 0 & 0 \\ 0 & 4^2 & 0 & 0 \\ 0 & 0 & 0.05^2 & 0 \\ 0 & 0 & 0 & (0.02 + 3smos\varepsilon)^2 \end{pmatrix}$$

Background error

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

ECMWF

EDA-SEKF soil moisture analysis (since June 2019)

Jacobians computation is based on the Ensemble Data Assimilation (EDA)

Use the EDA 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

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

de Rosnay et al, in prep

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

ECMWF

Soil moisture satellite observations

Active microwave data:

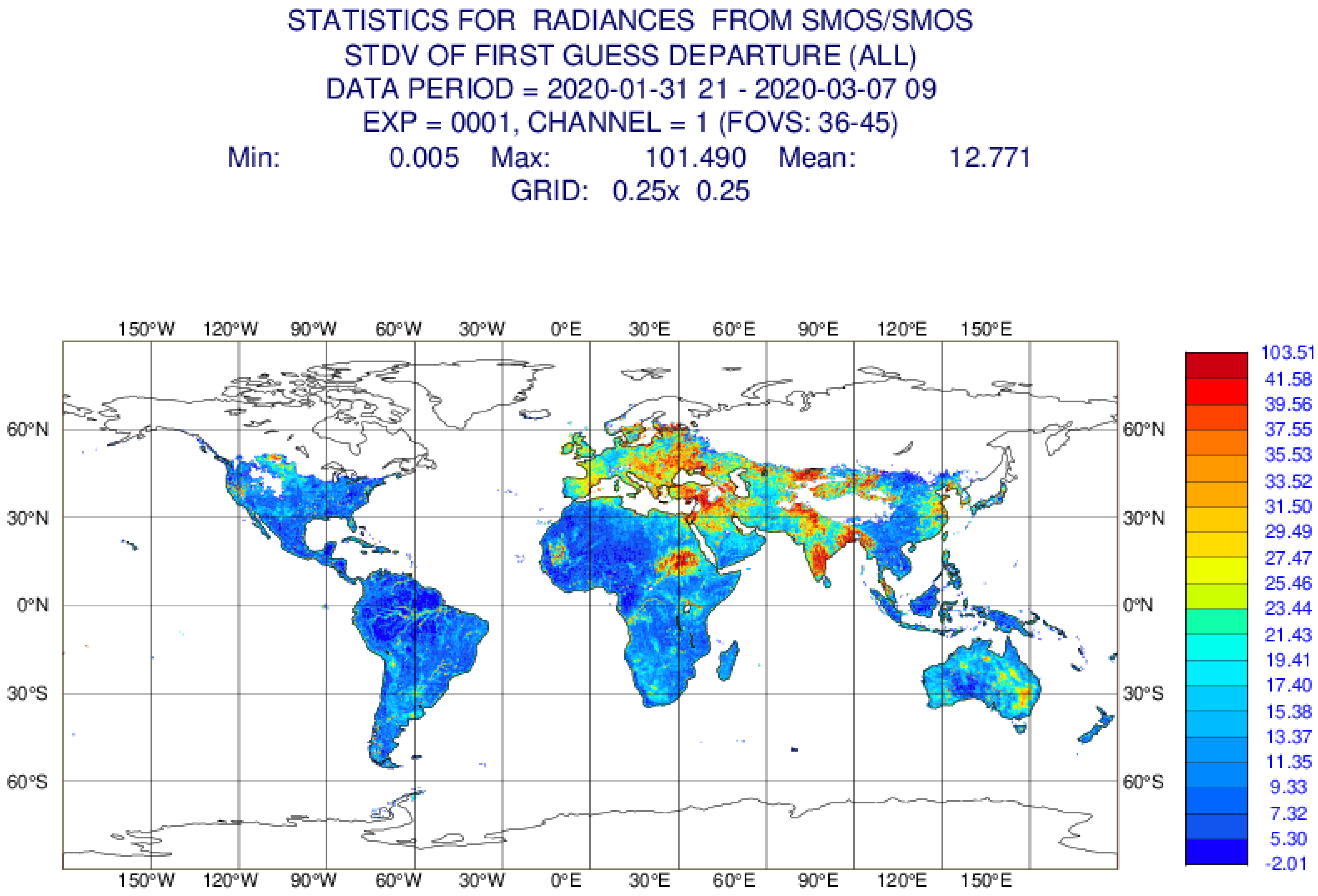
ASCAT: Advanced Sc

On MetOP-A (2006-),

C-band (5.6GHz) back

EUMETSAT Operatior

Passive microwave data:



Salinity (2009-)

