

Review of surface data assimilation in ALADIN/HIRLAM

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Land-Surface Model (LSM)

Run simultaneously in **COUPLED** mode with an atmospheric model to predict primarily surface-atmosphere **heat** and **moisture** transfer.

To provide these boundary conditions, land model **must have**:

- Necessary **atmospheric forcing** to drive the land model,
- Appropriate **physics** to represent **land-surface processes** (for relevant time/spatial scales),

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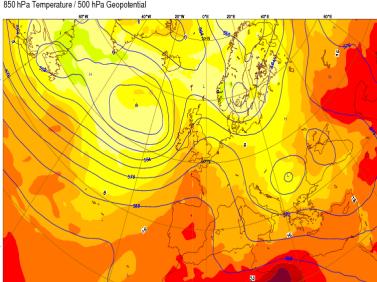
To provide proper these boundary conditions, land model **must have**:

- Corresponding **land data sets and associated parameters**, e.g. land use/land cover (vegetation type), soil type, surface albedo, snow cover, surface roughness, etc., and
- Proper **initial land states**, analogous to initial atmospheric conditions, though land states may carry more “memory” (e.g. especially in **deep soil moisture**), similar to ocean SSTs.

Land Surface Model (LSM)

Meteorological forcing

Friday 28 June 2015 00UTC (ECMWF Analysis) +0000 VT: Friday 28 June 2015 00UTC



```
ZMRIFPP(JLON)=-
(sqrt((ZETKE_R(JLON)*
&
(ZRITKE(JLON)*CX3TKEFREE+ZETK
E_P(JLON)))**2 &
& 4.0
*ZRITKE(JLON)*CX3TKEFREE*ZETK
E_R(JLON)*ZETKE_P(JLON)**2) &
& -
(ZRITKE(JLON)*CX3TKEFREE+ZETK
E_P(JLON))*ZETKE_R(JLON))/ &
& (2.0 *ZETKE_P(JLON))
```

Appropriate physics

$$\frac{\partial T_s}{\partial t} = C_r(R_n - H - LE) - \frac{2\pi}{\tau}(T_s - T_2) \quad (1)$$

$$\frac{\partial T_2}{\partial t} = \frac{1}{\tau}(T_s - T_2) \quad (2)$$

$$\frac{\partial w_g}{\partial t} = \frac{C_1}{\rho_w d_1} (P_g - E_g) - \frac{C_2}{\tau} (w_g - w_{geq}); \quad (3)$$

$$0 \leq w_g \leq w_{sat}$$

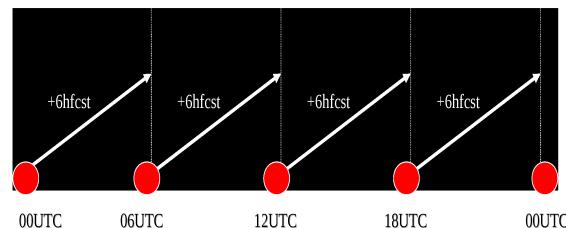
$$\frac{\partial w_2}{\partial t} = \frac{1}{\rho_w d_2} (P_g - E_g - E_{tr}) \quad (4)$$

$$- \frac{C_3}{d_2 \tau} \max[0, (w_2 - w_{fc})];$$

$$0 \leq w_2 \leq w_{sat}$$

$$\frac{\partial W_r}{\partial t} = vegP - (E_v - E_{tr}) - R_r; 0 \leq W_r \leq W_{rmax} \quad (5)$$

Proper initial state



Land data sets & associated parameters

$$C_k \frac{\partial T_k}{\partial t} = \frac{\partial FLUX}{\partial z}$$

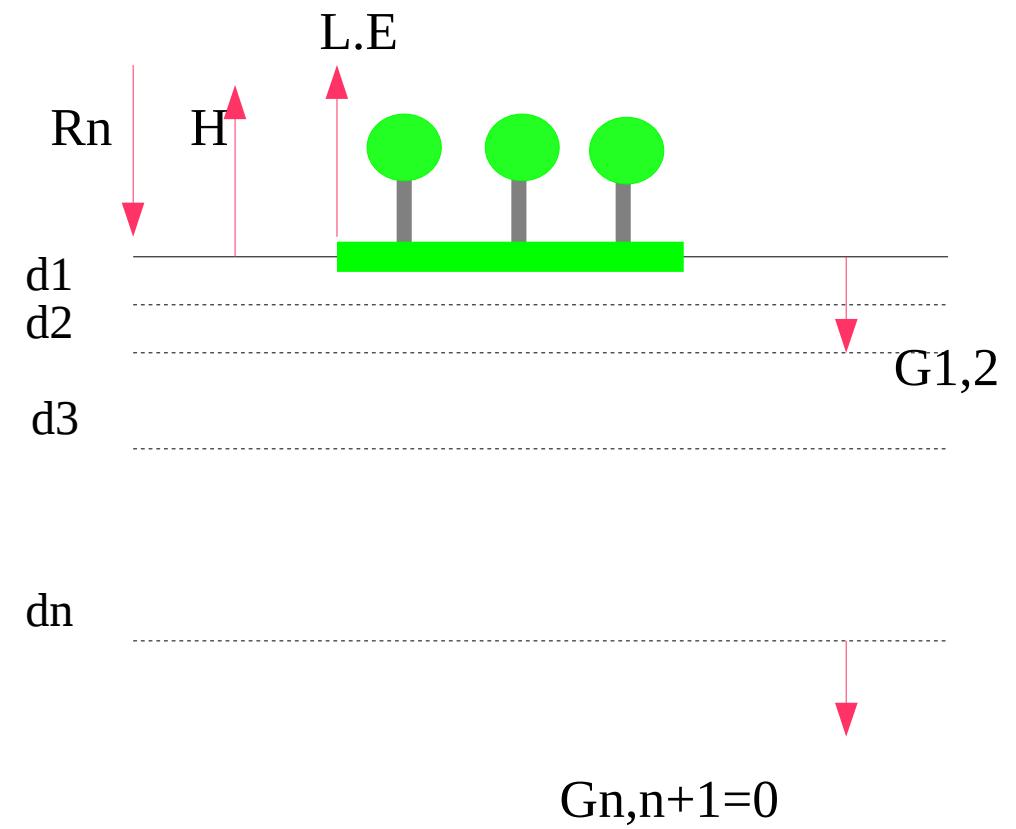
$$C_1 \frac{\partial T_1}{\partial t} = \frac{R_n - H - L.E - G_{1,2}}{d_1}$$

$$G_{1,2} = \bar{\lambda}_{1,2} \frac{T_1 - T_2}{(d_1 + d_2)} \\ \frac{2}{2}$$

$$\bar{\lambda}_{1,2} = \frac{d_1 + d_2}{\frac{d_1}{\lambda_1} + \frac{d_2}{\lambda_2}}$$

$$C_1 \frac{\partial T_1}{\partial t} = \frac{R_n - H - L.E}{d_1} - \frac{1}{d_1} \bar{\lambda}_{1,2} \frac{T_1 - T_2}{(d_1 + d_2)} \\ \frac{2}{2}$$

$$C_2 \frac{\partial T_2}{\partial t} = \frac{1}{d_2} \bar{\lambda}_{1,2} \left(\frac{T_1 - T_2}{(d_1 + d_2)} - G_{2,3} \right) \\ \frac{2}{2}$$



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...

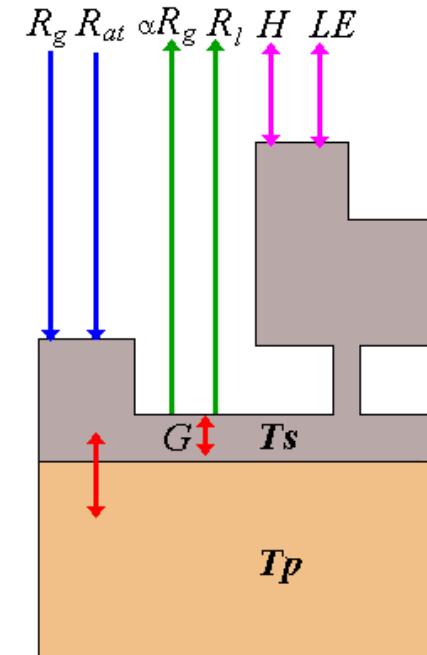
$$C_n \frac{\partial T_n}{\partial t} = \frac{1}{d_n} \left(\bar{\lambda}_{n-1,n} \frac{T_{n-1} - T_n}{\frac{(d_{n-1} + d_n)}{n}} \right)$$

Multilayer soil model, which is computationally very expensive.

$$C_s \frac{\partial T_s}{\partial t} = \frac{R_n - H - L.E}{d_1} - \frac{2\pi}{\tau} (T_s - T_2)$$

$$\frac{\partial T_2}{\partial t} = \frac{1}{\tau} (T_s - T_2)$$

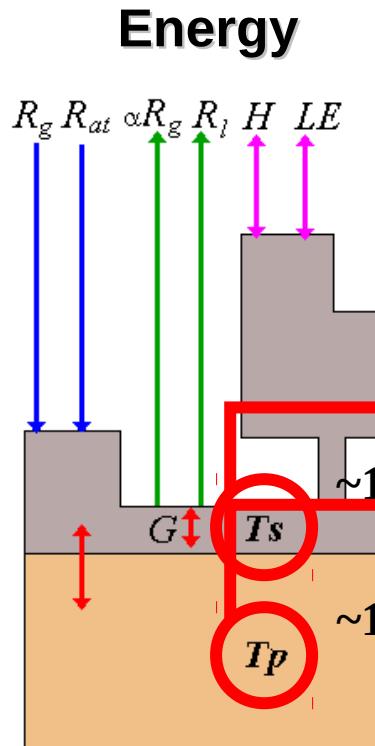
$$\tau = \text{diurnal period} = 86400 \text{ s}$$



In this model the ground is conceptually split into two layers, a relatively thin layer near the top with uniform temperature, and a deep soil layer also of uniform but different temperature. The net result is that flux from the deep soil layer tends to restore the top layer, opposing any radiative forcing from the atmosphere. This method is an alternative to a multilayer soil model, which is computationally more expensive.