mperature

soil moisture mission

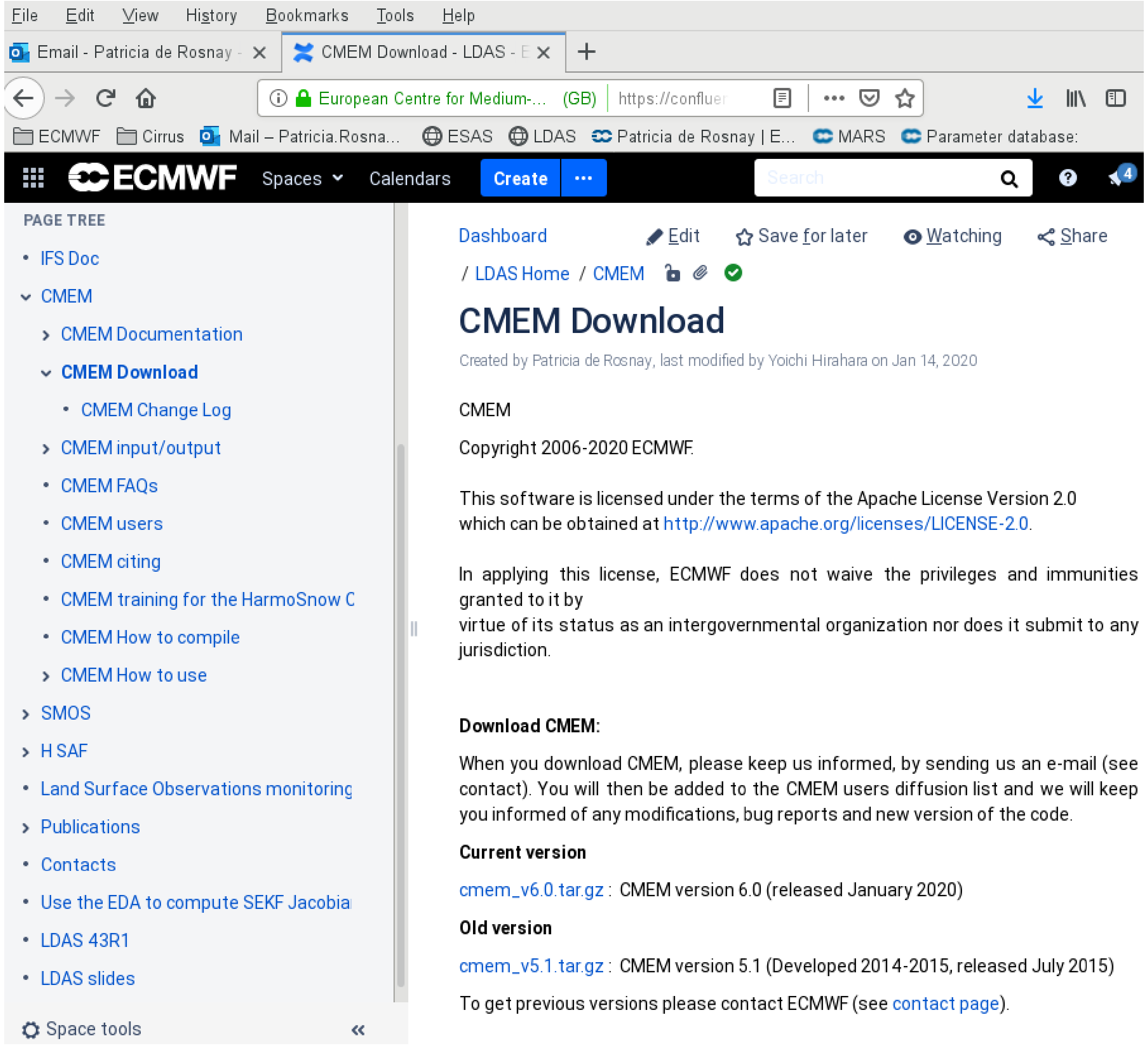
012)

Weston et al., 2020

Low frequency microwave emission modelling

Forward operator: Community Microwave Emission Modelling Platform (CMEM)

https://software.ecmwf.int/wiki/display/LDAS/CMEM



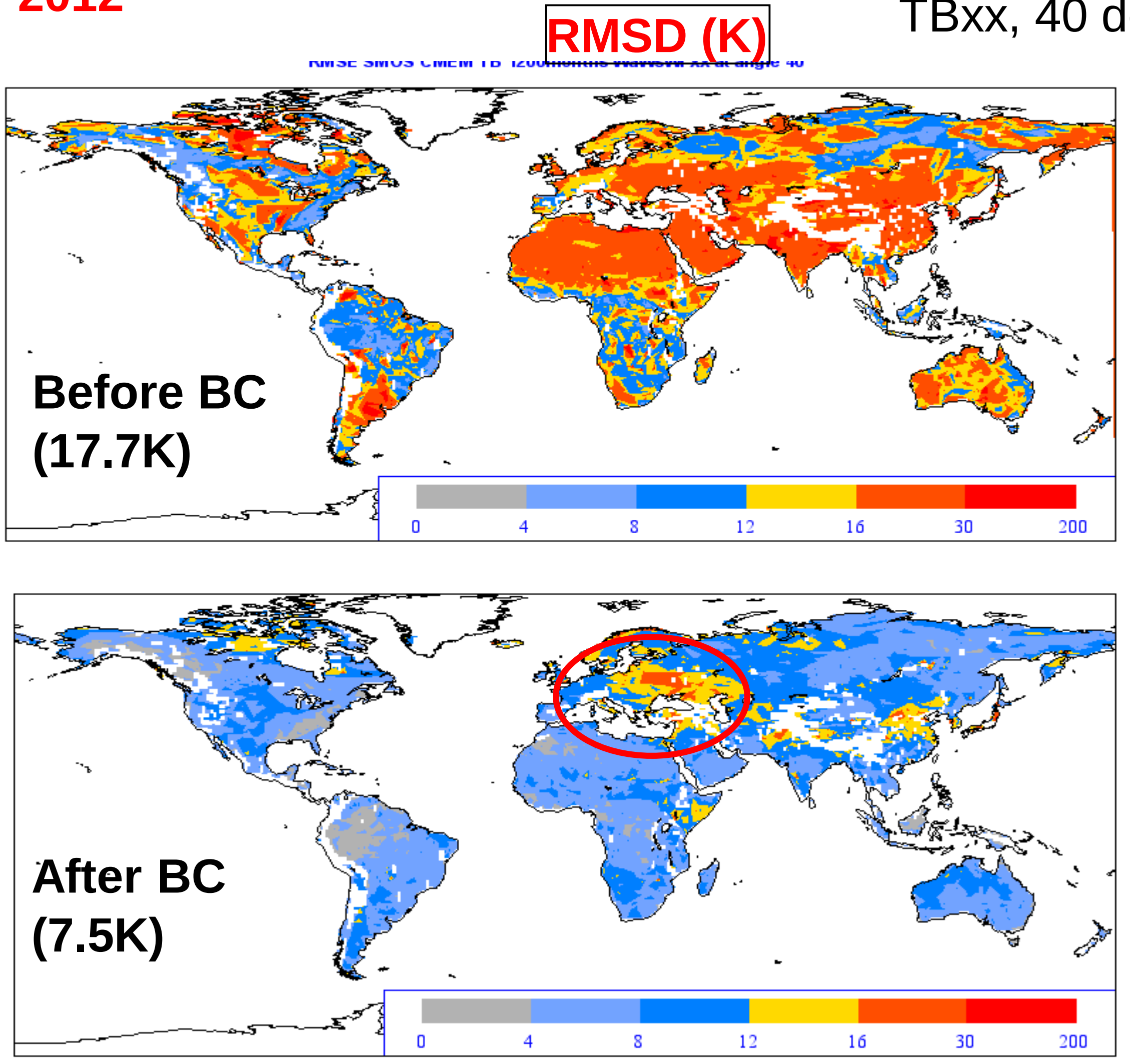
References:
Drusch et al. JHM, 2009
de Rosnay et al. JGR, 2009
de Rosnay et al. RSE 2020
Hirahara et al in prep 2020

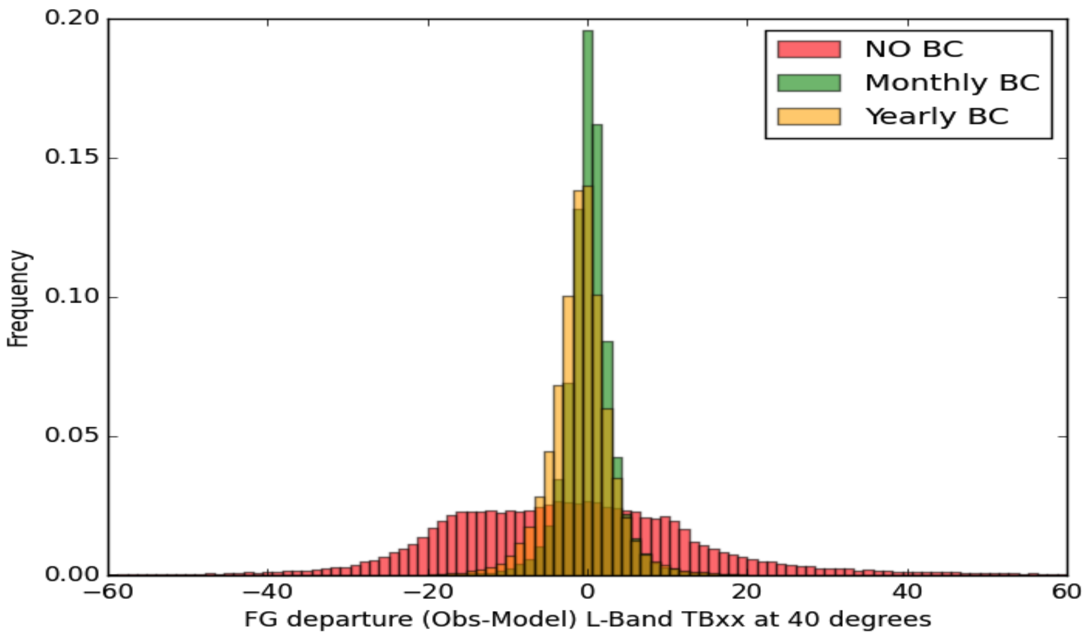
ECMWF L-band TB Bias correction

2012

RMSD between SMOS Obs and ECMWF TBxx, 40 degrees

Monthly CDF-matching

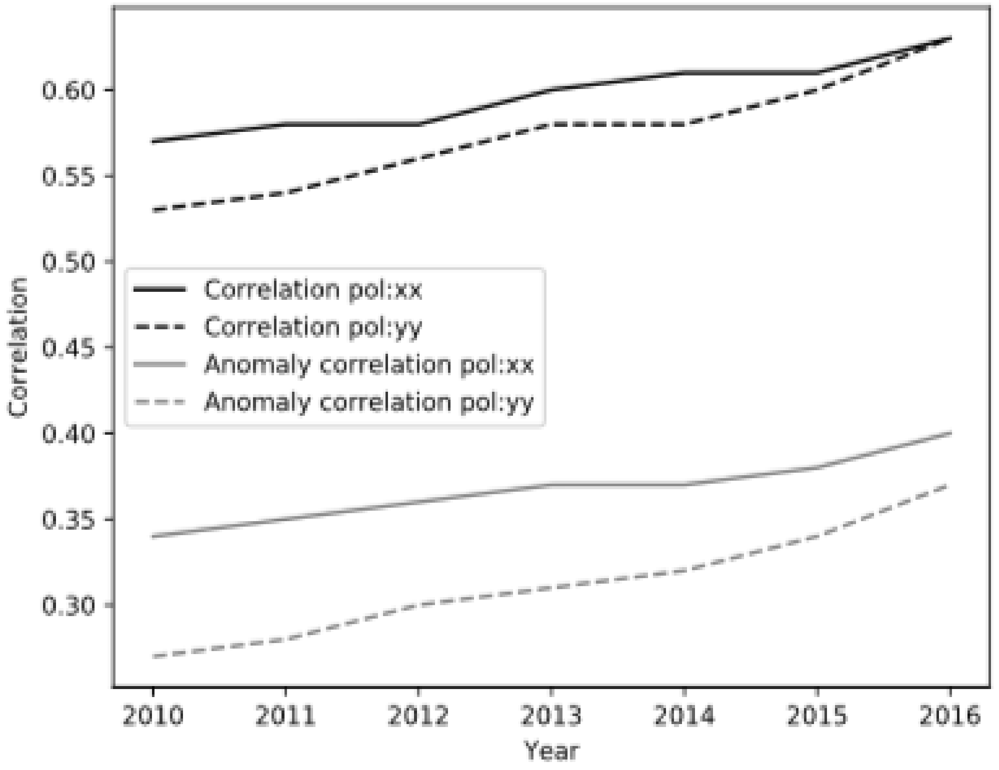




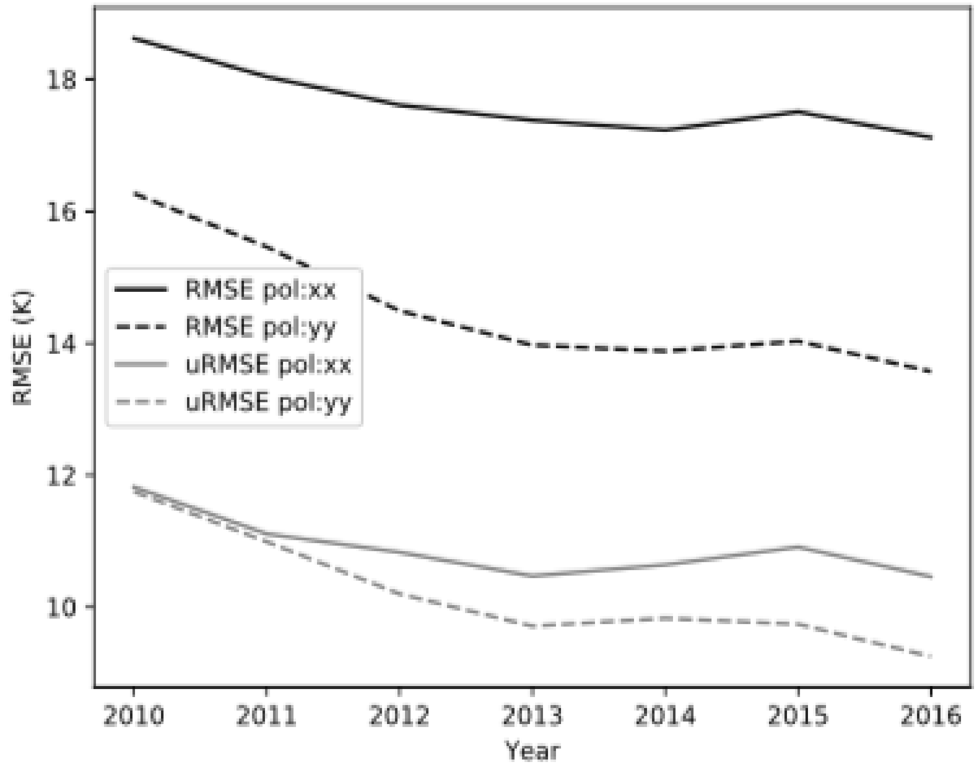
Described in details in de Rosnay et al, RSE, 2020

Low residual RMSD, except in areas affected by RFI (Radio Frequency Interferences)

Comparison between SMOS and ECMWF forward TB for 2010-2016



(a) Correlation



(b) Root mean square error