Surface Parameterization scheme (ISBA)

- The **ISBA-2L** scheme evolves 4 prognostic variables. (Giard and Bazile 2000)



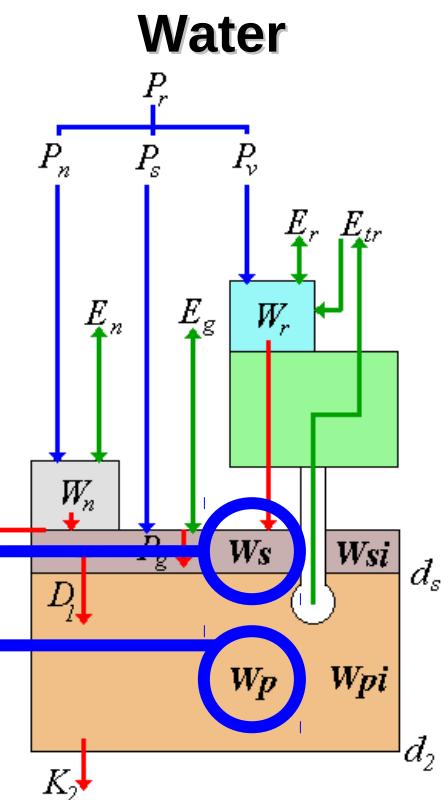
Analysis

{ surface temperature
 mean soil temperature
 superficial soil water content
 total soil water content

$$\begin{aligned}
 \frac{\partial T_s}{\partial t} &= C_T(R_n - H - LE) - \frac{2\pi}{\tau}(T_s - T_2) \\
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 \end{aligned}$$

$\sim 6\text{-}12 \text{ h}$

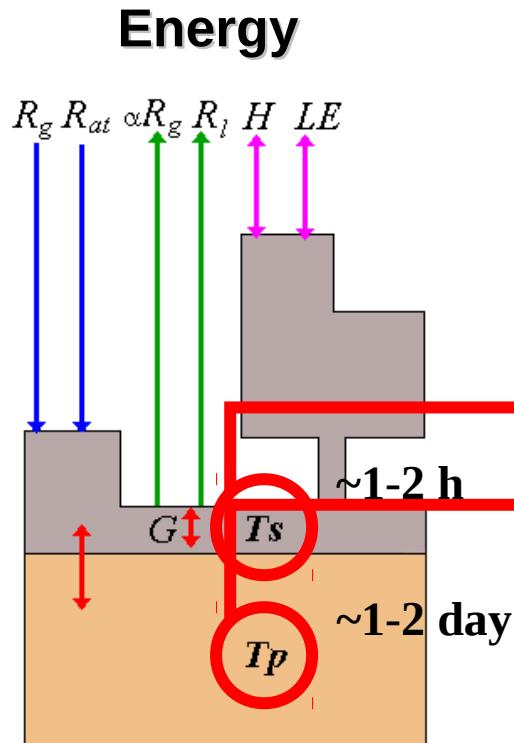
$\sim 10 \text{ days}!!!$



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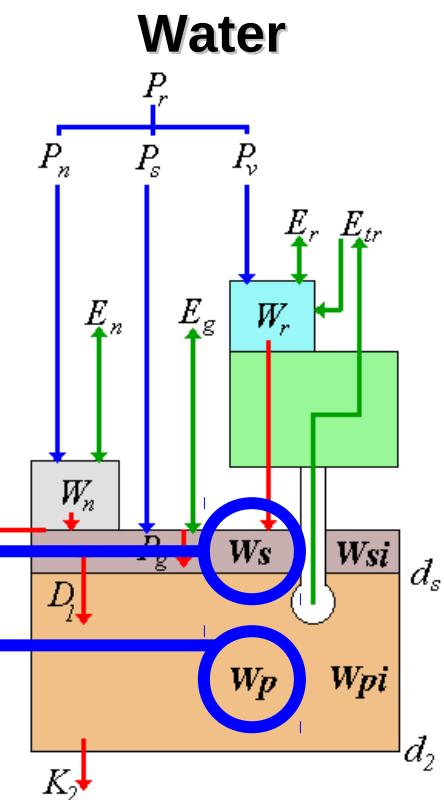


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 \end{aligned}$$

$\sim 6-12 \text{ h}$ $\sim 10 \text{ days!!!}$



- Research versions: interactive vegetation module (Calvet et al. 1998), sub grid-scale runoff and sub-root layer (Boone et al. 1999), explicit 3-layers snow scheme (one and Etchevers 2001)...

Soil moisture content

- Volumetric water content (m^3 of water / m^3 soil): W_p .
- Saturation water content or porosity = maximum amount of water that a given soil can hold : $W_{\text{sat}}=450 \text{ mm}$ (for 1 m soil depth)
- Water content at field capacity = value above which evaporation takes place at potential rate-when water excess has drained away : $W_{\text{fc}}=300 \text{ mm}$
- Water content at wilting point = value below which plants cannot extract soil water from their root system : $W_{\text{wilt}}=200 \text{ mm}$
- Soil Wetness Index = normalized soil moisture content :

$$SWI = \frac{(W_p - W_{\text{wilt}})}{(W_{\text{fc}} - W_{\text{wilt}})}$$

Link between soil moisture and surface boundary layer

- The main interaction of soil moisture and SBL is due to evaporation and vegetation transpiration process.
- Under strong solar radiation at the surface, soil moisture becomes very important because it determines the repartition of incoming net radiation into sensible and latent heat flux.

Net radiation at the surface :

$$R_n = R_G(1 - \alpha_t) + \epsilon_t(R_A - \sigma T_s^4) = H + LE + G$$

- For $W_p < W_{wilt}$: LE is almost negligible
- For $W_p > W_{fc}$: LE = potential evaporation
- Importance of soil moisture and temperature analysis because the impact of a prescribed initial error in the soil moisture field may degrade significantly the forecast during long period **up to several days**.

Available observations for surface analysis

● Precipitations observations (rain gauges, radars) :

- + direct link with the variations of soil water content

● Satellite observations:

- + global coverage
- + infrared: clear sky, low vegetation, geostationary satellites : high temporal and spatial resolutions (energy budget), strong sensitivity to low level wind, surface roughness
- + microwave: active and passive instruments measure directly the soil moisture in the first few centimeters (scatterometer (ERS,ASCAT), passive or active radiometers (SMOS, AMSR): resolution ~20/40km, frequency ~0.3/1 per day

● 2m observations (temperature and humidity):

- + good global coverage of existing network
- + close links with the fields in the ground in specific meteorological conditions

Optimum Interpolation: basic theory

- Based on Best Linear Unbiased Estimation (BLUE) :

$$X^A = X^G + \underbrace{BH^T (HBH^T + R)^{-1} (Y - HX^G)}_K$$

- with
 - X^A**: analyzed state vector
 - X^G**: background state vector
 - Y**: observation vector
 - H**: observation operator (model space to observation space)
 - B**: background error covariance matrix
 - R**: observation error covariance matrix
 - K**: gain matrix

1) Optimum Interpolation of T_{2m} and RH_{2m} using 2m observations interpolated at the model grid-point by a 2m analysis (2-D CANARI OI)

$$\Delta T_{2m} = T_{2m}^a - T_{2m}^b \quad \Delta RH_{2m} = RH_{2m}^a - RH_{2m}^b$$

2) Correction of 4 surface parameters (T_s , T_p , W_s , W_p) using 2m increments between analysed and forecasted values.

$$T_p^a - T_p^b = \Delta T_{2m} / 2\pi \quad T_s^a - T_s^b = \Delta T_{2m}$$

$$W_s^a - W_s^b = \alpha_{WsT} \Delta T_{2m} + \alpha_{WsRH} \Delta RH_{2m}$$

$$W_p^a - W_p^b = \alpha_{WpT} \Delta T_{2m} + \alpha_{WpRH} \Delta RH_{2m}$$

OI coefficients

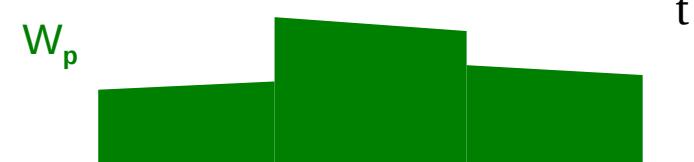
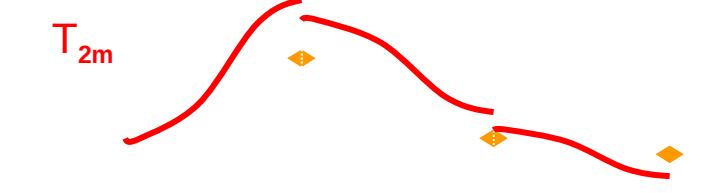
$$\alpha_{WsT} = \frac{\sigma_{WsT}^b}{\Phi \sigma_{T2m}^b} \left[1 + \left(\frac{\sigma_{T2m}^a}{\sigma_{T2m}^b} \right)^2 \right] \rho_{T2m, WsT} - \rho_{T2m, RH2m} \rho_{RH2m, WsT}$$

$$\alpha_{WsRH} = \frac{\sigma_{WsRH}^b}{\Phi \sigma_{RH2m}^b} \left[1 + \left(\frac{\sigma_{RH2m}^a}{\sigma_{RH2m}^b} \right)^2 \right] \rho_{RH2m, WsRH} - \rho_{T2m, RH2m} \rho_{T2m, WsRH}$$

$$+ \left(\frac{\sigma_{T2m}^a}{\sigma_{T2m}^b} \right)^2 \left[1 + \left(\frac{\sigma_{RH2m}^a}{\sigma_{RH2m}^b} \right)^2 \right] - \rho_{T2m, RH2m}^2$$

- Very strong dependency of these background error statistics to **physiographic properties** and **meteorological conditions**.