Consistent improvement of agreement between SMOS and ECMWF reanalysis at both polarisations, from 2010 to 2016

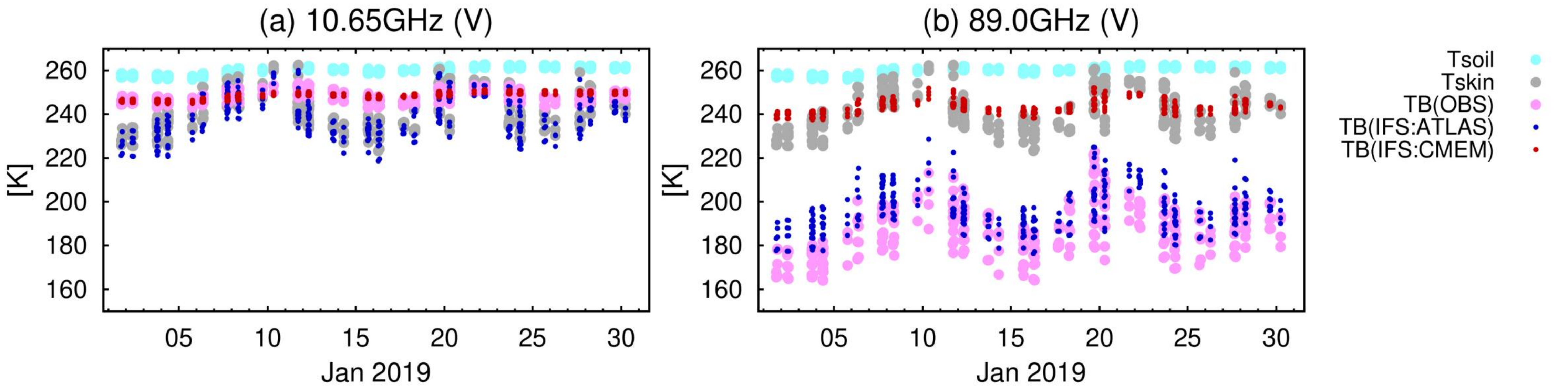
de Rosnay et al, RSE, 2020

Toward assimilation of surface-sensitive satellite data over land

- New interface between CMEM and RTTOV, processing of surface sensitive observations through the all-sky code path.

- Implementation of multi-layer snow radiative transfer scheme in CMEM

→ **support developments to extend the all-sky to all sky and all-surface approach**

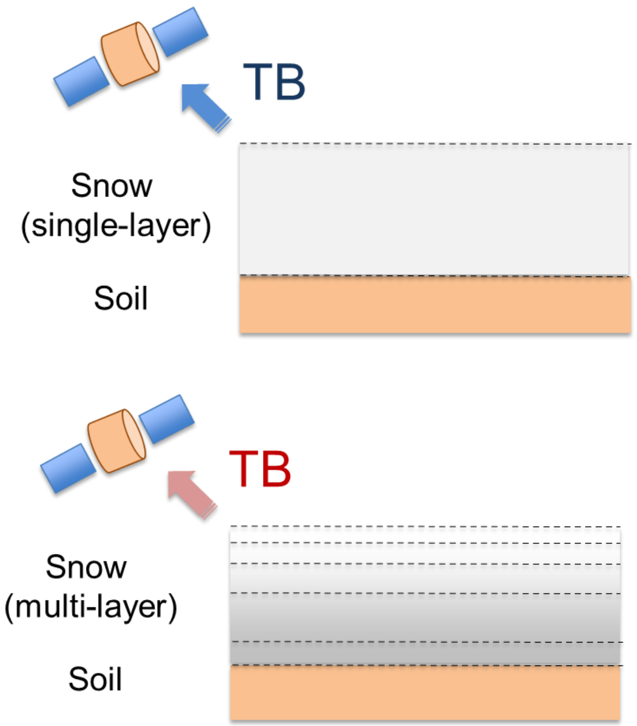


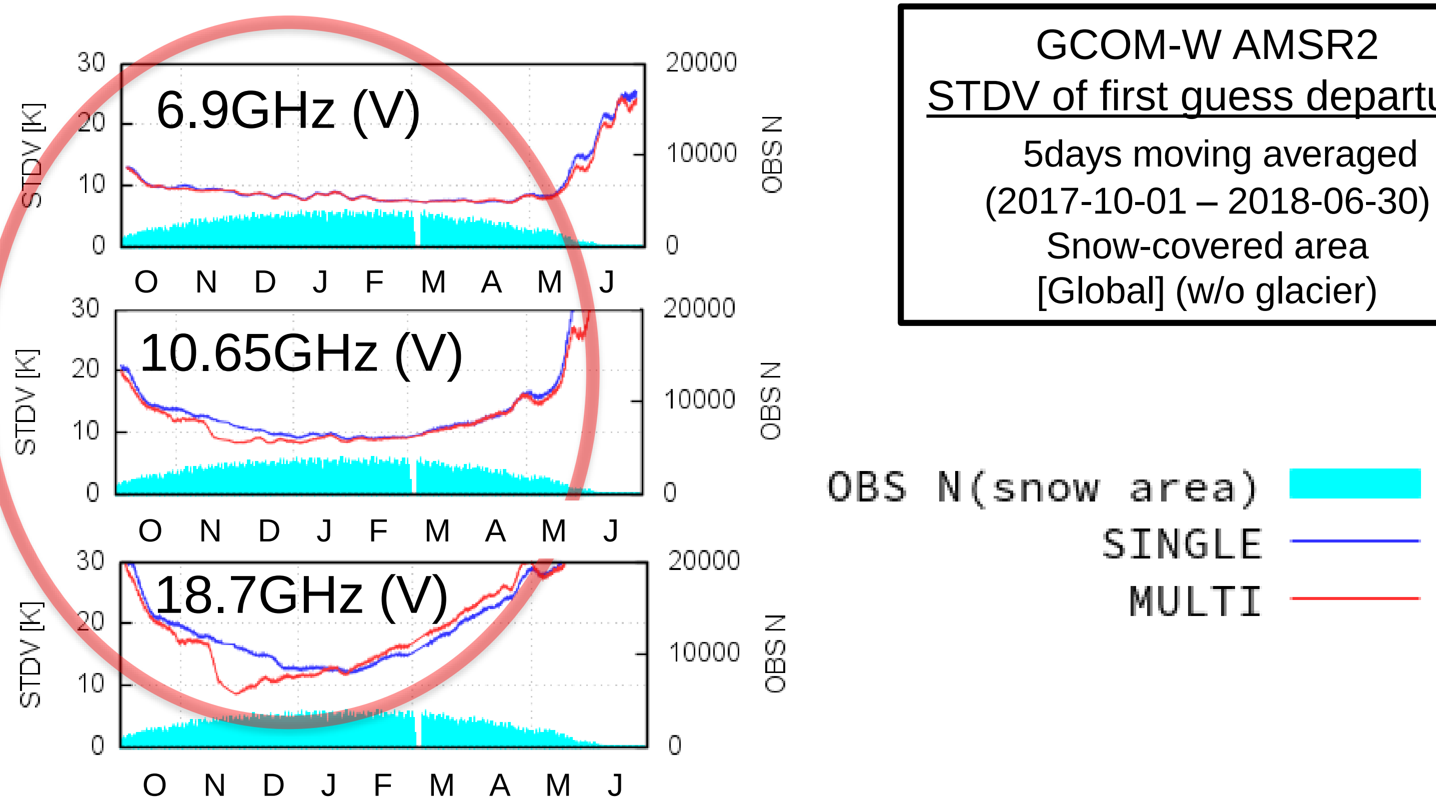
Hirahara et al, Remote Sens. **2020**, *12*(18), 2946; https://doi.org/10.3390/rs12182946

CMEM multi-layer snow-covered areas emission

- Importance of radiance assimilation over snow covered areas
- Relevance of multi-frequency multi-layer snow emission modelling
- First step towards initialisation of multi-layer snow conditions from satellite radiances coupled land-atmosphere assimilation

Hirahara et al, Remote Sens. **2020**, *12*(18), 2946; https://doi.org/10.3390/rs12182946