Sequential analysis (every 6h)



6-h 12-h 18-h

- ➊ OI coefficient values were originally calculated in 1-D experiments with a MonteCarlo method, and for a single grid point location under anticyclonic summer conditions.
- ➋ For the operational implementation a set of regressions allow to define the OI coefficients to each grid point according to : **vegetation fraction, LAI/R_{smin}, soil texture, and local solar time**. (Bouttier et al. 1993a, b)
- ➌ In the operational global surface analysis, the meteorological conditions have been taken into account through a weighting function that ranges between 0 and 1.

$$\alpha_{Wp/sT/RH} = f(t, veg, LAI/Rs_{min}, texture, atmospheric\ conditions)$$

- ➍ This function evaluates several quantities and modulate the OI coefficients on grid points exceeding given thresholds:

➎ Giard and Bazil (2000)

<u>Model Fields</u>		<u>Threshold</u>
Min solar time duration	J_min	6 h
Max wind velocity	Vmax	10 ms ⁻¹
Max precipitation	P_max	0.3 mm
Min surface evaporation	E_min	0.001 mm
Max soil ice	W_imax	5.0 mm
Presence of snow	Sn_max	0.001 kg

- **Linear observation operator:** The link between current available observations (T_{2m} , HU_{2m}) and soil variables is complex (non linear relation with surface evaporation fluxes, dependence with the vertical interpolation scheme and with the prognostic equation for the land surface scheme).
- **The OI coefficients** are obtained by statistical equations and it is difficult to correct objectively (Factor 6 reduction of OI coefficient on W_p).
- **Arbitrary thresholds:** Need to impose arbitrary thresholds to avoid soil analysis in conditions where forecast errors at screen level are not related to soil moisture.
- **Difficult to consider new variable to analyse:** The current OI coefficients for T_s and T_p are taken from the previous global analysis (since Mahfouf (1991) did not perform Monte-Carlo experiments for these variables). The complexity of the ISBA scheme will increase for future NWP applications: ISBA-3L, ISBA-DF, ISBA-Ags, ISBA-SBL,...
- **Difficult to consider new observations:** Some observations that are more directly informative about soil/vegetation state than screen level parameters are available

The Extended Kalman Filter (I)

- We consider a control vector \mathbf{X} (N_x) that represents the prognostic equations of ISBA (M) which evolves with time as: $\mathbf{X}_f^t = M(\mathbf{X}^0)$, with $N_x = 4$ and $\mathbf{X} = (W_p, W_s, T_p, T_s)$ the forecast \mathbf{X}_f^t is characterized by a (forecast) background error covariance matrix \mathbf{B} .
- An N_y dimensional observation vector \mathbf{Y}_o is available at the regularly spaced discrete times $t_k = t_0 + k \cdot \tau$, $k=1,2,\dots$ characterized by an error covariance matrix \mathbf{R} and assimilation interval τ (06h for example).

The Extended Kalman Filter (I)

An observation operator \mathbf{H} maps from model to observed variables

$\mathbf{Y}_f^t = \mathbf{H}(\mathbf{X}_f^t)$. For example, it can be a vertical interpolation scheme for T_{2m} and HU_{2m} or a microwave radiative transfer model for brightness temperatures.

Under the Tangent Linear (TL) hypothesis, the \mathbf{H} operator can be expressed by its first-order Taylor expansion $\mathbf{H}(\mathbf{X} + \delta\mathbf{X}) = \mathbf{H}(\mathbf{X}) + \mathbf{H} \cdot \delta\mathbf{X}$ \mathbf{H} is the Jacobian matrix of \mathbf{H} .

A new value \mathbf{X}_a^t is obtained by an optimal combination of the observations and the background (BLUE):

$$\mathbf{X}_a^t = \mathbf{X}_f^t + \mathbf{B}\mathbf{H}^T (\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1} (\mathbf{Y}_o^t - \mathbf{H}_I(\mathbf{X}_f^t))$$

The Extended Kalman Filter (II)

- In this low dimensional problem, the Jacobian matrix \mathbf{H} is obtained by finite differences:

$$H_{ij} [N_x \text{ rows}, N_y \text{ columns}] = \frac{\partial y_i}{\partial x_j} \simeq \frac{y_i(x + \delta x_j) - y_i(x)}{\delta x_j}$$

- The input vector \mathbf{x} is perturbed N_x times to get for each integration a column of the matrix \mathbf{H} .

The Extended Kalman Filter (II)

The analysis is cycled by propagating in time the two quantities \mathbf{X}_a^t and \mathbf{A} up to the next time where observations are available: $\mathbf{X}_f^{t+1} = \mathcal{M}(\mathbf{X}_a^t)$ and $\mathbf{B}^{t+1} = \mathbf{M}\mathbf{A}^t\mathbf{M}^T + \mathbf{Q}$, where \mathbf{M} is the Jacobian matrix of the model,

$\mathbf{A} = (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1}$ is the analysis error covariance matrix, and \mathbf{Q} a new matrix representing the model error covariance matrix which needs to be defined.

For the Simplified Extended Kalman Filter (SEKF), we take: $\mathbf{B}^{t+1} = \mathbf{B}^t = \mathbf{B}$ and $\mathbf{Q} = \mathbf{0}$.

The SEKF has been coded within SURFEX

The SEKF for \mathbf{W}_P analysis within SURFEX

- Let us consider a SURFEX guess \mathbf{S} and a perturbed state \mathbf{S}' , where \mathbf{W}_P has been modified by a small quantity $\delta \mathbf{W}_P$.
- The SURFEX integrations provide the 2m forecast sensitivity evaluated at time t_1 at which the observations of temperature, $T_{2m}^{S(1)}$ and relative humidity $RH_{2m}^{S(1)}$ are available: $\delta T_{2m}^{(1)} = T_{2m}^{S'(1)} - T_{2m}^{S(1)}$ and $\delta RH_{2m}^{(1)} = RH_{2m}^{S'(1)} - RH_{2m}^{S(1)}$.

The SEKF for W_p analysis within SURFEX

For a 06h assimilation interval, the matrices \mathbf{B} , \mathbf{R} and \mathbf{H}^T used for the computation of \mathbf{K} are:

$$B = (\sigma_{W_p}^2)$$

$$R = \begin{pmatrix} \sigma_{T_{2m}}^2 & 0 \\ 0 & \sigma_{RH_{2m}}^2 \end{pmatrix}$$

$$H^T = \begin{pmatrix} \frac{\delta T_{2m}^1}{\delta W_p^{(0)}} \\ \frac{\delta RH_{2m}^1}{\delta W_p^{(0)}} \end{pmatrix}$$

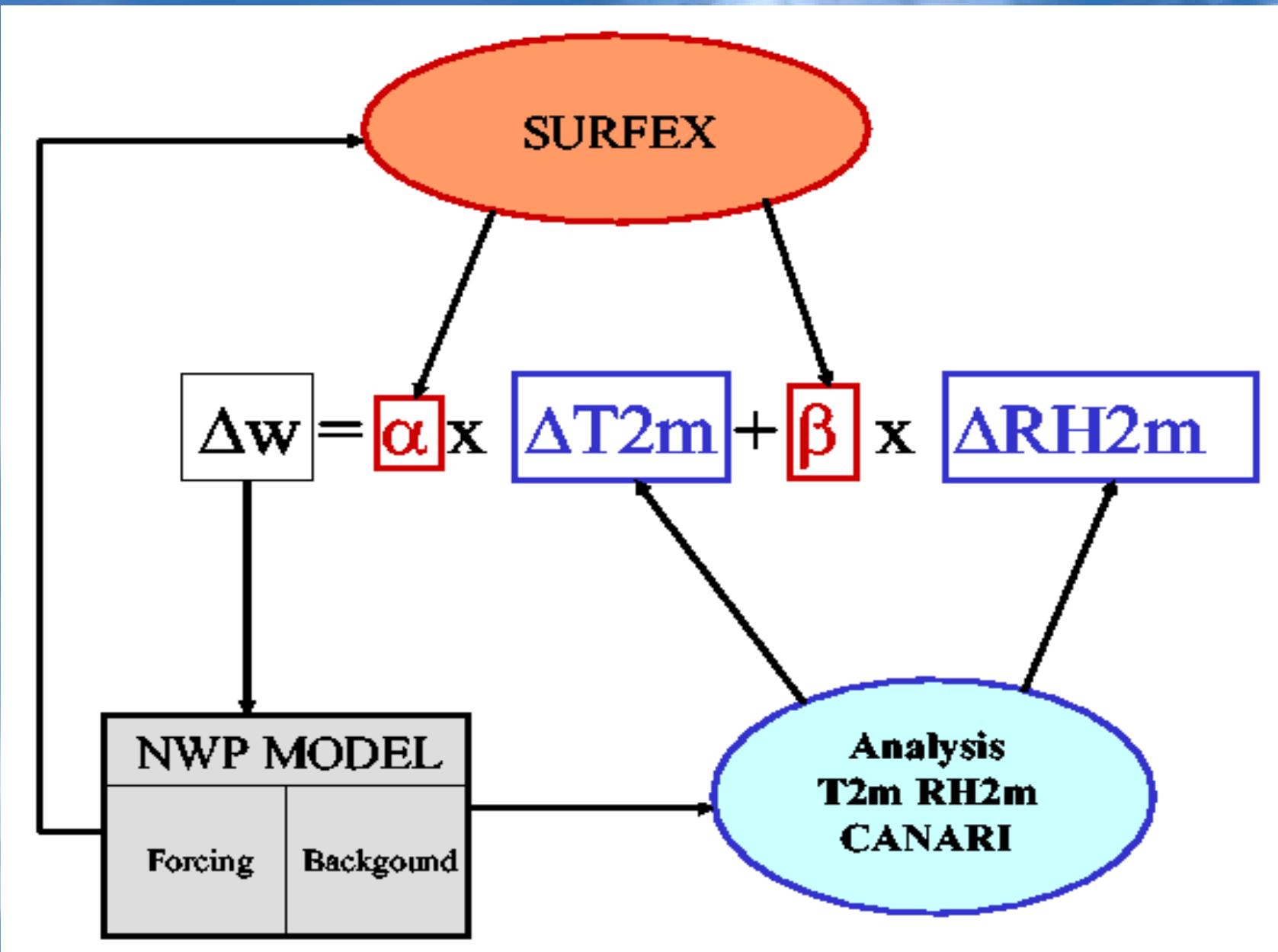
- If we expand the analysis correction according to the BLUE equation:

$$W_p^a = W_p^f + (k_1 \quad k_2) \begin{pmatrix} \Delta T_{2m}^1 \\ \Delta RH_{2m}^1 \end{pmatrix}$$

- k_1 and k_2 are the elements of the gain matrix. ΔT_{2m}^1 and ΔRH_{2m}^1 are innovation vectors at the time $t_1 = t_0 + 06h$.

$$W_p^a - W_p^b = \alpha_{WpT} \Delta T_{2m} + \alpha_{WpRH} \Delta RH_{2m}$$

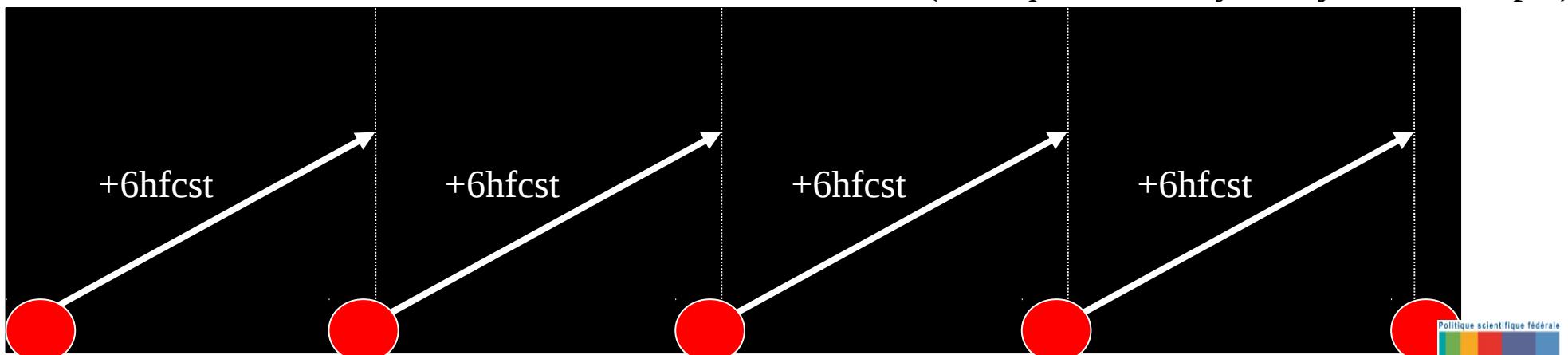
Coupling between atmospheric model and offline SURFEX



Surface analysis and upper-air analysis

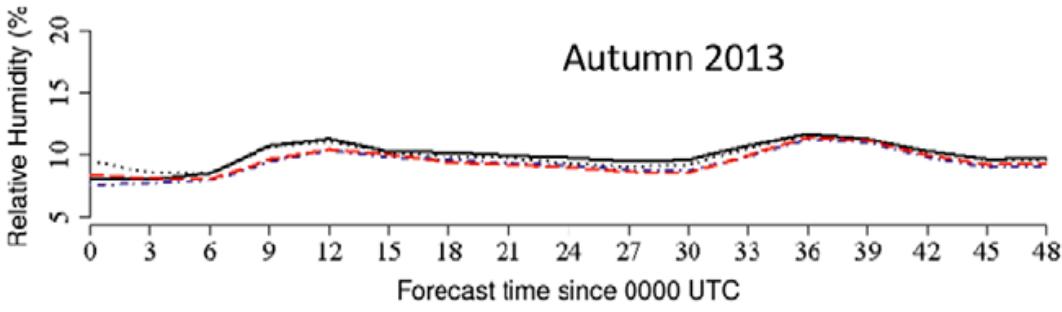
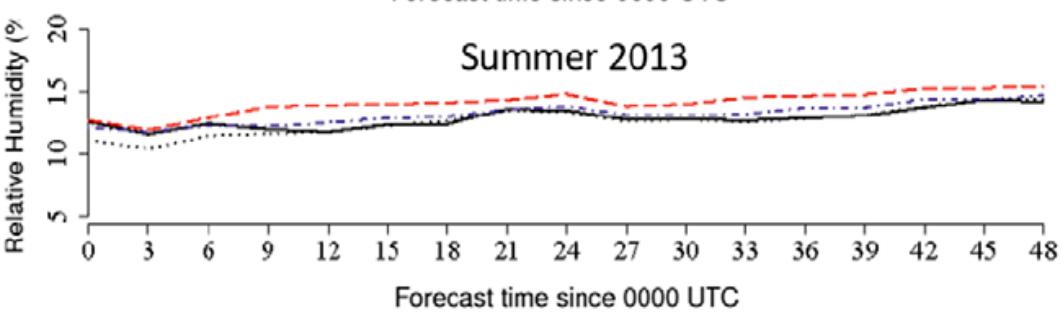
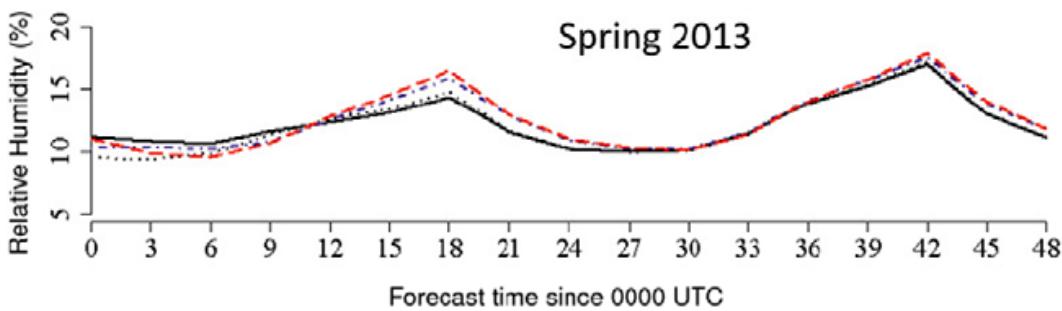
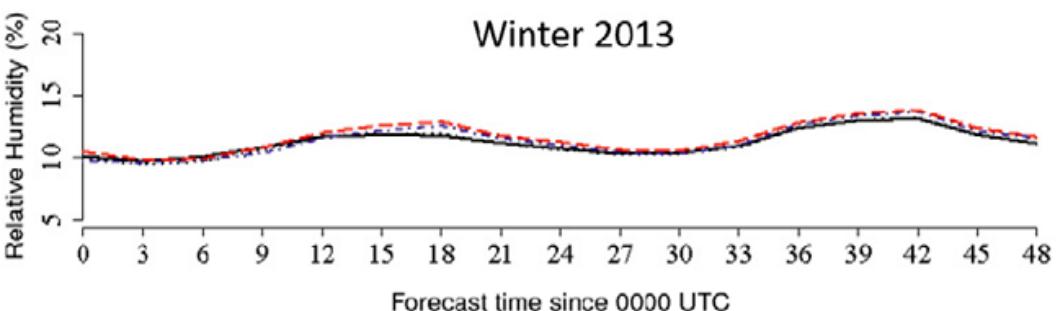
- For the time being surface analysis are performed separately from upper air analysis. In theory a single analysis would be better but it is much more difficult to implement: 1) definition of **B** between upper air and surface variables, 2) time scale evolutions may be different, ...
- For the time being several surface analysis are used for different surface parameters (Soil temperature and Soil moisture, Snow, SST, Sea ice, ...)
- Atmospheric analysis and several surface analysis are done separately and combined to provide the final analysis for the forecast.

(6h sequential analysis is just an example)

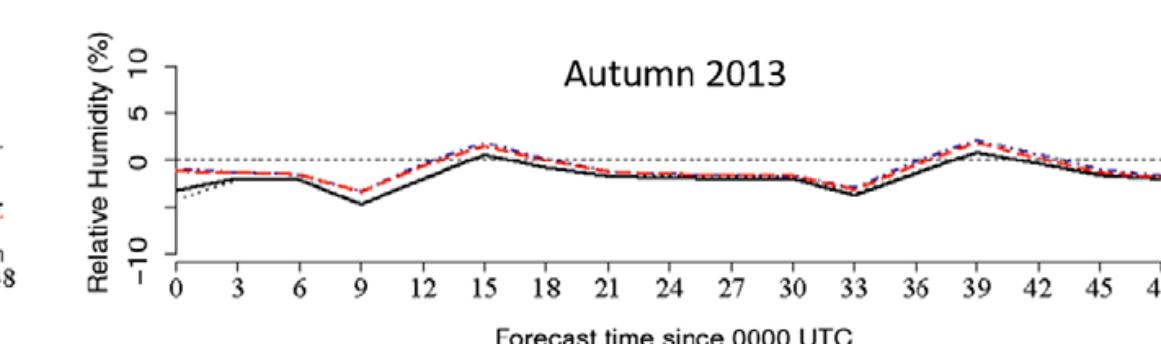
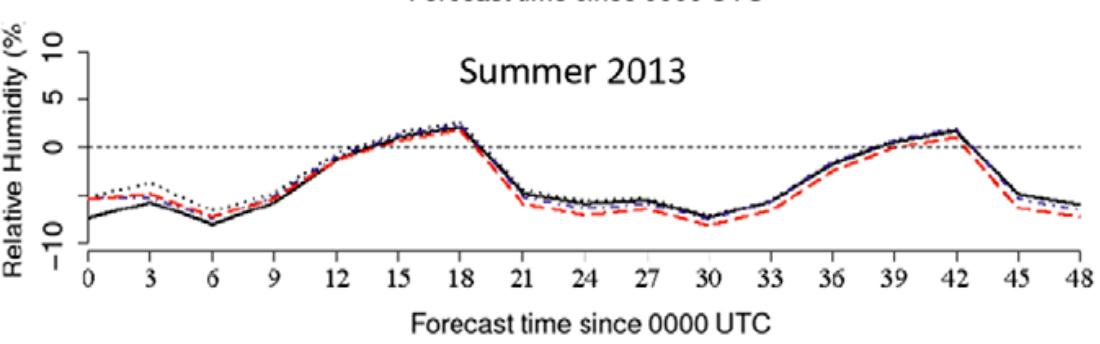
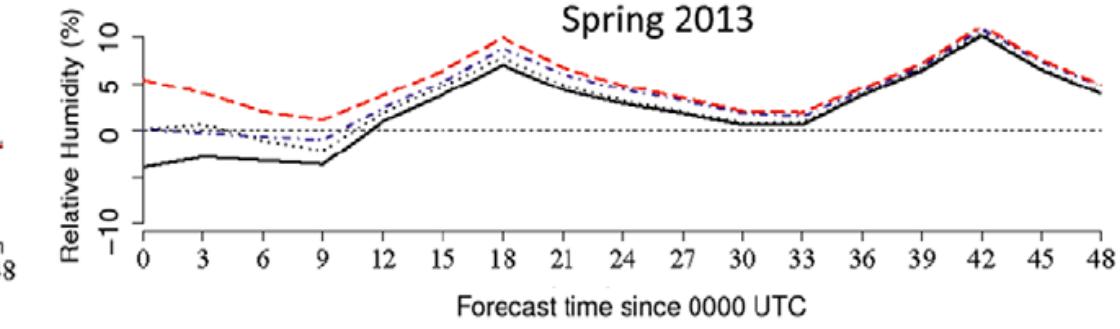
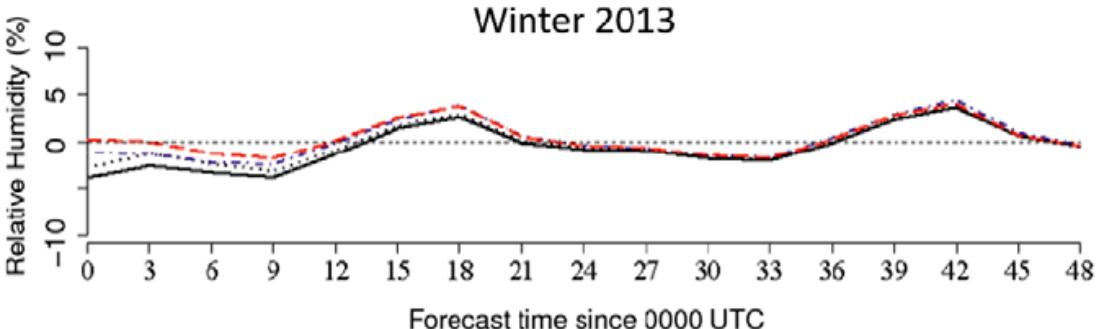