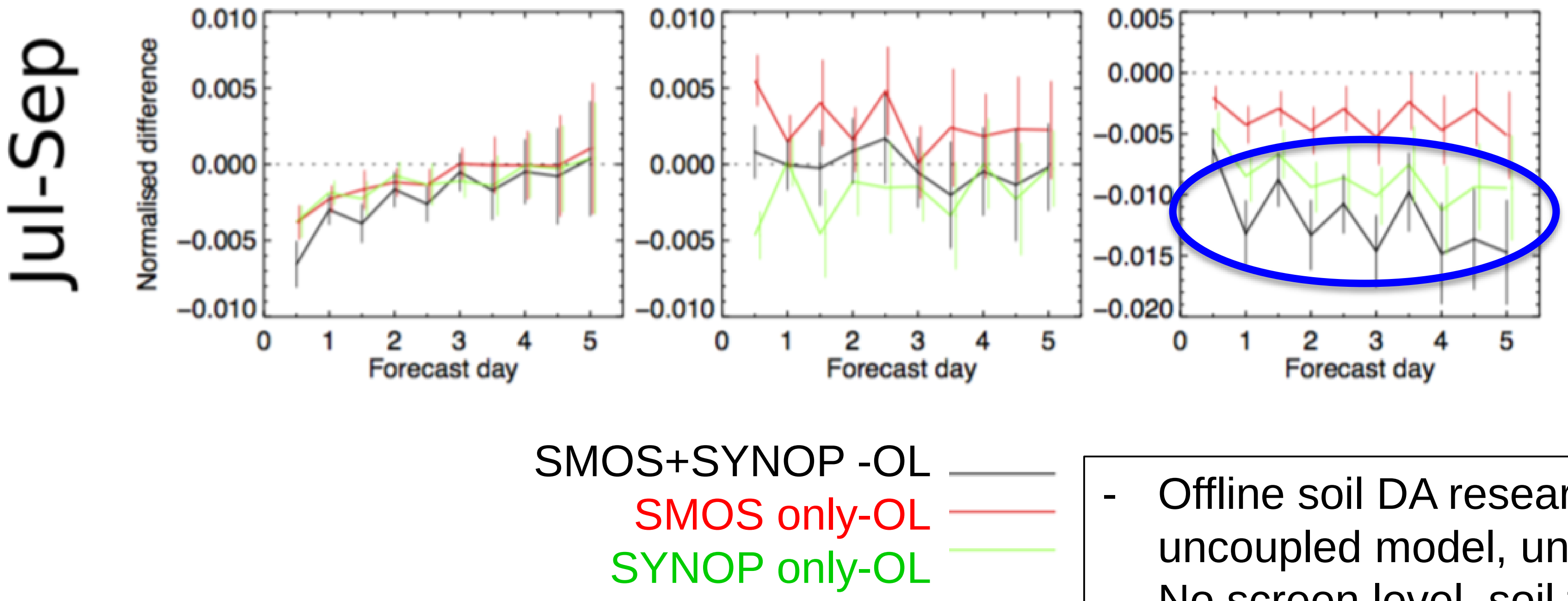


GCOM-W AMSR2
<u>STDV of first guess departure</u>
5days moving averaged
(2017-10-01 – 2018-06-30)
Snow-covered area
[Global] (w/o glacier)

SMOS Neural Network (NN) Soil Moisture assimilation in H-TESSEL

NN trained on offline H-TESSEL runs forced by ERA-Interim

Impact on two-meter air temperature forecasts (JAS 2012)
(Reference H-TESSEL with no assimilation: Open Loop 'OL')



- Offline soil DA research tool (24h DA window, uncoupled model, uncoupled atmosphere, B)
- No screen level, soil temp & snow analysis
- Uses of ERA-Interim Screen analysis as inpu 'SYNOP'
- Stand-alone atmospheric forecasts

→ Proof of concept of SMOS NN assimilation for NWP initialisation

Rodriguez-Fernandez et al, Remote Sensing, 2019

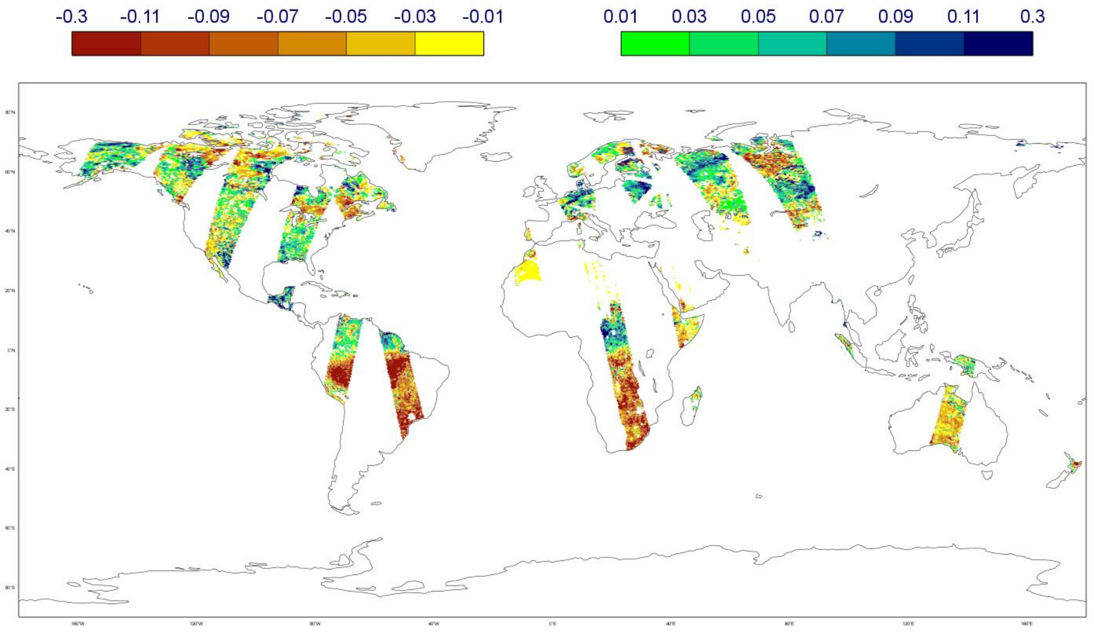
New soil analysis in 2019: Use SMOS NN and Ensemble approach