- 3dVar+EKF
- EKF
- Open Loop
- 3dVar+Open Loop

2m Relative Humidity RMSE

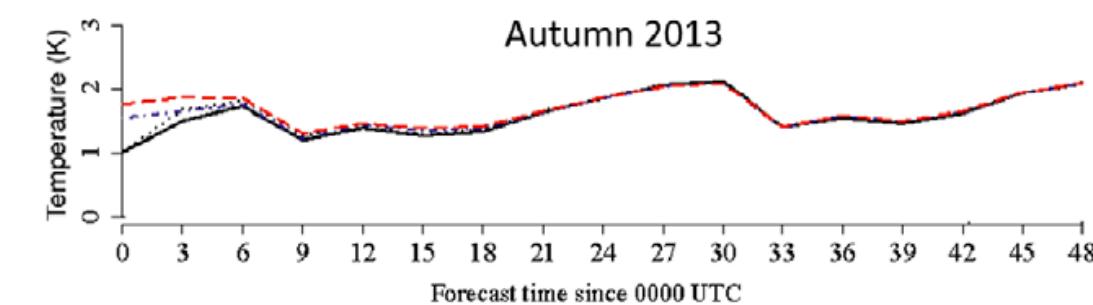
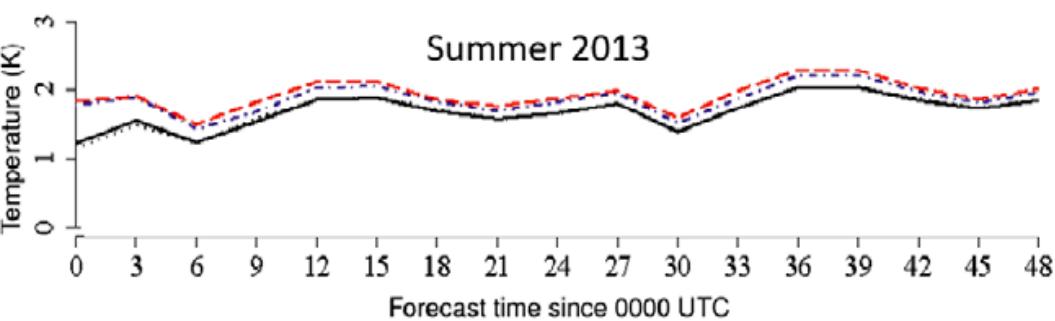
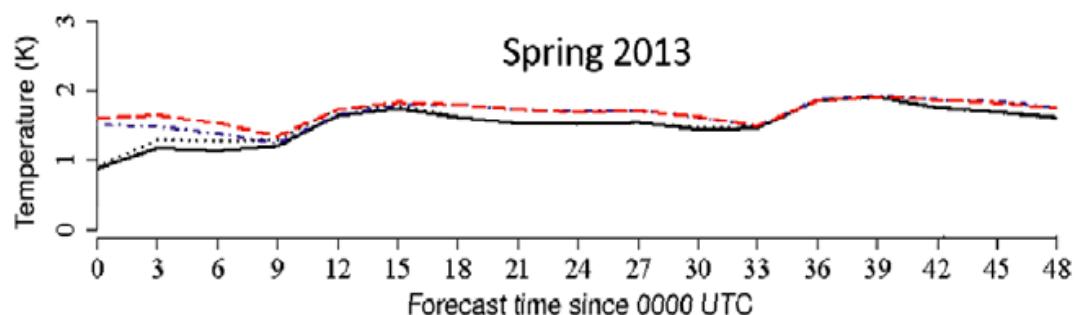
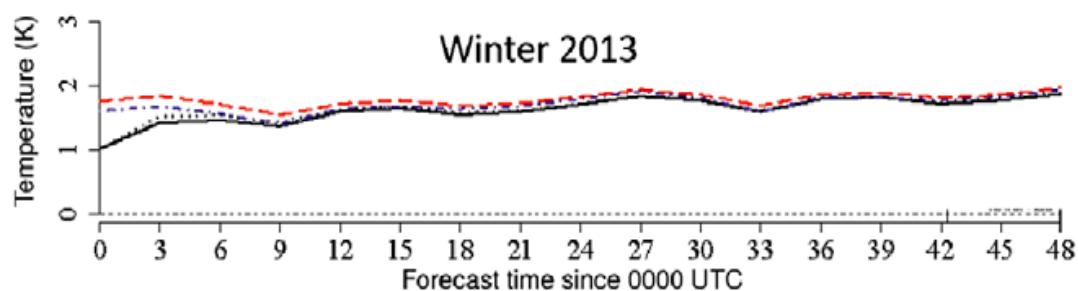


2m Relative Humidity BIAS

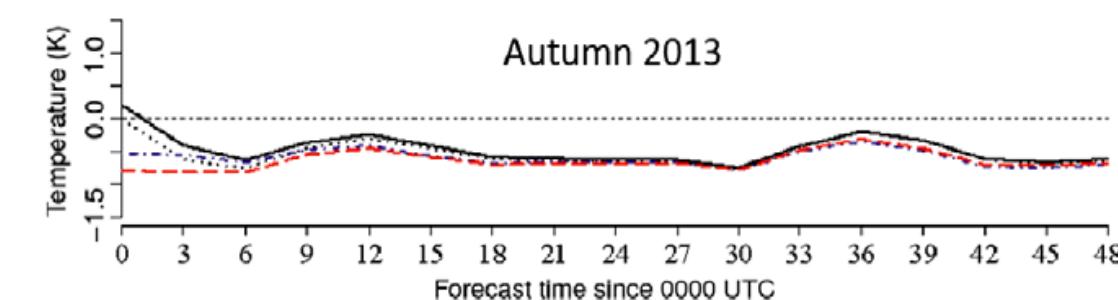
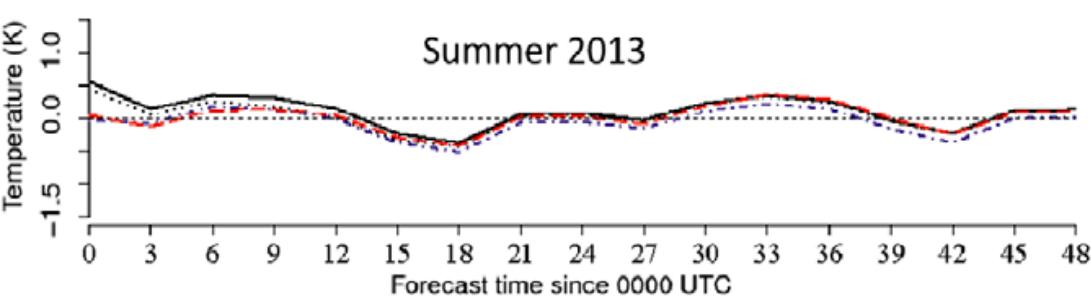
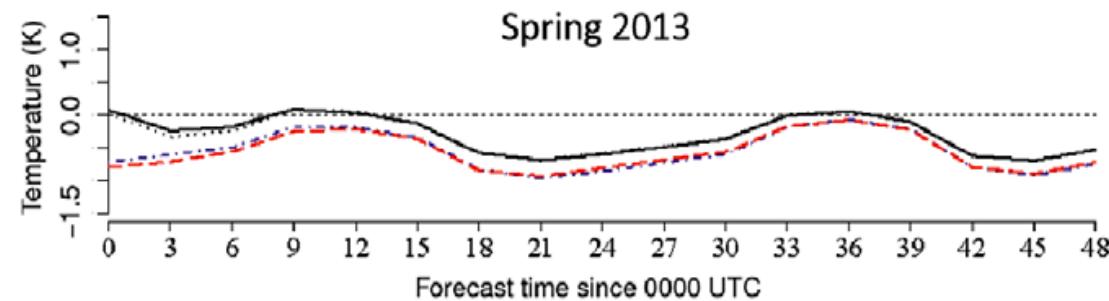
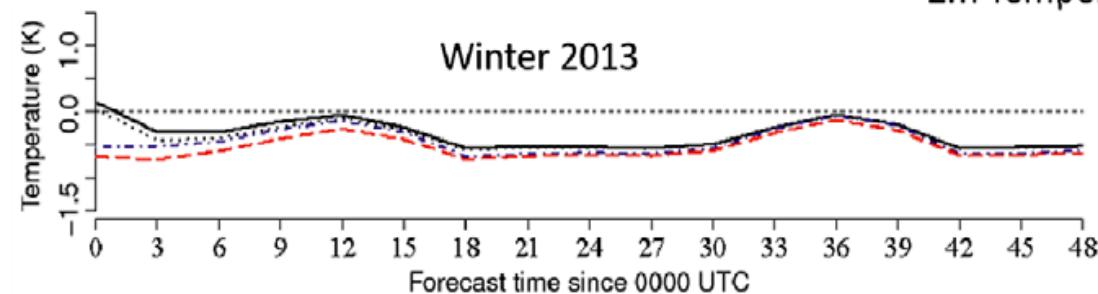


--- 3dVar+EKF
----- EKF
— Open Loop
..... 3dVar+Open Loop

2m Temperature RMSE



2m Temperature BIAS





Recent developments on land surface analysis for NWP at Météo France

Camille Birman, Jean-François Mahfouf, Yann Seity, Eric Bazile,
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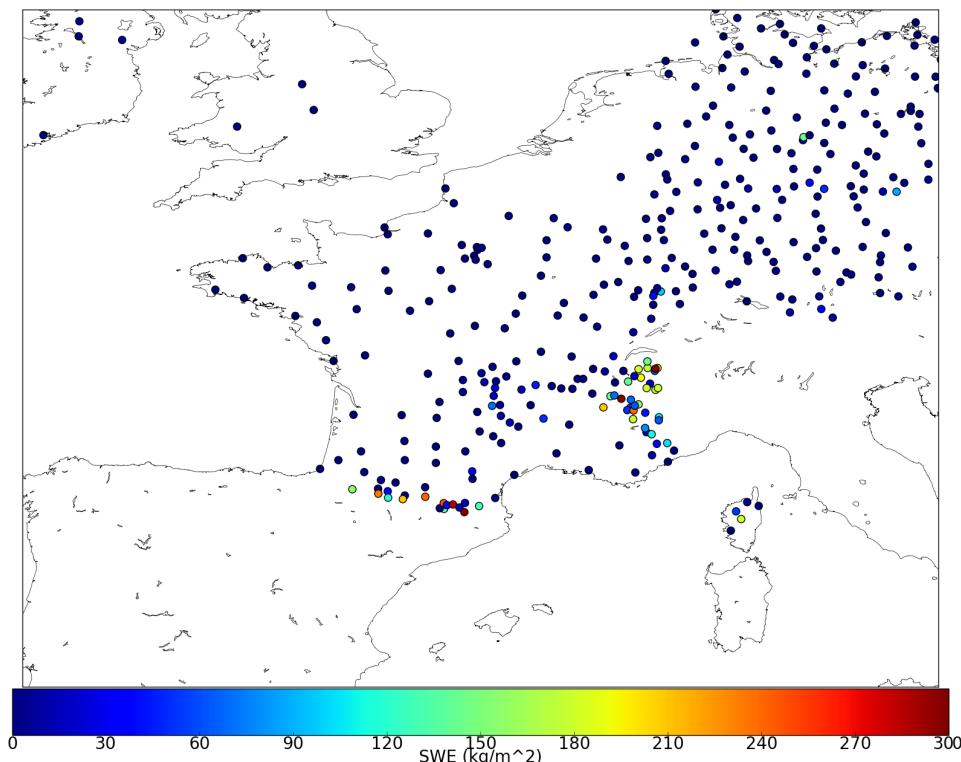
Joint ISWG & LSA-SAF Workshop, 26-28 June 2018, Lisbon, Portugal

Land surface assimilation system

- Météo France global model ARPEGE and limited area model AROME are coupled to the surface modelling platform SURFEX, which represents the exchanges between the atmosphere and the surface.
- Each grid box is divided into 4 tiles for nature, sea, lake and town fractions. The 4 tiles receive the same atmospheric forcing and the surface fluxes computed on each tile are averaged over the grid box.
- The 4 tiles have their own prognostic variables (and **analysed variables**):
 - Nature: ISBA-3L (3 layers) for NWP (Noilhan and Mahfouf, 1996; Boone et al., 1999), prognostic variables in the three superficial layers (liquid and solid fractions for soil water content, SWE for snow on the ground) → : T_s , T_2 , T_3 , w_g , w_2 , w_3 .
 - Town: TEB (Masson, 2000) → T_{roof} , T_{wall} , T_{road}
 - Lake → LST (FLake)
 - Sea → SST (CMO 1D)

Snow analysis

- Snow analysis over plains: necessary to correct for insufficient snow melt in the model
 - Case study February 2018

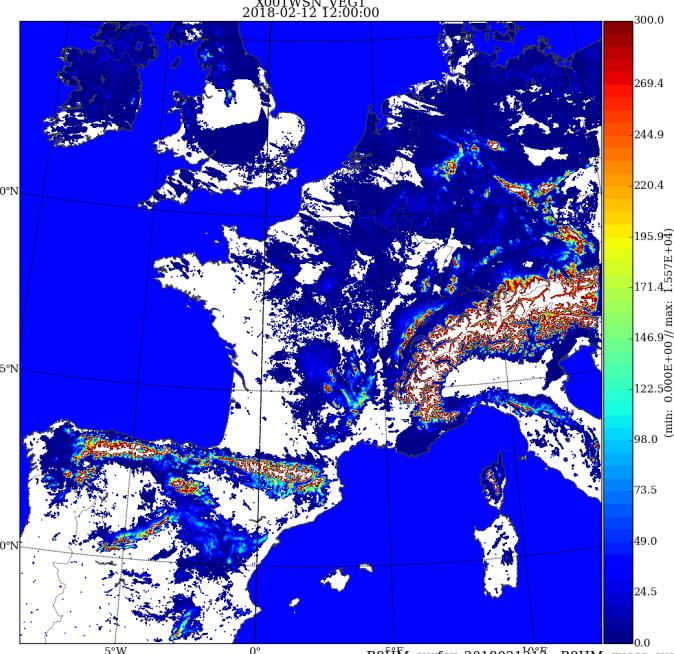


- Observations extracted over France
- Snow analysis performed using CANARI 2D OI
- Transfer of snow increments into SURFEX
- Prognostic variable: SWE → use of model density

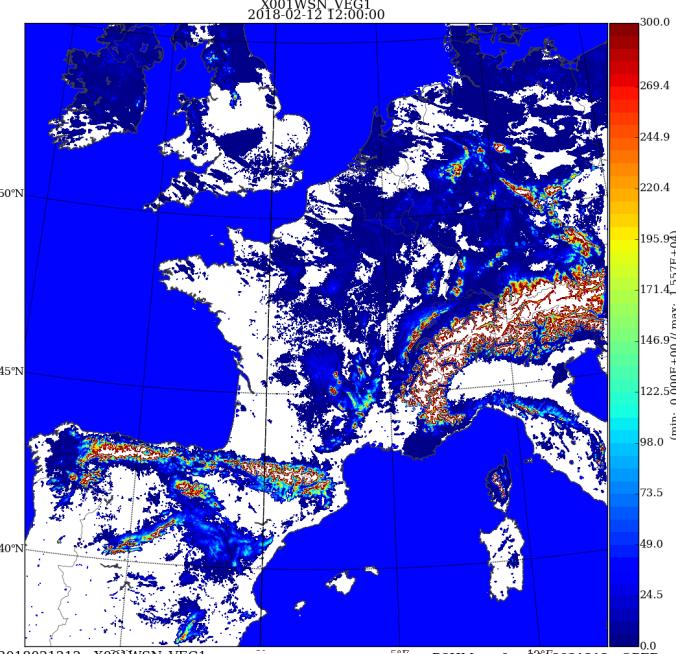
Snow observations over the AROME-France domain

Snow analysis: case study on 12th february 2018, 12:00

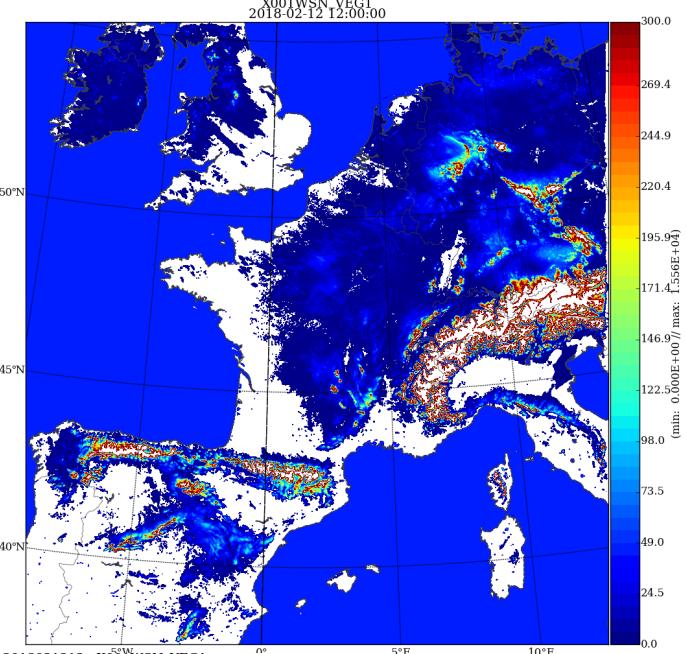
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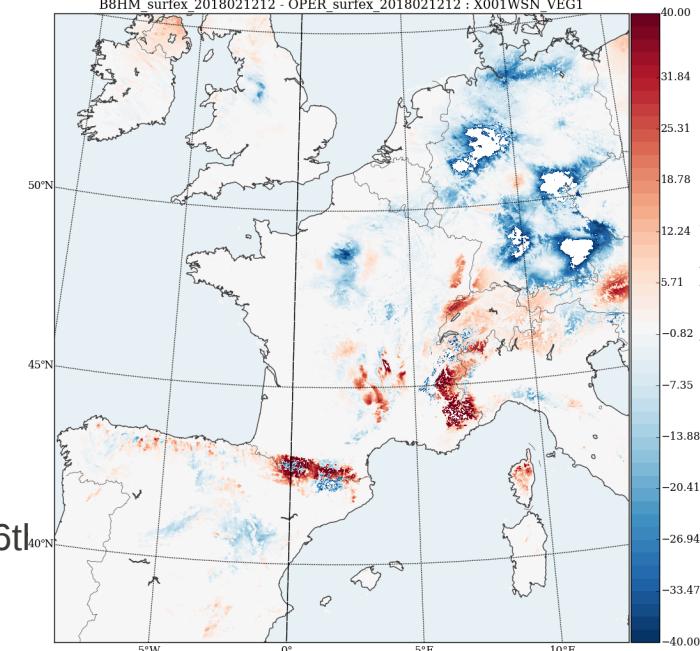
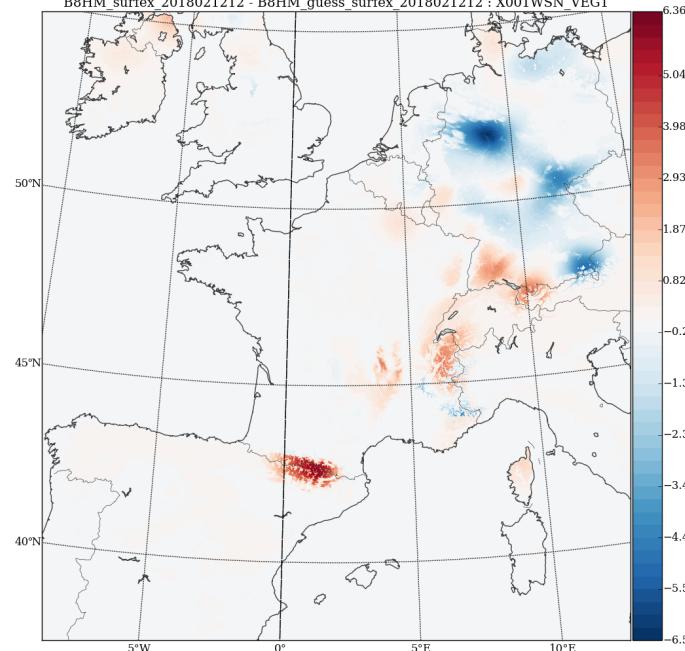
Analysis