Reduction of the SEKF CPU cost by a factor ~3.6

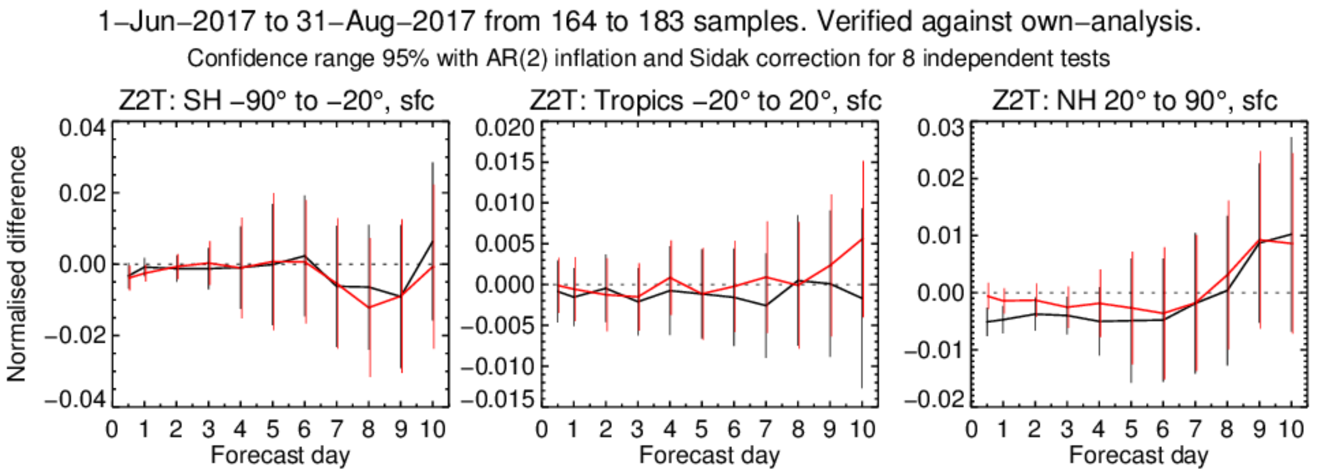
Resol.	NPES*THREADS	45r1	46r1
Tco 1279 (9km)	300*9	1580	435

Impact of:

- Use the Ensemble Data Assimilation (EDA) in the SEKF
- SMOS neural network soil moisture assimilation



SMOS innovation (obs-model)
01 August 2017 (m3/m3)