Oper



Analysis Increment



Analysis - Oper

Snow analysis: case study on 12th february 2018, 12:00

Background



Analysis



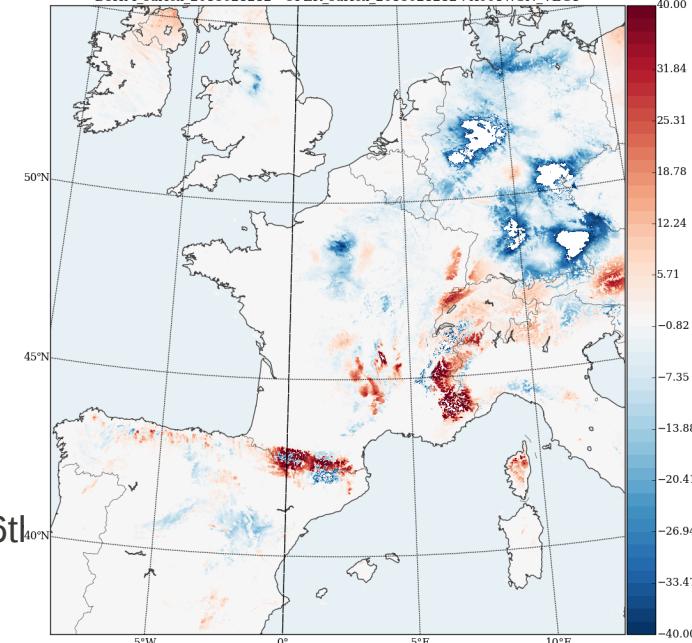
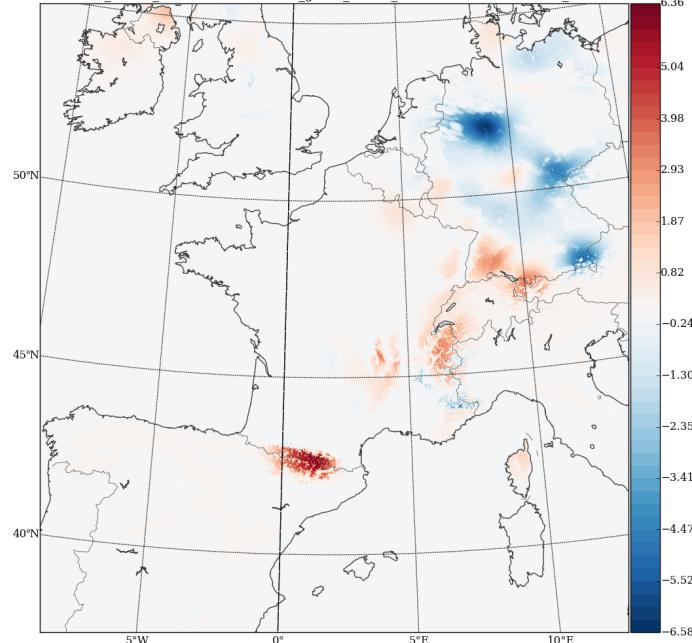
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- Slight improvement of near surface obs-guess (temperature and humidity).
- Future work on snow analysis:
 - Tuning of background and observation standard deviations and of structure functions (correlation lengths)
 - Use of satellite products of snow cover



Analysis Increment



Analysis - Oper

Diagnostics using ARPEGE EDA for surface analysis

- Optimal interpolation coefficients:
 - Covariances between the forecast errors of T_{2m} and RH_{2m} and the perturbed soil moisture values w_g and w_2 were obtained from a set of 100 single column model integrations where the initial soil moisture content was perturbed.

$$w^a - w^b = \alpha(T^o - T^b) + \beta(RH^o - RH^b)$$

$$\alpha = \frac{\sigma_w}{\Phi \sigma_T} \left\{ \left[1 + \left(\frac{\sigma_{RH}^o}{\sigma_{RH}^b} \right)^2 \right] \rho_{T,w} - \rho_{T,RH} \rho_{RH,w} \right\}$$

$$\beta = \frac{\sigma_w}{\Phi \sigma_{RH}} \left\{ \left[1 + \left(\frac{\sigma_T^o}{\sigma_T^b} \right)^2 \right] \rho_{RH,w} - \rho_{T,RH} \rho_{T,w} \right\}$$

$$\Phi = \left[1 + \left(\frac{\sigma_T^o}{\sigma_T^b} \right)^2 \right] \left[1 + \left(\frac{\sigma_{RH}^o}{\sigma_{RH}^b} \right)^2 \right] - \rho_{T,RH}^2$$

- Kalman filter approach:

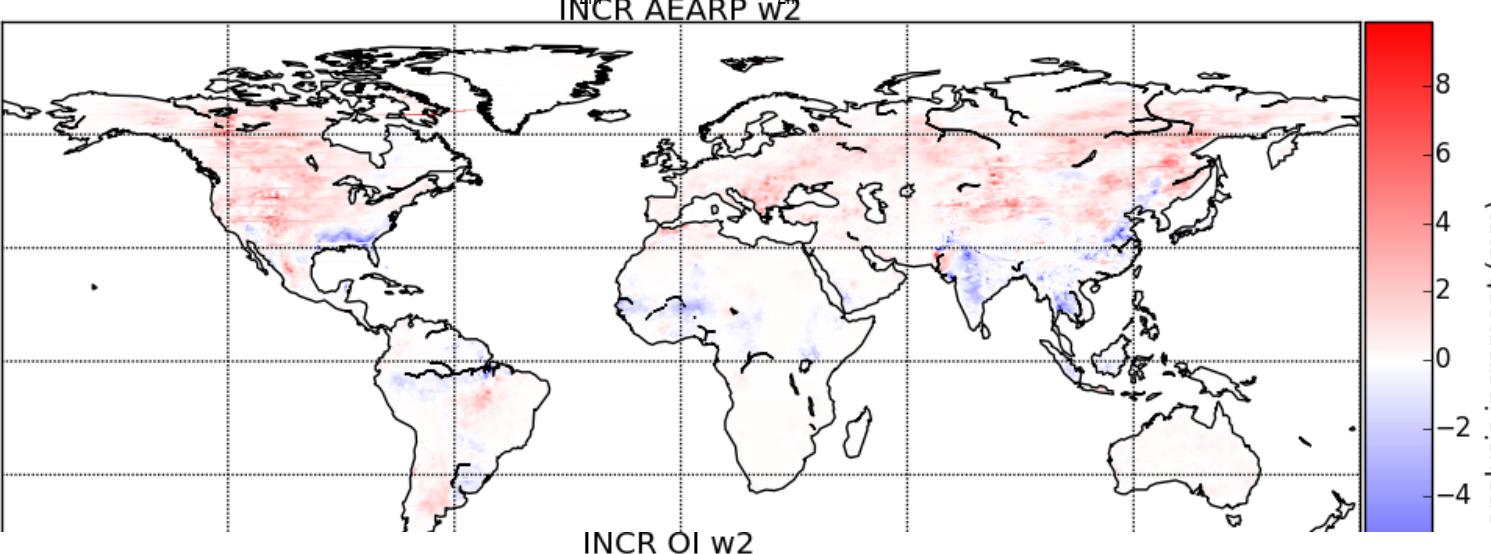
$$\Delta x = BH^T(HBH^T + R)^{-1}\Delta y$$

- Use of EDA (AEARP, 25 members) to compute standard deviations and covariances between surface variables and observed variables.

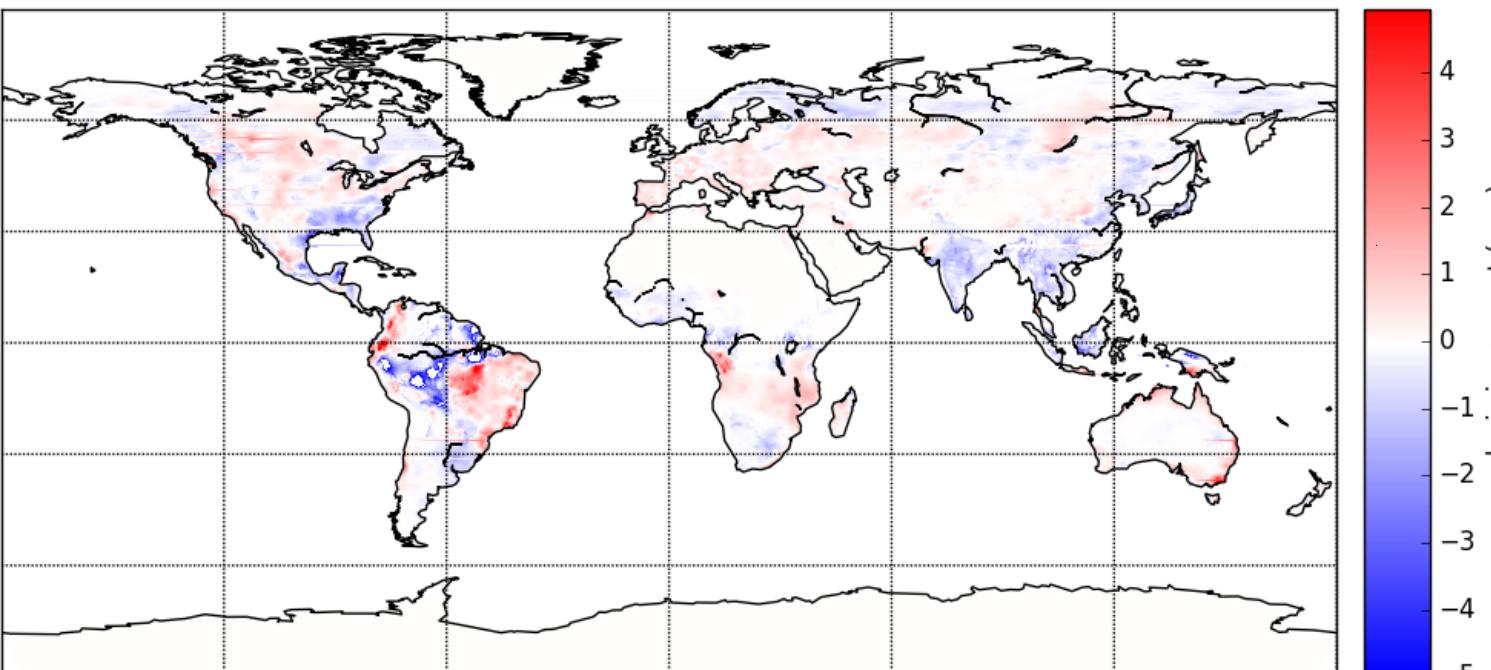
$$\Delta x = \text{cov}(x^b, y^b)[(\text{cov}(y^b, y^b) + \text{cov}(y^o, y^o)]^{-1} \Delta y$$

Diagnostics using ARPEGE EDA for surface analysis

- Analysis increments for soil variables and comparison with OI increments (operational T_s and RH_s increments)



Mean w2 increments during
August 2017 using EDA



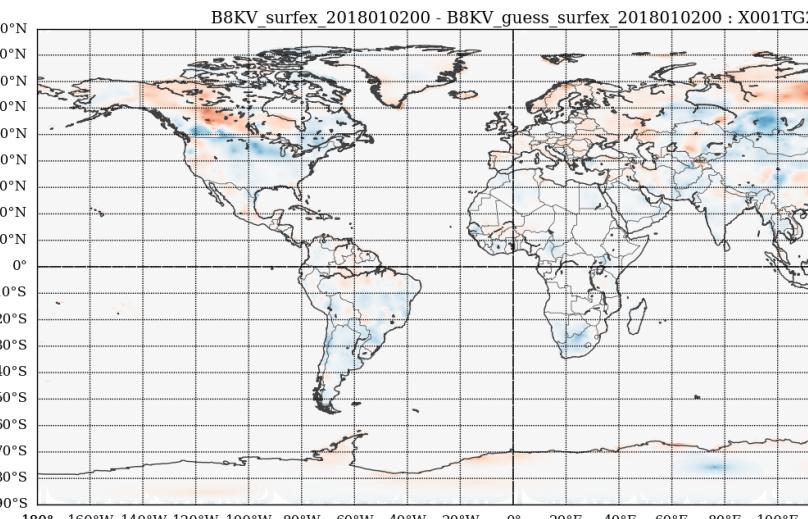
X 2

Mean w2 increments during
August 2017 using OI

Diagnostics using ARPEGE EDA for surface analysis

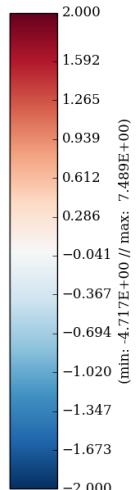
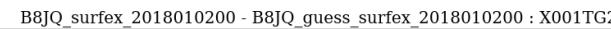
- Cycling of analysed surface fields computed from the EDA over assimilation cycles: increments in the 2nd layer of the soil at first analysis time (20180102H00)

OI increments

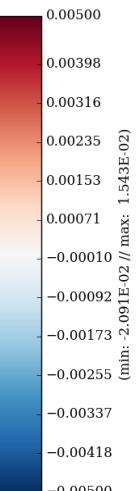
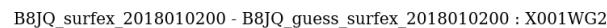
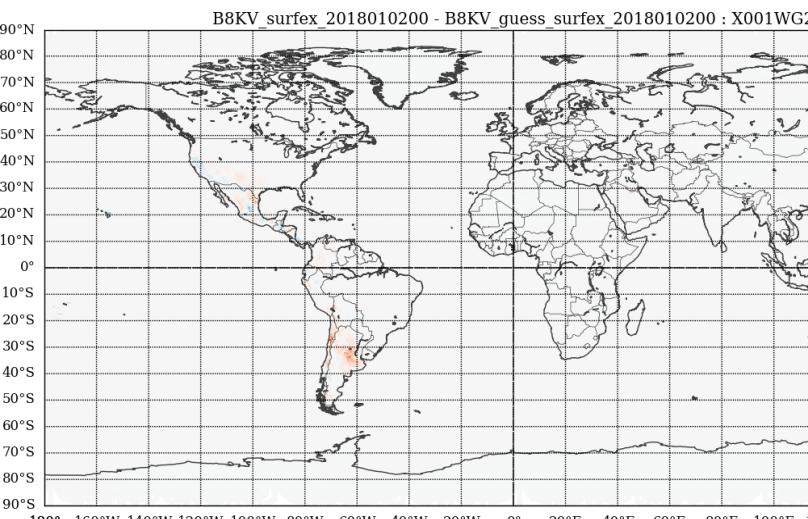


TG2

EDA increments



WG2



Conclusions and future work

- Analysis of surface parameters: snow depth, precipitation (2D optimal interpolation), ... (LAI); improvement of analysis techniques, in particular in areas of complex orography (MESCAN)
- Improvement of the land surface data assimilation system: ensemble methods (EnKF, particle filter...) and use of atmospheric ensembles produced by ensemble data assimilation systems (AEARP → global model ARPEGE, AEARO → limited area model AROME)
- Assimilation of satellite products, in particular for surface temperature (PhD Zied Sassi), for soil moisture (soil moisture product from ASCAT, and/or from L-band sensors SMOS/SMAP), for snow (snow cover products Nesdis-IMS/H-SAF product/Modis?) and for albedos (products from LSA-SAF)



HIRLAM Surface working week in Tromsø, Norway, May 2018



Conclusions from the HIRLAM Surface

working week in Tromsø, Norway, May 2018: Short term goals

In cy43h use SEKF with diffusion soil scheme and explicit snow scheme. First use conventional observations for assimilation (i.e. T2m and Rh2m) and then also satellite products. Later on cy43h will be updated with assimilation of sea-ice surface temperature in SICE but first this work will be done in the cy40h framework (required by external project).

Problems with crazy Jacobians is expected to be less with more advanced physics than with simple physics (Force-restore) but still we probably need some safety rules to avoid problematic behaviour.

We acknowledge problems with bad representation of LAI from ECOCLIMAP data base. During the discussion we conclude that STAEKF (technically implemented by Jelena in cy40h for EKF) is not going to solve the real problem since STAEKF will simply optimize LAI to fulfil good fit with observations (T2m, Rh2m). Such an optimisation may not necessarily lead to e.g. better evapotransportation. Thus, we conclude that it is probably more beneficial to first look for best available LAI climatology (e.g. ECOCLIMAP-SG) and then maybe complement with assimilation of a LAI satellite product (e.g. Balazs idea presented in Toulouse).

Conclusions from the HIRLAM Surface

working week in Tromsø, Norway, May 2018: Short term goals continuation

Snow assimilation work: Solve CANARI land/sea mask inconsistencies and use proper handling of snow density. (But see also CANARI slide later and gridPP slide...)

We suggest to not apply any assimilation for TEB right now: i) Observations representing town areas are missing and ii) as for FLake, town areas are smaller than nature areas.

Medium term goals for EKF

Regarding enhancements of above. Evolve B, check time scales and length of assim window + potential assimilation enhancements.

Include assimilation of FLake variables.

Conclusions from the HIRLAM Surface

working week in Tromsø, Norway, May 2018:

Medium / Longer term work EnKF

EnKF, assimilation of raw radiances (if available soil moisture, temperature and snow (smos)).

CMEM/HUT work with SSMIS, AMSR2 and MWRI and Sentinel 1 SAR data to be kept alive and coordinated.

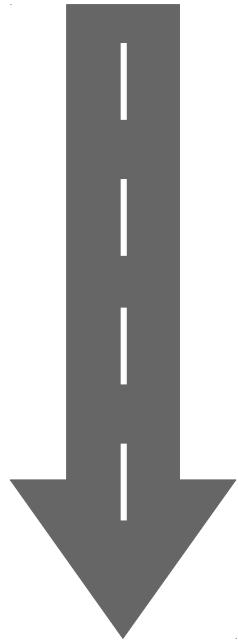
Pre-processing of satellite data

Clément will provide stand alone open-source tool based on cdf to be included in HARMONIE-AROME configuration.

Snow extent

Utilize development of assimilation of snow extent satellite product in the CARRA project and transfer this development to cy43h (based on e.g. H-SAF).

Summary road map for HIRLAM surface DA



by Tomas Landelius

Conclusions from the HIRLAM Surface

working week in Tromsø, Norway, May 2018:

Inconsistencies between land/sea mask (SURFIND.TERREMER(?) in climate/m* files) and SFX.FRAC_*(?) in climate Const.Clim.sfx cause problems in snow analysis.

Now first guess of T2m, Rh2m, and snow comes from grid-averaged values from previous cycle (e.g. ICMSHHARM+0003). So the idea is to transfer our preferred SURFEX fields:

Weighted new continuous fields of temperature and relative humidity, e.g.

NewT2m = (T2mopen_land where it exists or T2mfor where it exist or T2m_grid).

This new field needs to become available for CANARI and for SODA
(read_isban.F90).

For snow this field should be used DSN_T_ISBA, right?

The new fields should be provided to CANARI via ICMSHHARM+0003, the atmosphere.

Provide snow depth from SURFEX to CANARI to assimilate snow depth in CANARI which is then sent to SODA (this variable should also be send via ICMSHHARM+0003). Or give snow density to CANARI to replace the climatology snow density now used in CANARI.

This development has evolved fast (lead by Trygve) during the last few months and cy43h can now be setup in test mode at ECMWF using gridPP/TITAN for surface analysis (T2m, Rhm, snow) instead of CANARI. The analysis is read by SODA for OI or SEKF assimilation.

gridPP and TITAN are separate modules.

SODA is run as separate binary.

The implementation uses LSMixBC as a stand-alone program.

The snow update in CANARI now has an option LSWE to decide if the input values are SWE (CANARI) or snow depth (result of gridPP).

Hmm, these plans affect how to proceed with CANARI ideas mentioned before...

The HIRLAM plan is to seriously evaluate gridPP/TITAN/SODA as an alternative to CANARI. Why is gridPP/TITAN attractive for us?

We have “in-house” expertise of the system (developed for forecast post processing at MetNorway).

It is modern code structure (C++, python, R) which is more easy to develop/expand for us than CANARI.

It may be used offline (i.e. 2D gridPP/TITAN analysis + SODA + SURFEX)

Hamdi, R., Degrauwe, D., Duerinckx, A., Cedilnik, J., Costa, V., Dalkilic, T., Essaouini, K., Jerczynki, M., Kocaman, F., Kullmann, L., Mahfouf, J.-F., Meier, F., Sassi, M., Schneider, S., Váňa, F., and Termonia, P.: Evaluating the performance of SURFEXv5 as a new land surface scheme for the ALADINc36 and ALARO-0 models, *Geosci. Model Dev.* 7(1):23–39 • January 2014, doi: 10.5194/gmd-7-23-2014

Duerinckx, A., Hamdi, R., Mahfouf, J.-F., and Termonia, P.: Study of the Jacobian of an Extended Kalman Filter for soil analysis in SURFEXv5, *Geosci. Model Dev.*, 8:845–863 • March 2015 doi:10.5194/gmd-8-845-2015.

Duerinckx, A., Hamdi, R., Deckmyn, A., Djebbar, A., Mahfouf, J.-F. and Termonia, P. (2017), Combining an EKF soil analysis with a 3D-Var upper-air assimilation in a limited-area NWP model. *Q.J.R. Meteorol. Soc.*, 143: 2999–3013. doi: 10.1002/qj.3141.