Ensemble and SMOS DA impact
SMOS DA impact

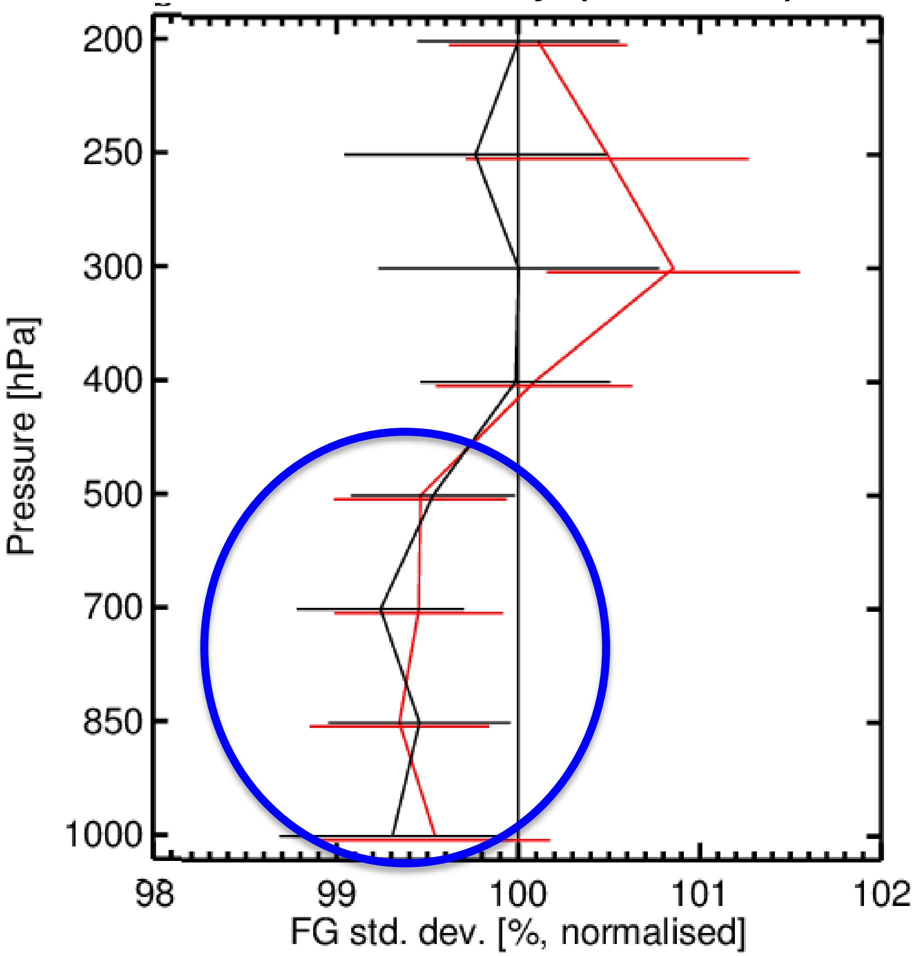
de Rosnay et al, in prep

Atmospheric forecasts impact (T2m) compared to CTRL

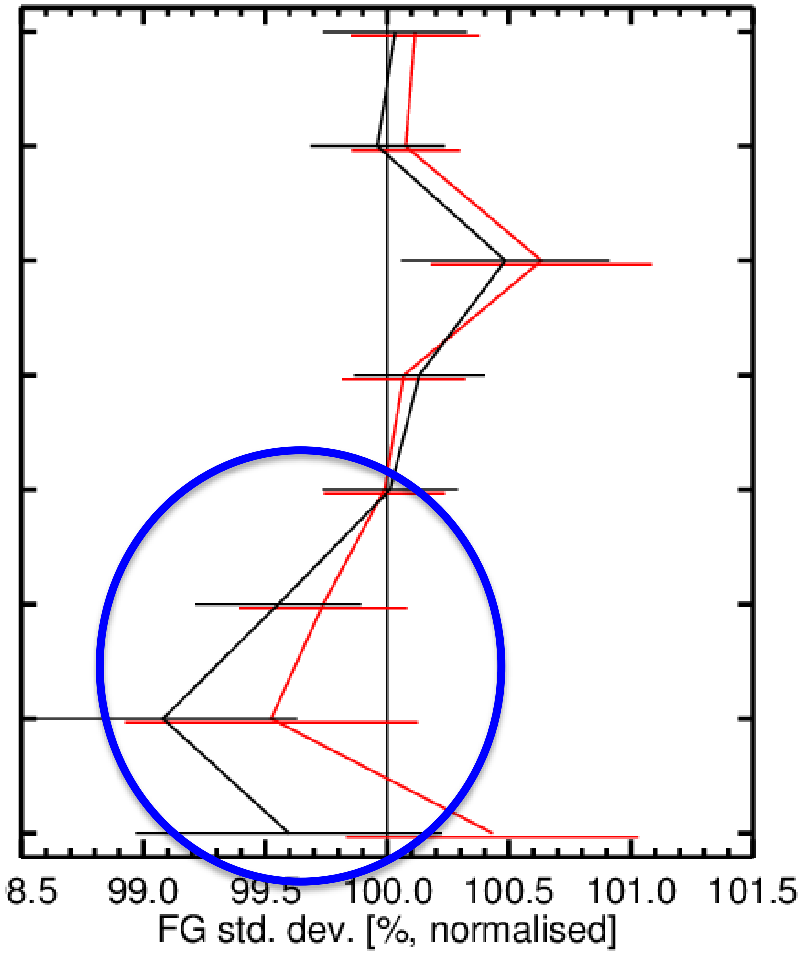
(CTRL has no Ensemble and no SMOS)

IFS impact (EDA-SEKF and SMOS neural network)

Aircraft humidity (JJA 2017)



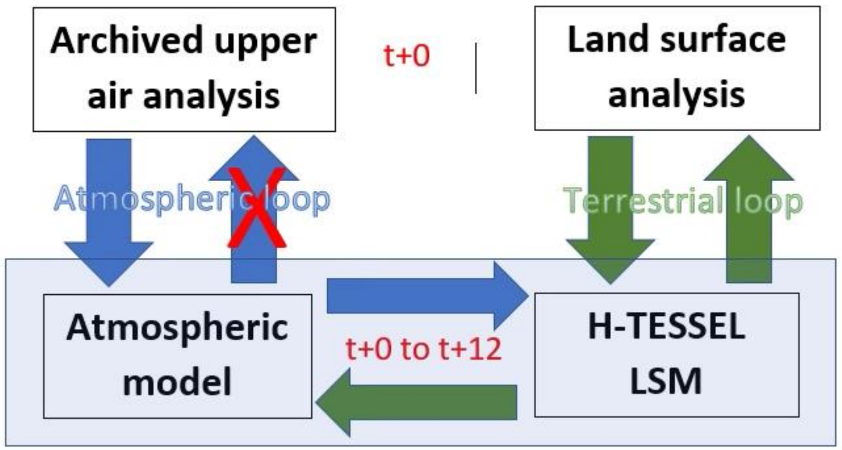
Aircraft temperature (JJA 2017)



SMOS impact
EDASEKF+SMOS impact

Improved fit
low troposphere

Stand-alone Surface Analysis and ASCAT soil moisture assimilation



Satellite data → Surface information
Top soil moisture sampling depth (e.g. 0-2cm for ASCAT)

Root Zone SM Profile variable of interest for soil-veg-atm interaction, climate, NWP and hydrological applications

→ Retrieval of root zone soil moisture using satellite data requires data assimilation approaches

New Stand-alone Surface Analysis (SSA) developed in the framework of the EUMETSAT H SAF
→ Much faster than weakly coupled DA (~20% runtime)
→ Land surface reanalysis capabilities

D. Fairbairn et al., JHM 2019

Summary and outlook for Land Data Assimilation

- Land DA: combine OI, and EDA-SEKF

- Satellite data used; SMOS, ASCAT, IMS

- Coupling developments: EDA-SEKF, multi-layer snow MW observation operator, coupling with hydrology, future outer-loop coupling → link OOPS; consistent with ocean coupling

- Observations usage plans: SMAP data, VOD assimilation, LST

- Ongoing developments for IMS DA in the SEKF, coupling through the observation operator over snow covered areas, future adaptive bias correction

- Consistency NWP, hydro, CO_2 →link to Copernicus Services (C3S, CEMS, CAMS)

Special Issue "Remote Sensing of Land Surface and Earth System Modelling"

- Special Issue Editors
- Special Issue Information
- Keywords
- Published Papers

https://www.mdpi.com/journal/remotesensing/special_issues/Land_Surface_Earth_System_Modeling

A special issue of *Remote Sensing* (ISSN 2072-4292). This special issue belongs to the section "Biogeosciences Remote Sensing".

Deadline for manuscript submissions: 31 May 2021

- Land surface data assimilation
- Land surface re-analysis
- Land surface forward modelling (VIS/IR/MW),
- Inverse modelling and machine learning
- Land surface parameter retrieval
- Coupled assimilation (land-hydrology-atmosphere)
- Intercomparison (model and DA)

Special Issue Editors

Guest Editor
Dr. Patricia De Rosnay
European Center For Medium-Range Weather Forecasts, UK
Website | E-Mail
Interests: Land surface data assimilation; coupled assimilation; Earth system modelling; Land surface observations; Forward modelling

Guest Editor
Dr. Clement Albergel
Affiliation: Météo-France/ Centre National de Recherches Météorologiques (CNRS), France
Website | E-Mail
Interests: land surface modelling; climate change; hydrology; data analysis

Guest Editor
Dr. Sujay Kumar
Hydrological Sciences Lab, NASA Goddard Space Flight Center, 8800 Greenbelt Rd, Greenbelt, MD, 21042, USA
Website | E-Mail
Interests: land surface modelling; hydrology; data assimilation; remote sensing; Optimization